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Discrimination of earthquakes and quarries in Kula District (Manisa, Turkey) and its vicinity by using linear discriminate function method and artificial neural networks

Aylin TAN[a*], Gündüz HORASAN[b], Doğan KALAFAT[c] and Ali GÜLBAĞ[d]

[a] *Sakarya University, Geophysical Engineering EABD, Institute of Science, Sakarya, Turkey*
[b] *Sakarya University, Faculty of Engineering, The Department of Geophysical Engineering, Sakarya, Turkey*
[c] *Boğaziçi University Kandilli Observatory and Earthquake Research Institute, , İstanbul, Turkey*
[d] *Sakarya University, Faculty of Computer and Information Sciences, The Department of Computer Engineering, Sakarya, Turkey*

Research Article

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ABSTRACT

In this study, seismic events in Kula district (Manisa, Turkey) and its vicinity have been investigated and then natural and artificial seismic activities are discriminated. Total of 77 digital vertical component velocity seismograms of seismic activities with $M_L \leq 3.5$ magnitude from seismic activity catalogs between 2009 to 2014 recorded by Manisa Kula (KULA) broadband station operated by Bogazici University, Kandilli Observatory and Earthquake Resarch Institute Regional Earthquake-Tsunami Monitoring Center (RETMC) were used in this study. The maximum S-wave and maximum P-wave amplitude ratio (Ratio) of vertical component velocity seismograms and power ratio for (1 and 12 sec.) (Complexity-C) and total signal duration (Duration) of the waveform were calculated. The earthquakes and the quarry blasts have been discriminated using linear discriminant function (LDF) and Back Propagation-Feed Forward Neural Networks (BPNNs) that is one of the learning algorithms at the artificial neural networks (ANNs) methods taking correlation between these parameters into consideration. 39 (51%) of the 77 seismic activities were identified as quarry blasts and 38 (49%) of them as earthquakes LDF and ANNs methods have been applied together for the first time for Ratio-C, Ratio-logS and Ratio-duration parameter pairs with the data of Manisa and surroundings, and earthquakes and quarry blasts have been distinguished from each other. LDF and ANNs methods were compared for each pair of parameters. Both of two methods are successful but the ANNs method has higher accuracy percentage values than LDF method when there is sufficient number of data. The accuracy percentages are different for a pair of Ratio versus C, for a pair of Ratio versus logS and for a pair of Ratio versus duration, respectively.

1. Introduction

While seismic recorders record seismic events in a region, they also record artificially induced seismic activities such as mines and quarries along with earthquakes of natural origin. Taking these events together in earthquake catalogs may cause errors in scientific studies. Therefore, problems may occur in the preparation of earthquake catalogs. In order to determine the real seismic activity in the study areas, earthquakes and quarry blasts should be distinguished from each other. For this differentiation process, it may not be sufficient to use the location, distance and time of occurrence parameters of the area where the blast

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**Corresponding author: Aylin TAN, aylin.tan@ogr.sakarya.edu.tr*

is made. In such a case, the waveform of the seismic event should also be examined (Horasan et al., 2006).

So far, about to be distinguished from each other by using different methods of earthquakes and quarry blasts in the world and in Turkey has been much scientific research. Baumgardt and Young (1990) studied the separation of earthquakes and blasts using the Pn / Sn and Pn / Lg ratio method in Western Norway. Dowla et al. (1990), similar to the LDF method, used the ANNs method to distinguish between natural earthquakes and underground nuclear blasts in the United States. Wüster (1993) distinguished earthquakes and explosions with Lg / Pg and Lg / Rg ratio methods in Vogland (Germany-Czechia) region. Horasan et al. (2006; 2009) distinguished earthquakes and explosions in İstanbul with the LDF method. Deniz (2010) in Bursa, Öğütcü et al. (2010) in Konya and Kartal (2010) in Trabzon made the separation analysis of earthquake and quarry blast with Linear Discrimination Method. Kalafat (2010) has distinguished earthquakes and quarry blast with extraction methods in the immediate vicinity of Turkey. Kekovalı et al. (2010; 2012*a*) have characterized the seismic events with the help of the LDF process in Turkey. Küyük et al. (2011*a*) conducted earthquake and blast separation analysis in İstanbul using LDF, Quadratic Discrimination Function (QDF), Diaquadratic Discrimination Function (DDF) and Mahalabonis Discrimination Function (MDF) methods. Yılmaz et al. (2013) using the LDF methods have characterized earthquakes and quarry blasts in the Eastern Black Sea region of Turkey. Budakoğlu and Horasan (2018) distinguished earthquakes and explosions in Sakarya province using the LDF method. Yavuz et al. (2018) classified the seismic events in Armutlu by using LDF and QDF methods. Ceydilek and Horasan (2019) have distinguished seismic activities in and around Manisa using the LDF method. In addition to these methods, various ANNs algorithms are used to distinguish earthquakes and blasts from each other. Gitterman et al. (1998) tried to distinguish natural and artificial earthquakes in the Middle East Region from each other by using LDF and ANNs methods. Ursino et al. (2001) developed a direct method in an automated consulting classification to distinguish between earthquakes and blasts in the southeast of Sicily. Del Pezzo et al. (2003) developed a classification in Italy using a consulting learning algorithm based on multiple neural network (MCN) structure. Küyük et al. (2009) tried to distinguish natural and artificially induced earthquakes in the İstanbul region using the reaction surface, multivariate regression and Learning Vector Quantization (LVQ) methods. Küyük et al. (2010; 2011*b*) tried to distinguish earthquakes and explosions from each other with the Self-Organizing Map (SOM) method in İstanbul. Yıldırım et al. (2011) studied the separation of natural and artificial earthquakes using Feedback ANNs (BPNNs), Matched Neural Fuzzy Logic Inference Systems (ANFIS) and Probabilistic Neural Networks (PNN) algorithms. Kekovalı et al. (2012*b*) made a segregation analysis with data mining application in Tuncbilek-Kutahya region. Kundu et al. (2012) used seismograms to distinguish between local earthquakes and chemical explosions recorded on the Gauribidanur Road in India, using an ANNs method known as the "Back Propagation Network", known as the Multilayer Artificial Neural Network (MLP). Küyük et al. (2012) used K-mean, Gaussian Mixing Model (GMM), LDF and Quadratic Discrimination Function (QDF) methods and ANNs algorithms to distinguish earthquakes and explosions with high accuracy in İstanbul. Hammer et al. (2013) classified seismic events, which they divided into three classes as earthquakes, blasts and rock falls, with the help of ANNs method according to the records in the Swiss Alps. Kortström et al. (2016) distinguished natural and artificial earthquakes in Finland using the Support Vector Machine (SVM) method. Mousavi et al. (2016) used a machine learning technique to investigate the relationship between the seismic properties and the location of the focal centers where the events belong to the signals recorded in the time, frequency and time-frequency domain in the United States. Kaftan et al. (2017) have calculated the monthly frequency of earthquakes in western Turkey by using multilayer neural network (MLP), Radial Basic Function ANNs (RBFYS), and compatible Neural Fuzzy Logic Inference Systems (ANFIS) methods. In addition, many researchers have studied using LDF and ANNs methods together or separately (Çetin et al., 2006; Gülbağ, 2006; Üstün, 2009*a*, *b*, *c*, Üstün and Yıldız, 2009; Küyük et al., 2009; Yıldırım et al., 2011; Çayakan, 2012, Yıldırım, 2013).

In this study, the distribution of seismic activities in and around Manisa and the location of the KULA station are shown in figure 1. GMT program was used for drawing the maps (Wessel and Smith, 1995). Most

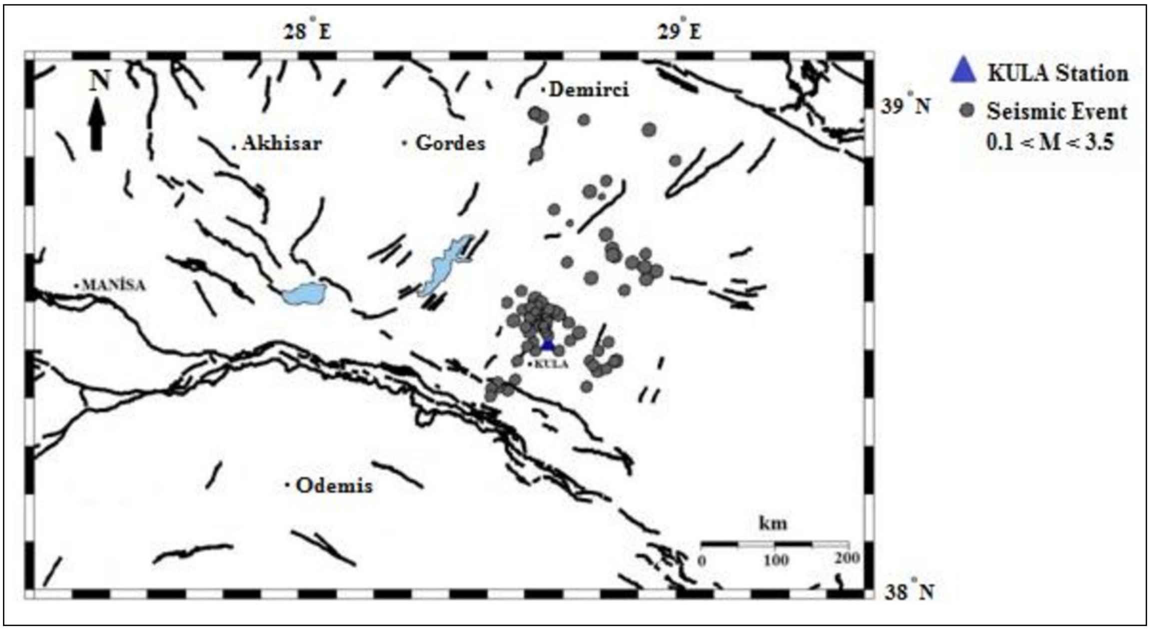

Figure 1- The distribution of seismic events with $M_L \leq 3.5$ that occurred between May 2009 and February 2014 in the study area and the location of the KULA station (KRDAE, BDTİM). The faults were taken from Şaroğlu et al. (1992) and Emre et al. (2013).

of the artificially sourced blasts recorded in the study area originate from the mines and quarries operated in the region to obtain mining and construction materials. The aim of this study is to distinguish the blasts in Kula (Manisa) and its surroundings from earthquakes using LDF and ANNs methods, using the numerical vertical component velocity seismograms recorded at the KULA station between May 2009 and February 2014. Thus, correct information can be used in seismicity studies. In addition, reliable data will be obtained in the creation of earthquake catalogs in earthquake research centers. Thus, contribution will be made to the preparation of catalogs containing natural seismic activity in the region. In this case, the amount of error will be significantly reduced in the determination of active faults, seismic risk studies and studies involving seismic activity in the region.

2. Data Acquisition

In this study, the numerical vertical component velocity seismograms of 77 seismic events with magnitude $M_L \leq 3.5$ recorded at the KULA station between May 2009 and February 2014 in the region between latitudes 38°-39.30°N and longitudes 28° -29.30°E were examined. The data were taken from Bogazici University Kandilli Observatory and Earthquake Research Institute (KRDAE, BDTİM). The Manisa-Kula (KULA) station, which is broadband, was established on January 15, 2007 (Figure 1). Digital data were recorded at 50 samples per second.

When the distribution of the total number of seismic activities in the study area and only the number of earthquake activities according to the occurrence time is plotted, the histogram obtained is shown in figure 2.

While earthquakes and blasts are distinguished from each other, it is not sufficient to compare them only by day and time. Therefore, vertical component velocity seismogram and spectrum are used since these show significant differences in distinguishing quarry blast and earthquake data from each other. When the blast seismogram was examined, it was seen that the P-wave amplitude was higher than that of the earthquake. It is also observed that the direction of the first movement on the signal is upwards (Figure 3). The frequency contents of seismic events used in this study are shown in figure 4. Spectral corrugation is observed on the detonation spectrum when looking at figure 4. This is due to the delayed arrival of wave energy to the station during quarry blasts. Although the waveform and spectrum are used to visually distinguish earthquakes and explosions, the parameters obtained from them are compared in

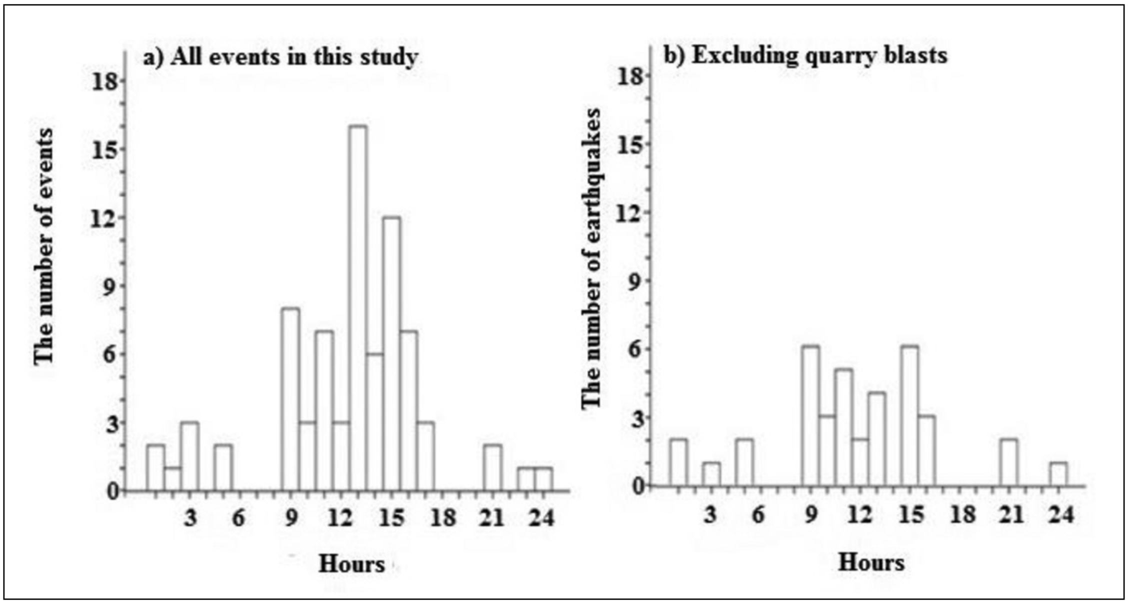

Figure 2- The distribution of the number of seismic activities (occurrences) in each hour (UTC) between 38-39.30˚N and 28-29.30˚E, May 2009-February 2014 in the study area. a) During the day, maximum activity is observed at 13:00 and a large increase in the number of events is observed between 13:00 and 15:00, b) Distribution of the number of earthquakes after the events determined as quarry blast as a result of this study were eliminated.

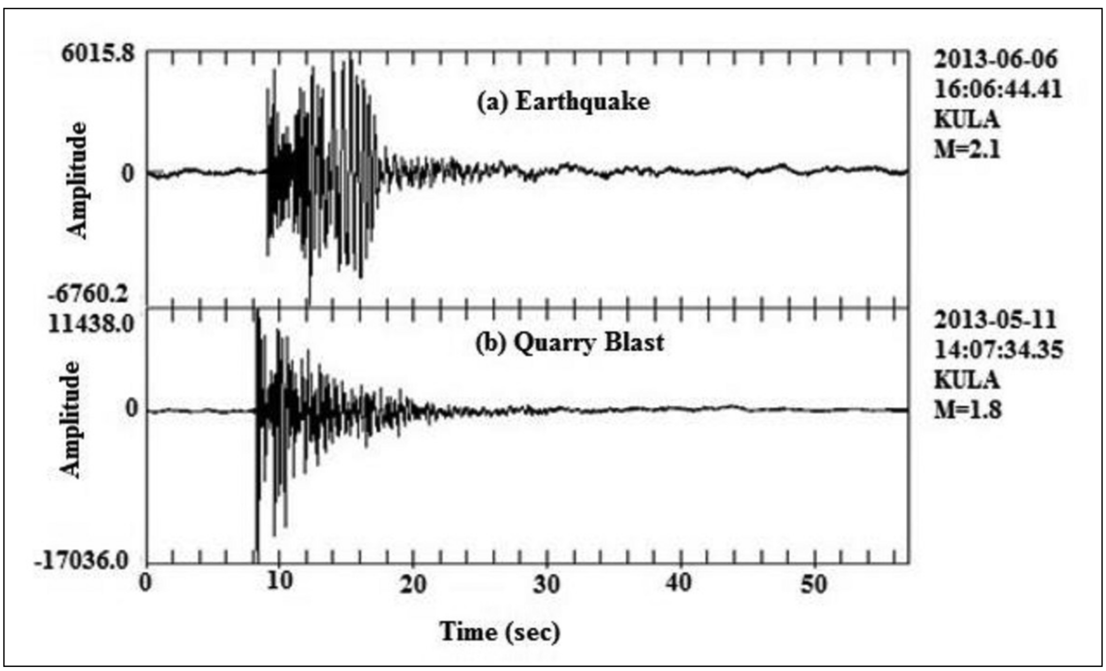

Figure 3- Vertical component velocity seismogram recorded at KULA station; (a) Earthquake, (b) Quarry Blast.

practice. Therefore, different parameter pairs will be calculated and the distribution between these parameter pairs will be examined.

In order to obtain the parameters, the ratio of the maximum S-wave amplitude to the maximum P-wave amplitude of the vertical component velocity seismograms, the ratio of their complexities (Complexity-C) and the total signal duration of the waveform were calculated. These parameters are described below.

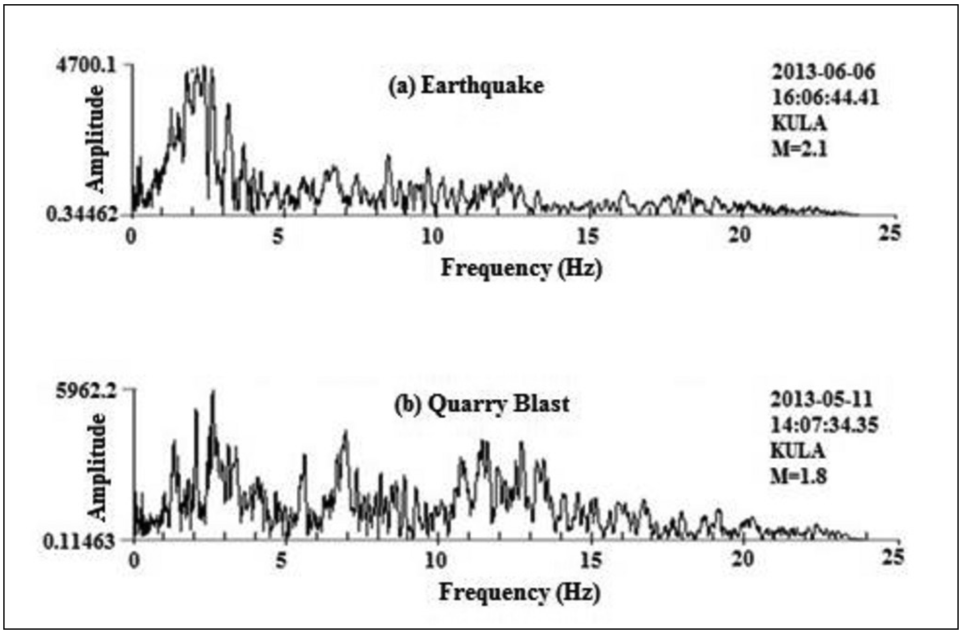

Figure 4- Normalized amplitude spectrum of the signal recorded at the KULA station; (a) Earthquake, (b) Quarry Blast.

2.1. Calculating the Ratio (C) of the Powers of the Two Time Windows Defined in the Seismogram

The ratios of the vertical component velocity seismograms for each seismic event, i.e. the complexity (C), are calculated according to the equation 1 below (Arai and Yosida, 2004).

$$C=\int_{t_1}^{t_2} S^2(t)dt / \int_{t_0}^{t_1} S^2(t)dt \quad (1)$$

where

t_0 is expressed as arrival time of the P wave

t_1 and t_2 are expressed as time window range.

In this study, t_1 and t_2 values are taken as 1 and 12 seconds for the KULA station, respectively. The 1-second time window is based on the P wave signal. The second time window is determined by considering the time difference ts-tp of events at different distances used in the study.

2.2. Calculation of Amplitude Ratio (S / P Maximum Amplitude Ratio, Ratio)

After defining the maximum P-wave and maximum S-wave amplitudes from the vertical component velocity seismograms of earthquakes and blasts, the S / P maximum amplitude ratio (Ratio) for seismic events was calculated.

2.3. Defining Total Signal Duration (Duration)

The duration parameter is determined from the duration of the signal. After these parameters were calculated, normalization process as [-1, +1] was applied to the data set. The reason for this is to provide ease of establishing relationships between parameters. According to Patro and Sahu (2015), normalization process is shown in equation 2:

$$A^* = \left(\frac{\text{(A-Maximum value of A)}}{\text{(Maximum value of A)-(Minimum value of A)}}\right) * (E-D) + D \quad (2)$$

A*: Maximum-Minimum normalized data

[D, E]: Predefined border

A: Original data set

For [-1, +1]; D = -1 and E = +1

After the data set was normalized, LDF and ANNs methods were applied to distinguish earthquakes and explosions using the parameters described above.

3. Methods

3.1. Linear Discrimination Function (LDF) Method

LDF method is used to distinguish different data groups from each other (Fisher 1936). Linear

Discrimination Functions are generally shown in equation 3 in a simplified form:

$$F_{LDF} = a + b_1X_1 + b_2X_2 + \ldots + b_mX_m \quad (3)$$

a: Constant number

$b_1, \ldots, b_m$: Regression coefficients

$X_1, \ldots, X_m$: normalized values of discrimination parameters.

Using the vertical component velocity seismograms of the KULA station in the study area, the ratio of the maximum S-wave amplitude to the maximum P-wave amplitude is plotted against the ratio (C) of the powers of the two time windows defined in the seismogram. In this graph (Figure 5a) earthquakes and explosions are distinguished from each other by linear discrimination function. For this, Statistical Package Program of Social Sciences (SPSS, 2005) was used.

For the LDF method, the amplitude ratio versus logS and signal duration graphs are shown in figure 5b, c. The accuracy percentage results and diagnoses obtained by the LDF method for each parameter pair (Ratio-C, Ratio-logS and Ratio-Duration) of the data set belonging to KULA are shown in table 1.

3.2. Artificial Neural Networks (ANNs) Method

Seismic events in the region were also distinguished from each other by the method called Artificial Neural Networks (ANNs). According to Gülbağ (2006), the

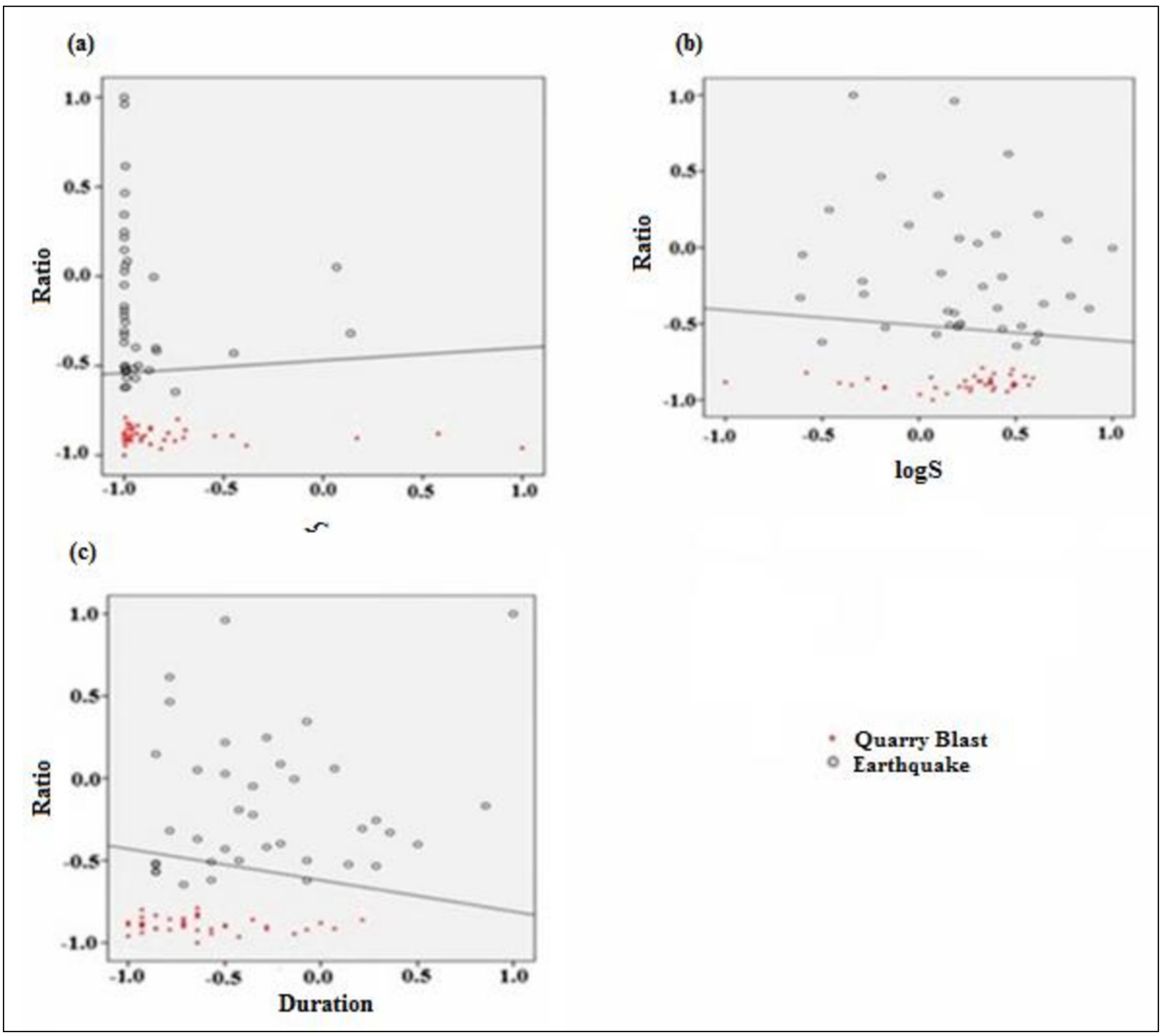

Figure 5- Percent accuracy values obtained by LDF method according to parameter pairs for KULA data. (a) 94% for Ratio-C parameter pair; (b) 93.5% for ratio-logS parameter pair and (c) 89.6% for Ratio-Duration parameter pair.

Table 1- Distinguishing seismic events recorded at Kula station by LDF method. Criteria: 1: The accuracy percentage obtained for the Ratio-C parameter pair is 94%; 2: The accuracy percentage obtained for the ratio-logS parameter pair is 93.5% and 3: The accuracy percentage obtained for the Ratio-Duration parameter pair is 89.6%.

Criteria		Classification	Predicted group		Total
			Quarry Blast (QB)	Earthquake (E)	
1	Total Number	Quarry Blast	39	0	39
		Earthquake	5	33	38
	%	Quarry Blast	100	0	100
		Earthquake	13.2	86.8	100
2	Total Number	Quarry Blast	39	0	39
		Earthquake	5	33	38
	%	Quarry Blast	100	0	100
		Earthquake	13.2	86.8	100
3	Total Number	Quarry Blast	39	0	39
		Earthquake	8	30	38
	%	Quarry Blast	100	0	100
		Earthquake	21.1	78.9	100

human brain is a complex system consisting of nerve cells called neurons and the connections between them. Neurons communicate with each other through these connections. ANNs learning algorithms are inspired by human nervous system architecture. According to Yıldırım (2013), after determining the problem, while deciding to train the network; "Unsupervised learning" with only inputs and "supervised learning" with input-output pairs are taken into account according to the type of learning. Choosing the learning algorithm that will train the artificial neural network is very important. There are different learning algorithms such as ANFIS (Compatible Neural Fuzzy Logic Inference Systems), LVQ (Learning Vector Quantization), BFNNs (Feedback ANNs), PNN (Probabilistic ANNs), BPNNs (Backpropagation - Feed Forward ANNs), MLP (Multi Layered ANNs) and RBFYSA (Radial Basic Function ANNs) (Çetin et al., 2006; Gülbağ, 2006; Küyük et al., 2009; Üstün, 2009a, b, c; Üstün and Yıldız, 2009; Yıldırım et al., 2011; Çayakan, 2012; Yıldırım, 2013; Kaftan et al., 2017).

3.2.1. Back Propagation - Feed Forward Anns (Bpnns) Learning Algorithm

The learning algorithm used in this study was selected as Back Propagation-Feed Forward Neural Networks. The reason for this is that it is a solution to our problem and it is a reliable learning algorithm because it is widely used (Çetin et al., 2006; Gülbağ, 2006; Küyük et al., 2009; Üstün, 2009a, b, c; Üstün and Yıldız, 2009; Yıldırım et al., 2011; Çayakan, 2012; Yıldırım, 2013; Kaftan et al., 2017). This algorithm got this name because it tries to reduce errors backwards, ie from output to input (Çetin et al., 2006). This network structure is simple and although it gives a lot of correct results, it is a slow learning algorithm (Çayakan, 2012). The weights according to the amount of error between the desired output and the actual value are arranged with this learning algorithm to obtain the most appropriate output values (Yıldırım, 2013). After deciding on the learning algorithm, the network topology, ie architecture, of the artificial neural network was created. In general, the elements of the network topology are shown as in figure 6 (Gülbağ, 2006).

After the learning algorithm is determined according to the type of the problem, a network structure in the form of input layer, hidden layer and output layer is created. In general, the elements of the network topology are defined as inputs, outputs, weights, sum function, activation (Transfer) function (Rumelhart et al., 1986). Entries are information entering the cell from other cells or external environments, and enter the cell over the weights on the connections. The weights (w) determine the effect of the relevant input on the cell (Figure 6).

In this study, the artificial neural network represents the feed forward artificial neural network according to its structure and the counseling learning according to the learning algorithm. In the artificial neural network model that we have determined

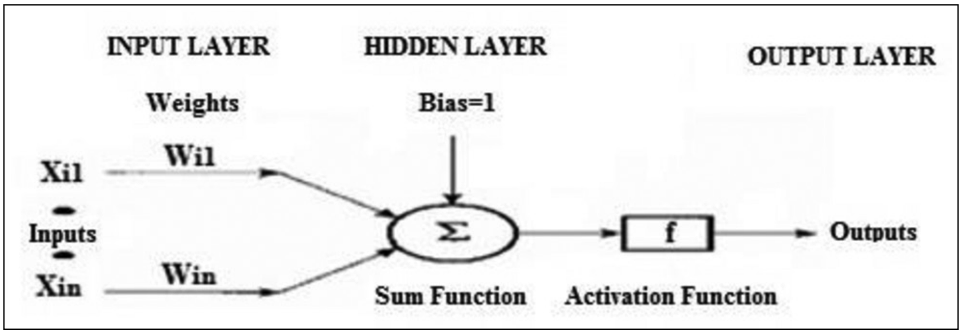

Figure 6 - Elements of network topology (Gülbağ, 2006).

according to our problem, in the learning algorithm applied to the network topology we have created, the artificial neural network is given both input values and output values that must be produced in response to this input, consulting learning has been applied according to the learning algorithm. In addition, the parameter pair to be tested was used as the input parameter to the system, and the diagnosis as the output parameter. These parameter pairs are, respectively, the ratio of the maximum S wave amplitude to the maximum P wave amplitude (Ratio) and the power ratio (C) (Figure 7a), the ratio of the maximum S wave amplitude to the maximum P wave amplitude (Ratio) and the logarithm of the maximum S wave amplitude (log S) (Figure 7b) and the amplitude ratio (Ratio) of the maximum S wave to the maximum P wave and the total signal duration (Duration) of the waveform (Figure 7c).

3.2.2. Choosing the Number of Neurons (Nn)

While creating an artificial neural network topology, the choice of the number of neurons (Nn) is of great importance on the learning process (Gülbağ, 2006). The same researcher emphasized that the number of neurons is of great importance to achieve generalization. In general, a very small number of neurons normally causes less learning, ie poor learning, while an excessive number of neurons indicates that it can lead to over learning, or memorization. The problem of finding an optimal network architecture complicates the solution because each unique architecture has its own unique set of suitable parameters (Kermani et al., 2005). The choice of the number of neurons is very important in ANNs as it is one of the determining factors in distinguishing data groups. Using less than necessary number of neurons in the hidden layer results in less sensitive output than input data. Likewise, if more neurons are used than necessary, difficulties arise in processing new types of data groups within the same network (Çetin et al., 2006). While creating the structure of the ANNs, the number of neurons (Nn) is decided by trial and error method (Yıldırım, 2013; Kaftan et al., 2017).

At the stage of determining the appropriate model, the number of neurons in a certain range, with a certain amount of increase is given to the algorithm, and then the artificial neural network model is selected with the highest percentage of accuracy (Gülbağ, 2006). In the literature, researchers have determined the number of neurons in increasing values with different number intervals. Gülbağ (2006) created ANNs models with the number of neurons increasing by 10 between 0 and 100. Küyük et al. (2009) compared the models with an increasing number of intermittent neurons increasing by 1 from 1 to 20 in their study and created an artificial neural network model with 5 neurons with the least error, that is, the best result. Yıldırım (2013) created ANNs topology with the number of neurons increasing by 2 between 0 and 22. Kaftan et al. (2017) created their own network network models by using the number of neurons increasing by 1 between 1 and 6.

In this study, before the application of the ANNs Method, the models with the number of neurons in increasing intervals of 5 from 1 to 25 were compared. Then, the number of neurons (Nn = 10 for Ratio-C, Nn = 5 for Ratio-log S, Nn = 5 for Ratio-Duration) was determined for both parameter groups that were different from each other. An artificial neural network model has been created with the least error, that is, the number of neurons that give the best result. Training continued until the determination coefficient (R^2) approached 1. When the value of the determination coefficient (R^2) approaches 1, it actually means the

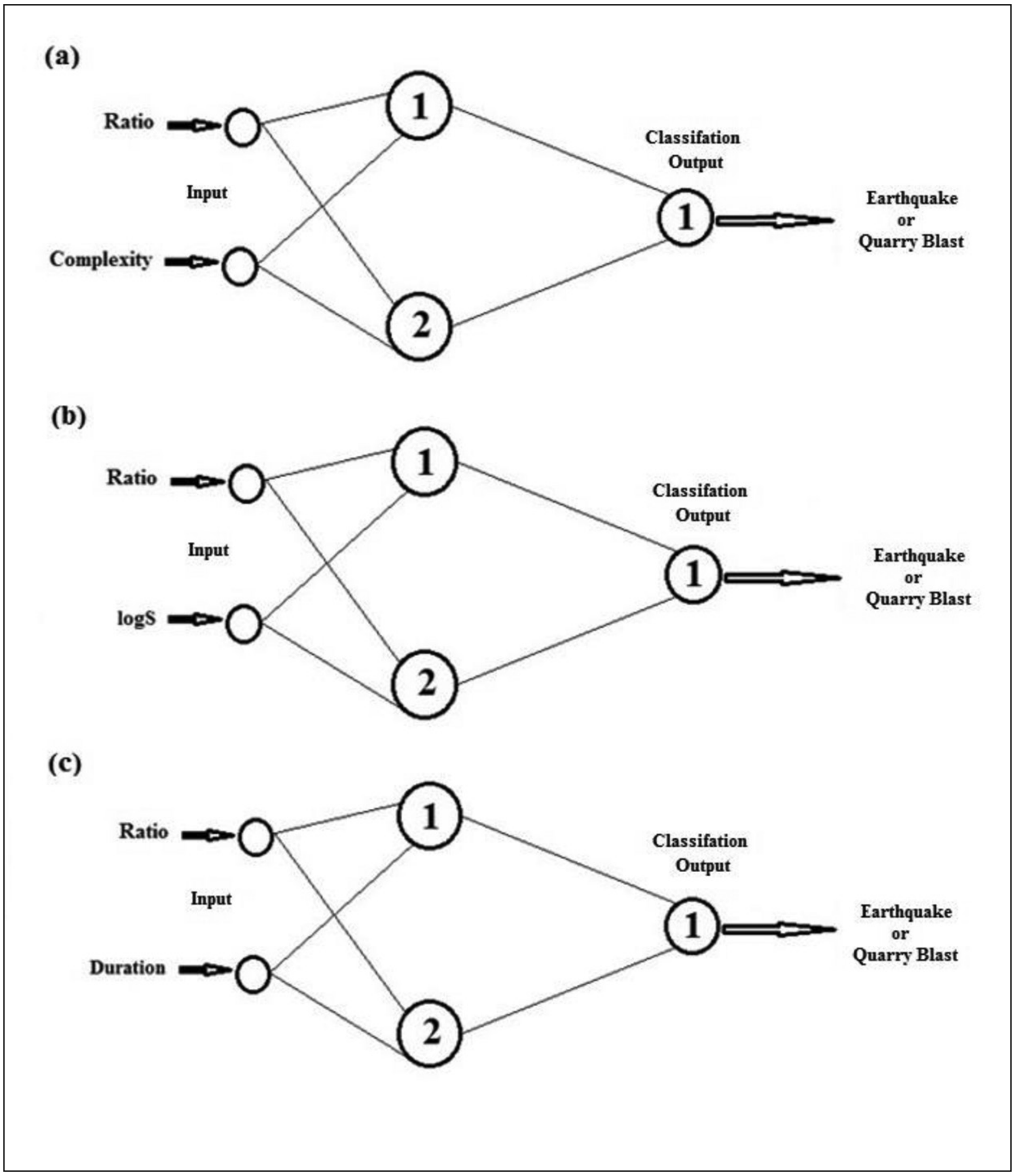

Figure 7- Artificial neural network structure for seismic events a) ratio versus C, b) ratio versus logS, c) ratio versus duration.

stopping criterion. At the same time, this means that the learning algorithm is successful for these parameters on the network structure created. Once the proper value has been obtained, the network has been tested.

Since it is necessary to decide on the number of neurons first, the number of neurons obtained in the following table (Table 2) is obtained by trial and error method. While creating an artificial neural network suitable for the problem in this study, the obtained

Table 2- The change of the total number of data and its relation with the Number of Neurons (Nn) for the parameter pairs belonging to the Manisa study area. Parameter pair for all data set belonging to KULA station Criteria: 1: Ratio-C, 2: Ratio-logS, 3: Ratio-Duration.

Criteria	ANNs (%) Nn:5	ANNs (%) Nn:10	ANNs (%) Nn:15	ANNs (%) Nn:20	ANNs (%) Nn:25
1	88	100	100	88	100
2	100	100	100	96	96
3	100	100	100	100	100

accuracy percentage values are shown in table 2 against the number of neurons determined for each parameter pair.

Since the number of neurons is decided according to the accuracy percentage values in the ANNs method, the number of neurons in the situation with the highest accuracy percentage value is selected. But if the accuracy percentage values are equal, the lowest value of the number of neurons is taken. This is because the artificial neural network model is desired to be less complex (Gülbağ, 2006). Therefore, Nn: 10 for the Ratio-C parameter pair, and Nn: 5 for Ratio-logS and Ratio-Duration parameter pairs were selected according to the ANNs method.

In addition, the training algorithm used in this study is Levenberg-Marquardt and the activation function is Tangent-Sigmoid activation function. Application of Levenberg-Marquardt ANNs learning has been explained in some studies (Hagan and Menhaj, 1994; Kermani et al., 2005). This algorithm (up to several hundred weights) has been shown to be the fastest method for advanced feed-forward ANNs learning. At the same time, the effective representation of the function in matrix form, as in the MATLAB programming language, offers an important solution in some studies (Charrier et al., 2007; Matlab, 2011).

With the help of MATLAB programming language "nntool", ANNs model with inputs, weights and activation function was developed and Levenberg-Marquardt was chosen as the training algorithm (Levenberg, 1944 and Marquardt, 1963) (Matlab, 2011) since this training algorithm has an important role in the functioning of this process. Kipli et al. (2012) also used the Levenberg-Marquardt training algorithm in their studies.

For the network architecture determined in this study, the hyperbolic tangent sigmoid activation function, also known as the tangent sigmoid activation function, is used. Tangent-Sigmoid, $\varphi(v)$, describes the neuron output with respect to the local induced υ field. In fact, this activation function assumes a continuous function in the value range from -1 to +1. Therefore, the activation function expresses the positive function of the induced local area, as seen in equation 4.

$$\varphi(v) = \begin{cases} 1 & if \;\; v>0 \\ 0 & if \;\; v=0 \\ -1 & if \;\; v<0 \end{cases} \tag{4}$$

This function is shown in combination as a sign function. For the corresponding form of the sigmoid function, the hyperbolic tangent sigmoid function was used in the form as shown below:

$$\varphi(v) = \tanh(v) \tag{5}$$

The hyperbolic tangent sigmoid activation function takes positive and negative values as indicated in equation 5 (Haykin, 2009).

Therefore, the hyperbolic tangent function, which was examined at the beginning, is used for values that provide input to all output layers except output layer. The hyperbolic tangent sigmoid activation function is defined as in equation 6.

$$\varphi(v) = \frac{2}{1+e^{(-2v)}} - 1 \tag{6}$$

In equation 6, $\varphi(v)$ is "Hyperbolic tangent sigmoid activation function". The change of the function is [-1 1] and this function varies according to the total input and the number of neurons. (Gradshteyn and Ryzhik, 2007).

3.2.3. Preparation of Data Set for ANNs Network Topology

After the number of neurons is determined, data sets of inputs and outputs are started to be arranged. After the normalization process, a new data set is created by randomly selecting a certain percentage of the data as training data and the rest as test data from the whole data set. Similarly, Kermani et al. (2005) randomly selected their data in their study. The reason for this is that the training data is trained with the learning algorithm used in ANNs and the training is completed when the determination coefficient (R^2) value approaches 1. The reason for continuing the ANNs process with test data is to provide the rule that "The designed artificial neural network has learned the learning algorithm with training data, so it can test its knowledge with test data". Then, the obtained results are compared with the test outputs and the accuracy percentage is calculated.

Different researchers prepared data sets using different percentage values to distinguish between training data and test data. Ursino et al. (2001) used 50% of the data set as training set and the other 50% as test data. Gülbağ (2006) created the ANNs data set as 84% training data and 16% test data in his study. Yıldırım et al. (2011) organized 25% of the data set as training and 75% as test data in their study, in accordance with their own problems. Kundu et al., (2012) allocated 51% of their data as training data and 49% as test data. In addition, Yıldırım (2013) divided 80% into training data and 20% as test data by selecting random data from the data set in his study. Kaftan et al. (2017) separated 85% of their data as training data and the remaining 15% as test data.

In this study, random data was selected from the whole data set belonging to the KULA station, and 70% of the data was divided into training data and 30% as test data. In this case, since all data is 77, training data is 53 and test data is 24.

In addition, reasonable results were obtained by applying the k-fold cross validation method (James et al., 2017) to the data. Thus, by obtaining reasonable results similar to the high accuracy percentages obtained by the ANNs method, the ANNs method was once again verified.

Each pair of parameters used in the LDF method is also used in the second method, the ANNs method, to distinguish earthquake and quarry blast data.

The determination coefficient (R^2) values corresponding to the number of neurons (Nn) values determined by ANNs method for ratio versus C, ratio versus logS and ratio versus duration values in Manisa are given in table 3. It is seen in this table that the R^2 values are different for each parameter pair. When R^2 values are close to 1, it can be said that the created artificial neural network structure is successfully created according to these parameter pairs. The R^2 values seen in table 3 are accepted as a stopping criterion for the feed-back learning algorithm that we use in this study. It shows that when the R^2 value approaches 1, the predicted artificial neural network structure has been successfully learned. The number of neurons (Nn) is designed to increase by 5 between 5 and 25 (Table 3).

R values alone are not sufficient to decide the number of neurons (Nn) representing the model, they are only a stopping criterion. Accuracy percentages of ANNs models corresponding to these neuron numbers selected with the help of table 3 are shown in table 4.

Accordingly, it was found that the accuracy percentage values obtained by the ANNs method were high and this method was also successful. In addition, the numbers of earthquakes and quarry blast in the training and test data of KULA data are shown in table 5.

For ANNs method, amplitude ratio versus complexity (C), logS and signal duration values are given in figure 8a, b, c.

Table 3- The change in the relationship between the coefficient of determination (R^2) and the number of neurons (Nn) for the parameter pairs belonging to the Manisa study area. Parameter pair for the data set of the Kula station Criteria: 1: Ratio-C, 2: Ratio-logS, 3: Ratio-Duration.

Criteria	Determination Coefficient				
	Nn:5	Nn:10	Nn:15	Nn:20	Nn:25
1	0.96	1	1	0.96	1
2	1	1	1	0.93	0.93
3	1	1	1	1	1

Table 4- The change of the number of incorrectly defined earthquakes and quarry blasts with the number of data in the training and test data set for the whole data set of the KULA station using the ANNs method, and the percentage of accuracy.

Criteria	Station	Total Number of Data	Number of Data in the Training Set	Number of Data in the Test Set	Misclassified Earthquake (ME)	Misclassified Quarry Blast (MQB)	ANNs (%)
1	KULA	77	53	24	0	0	100
2	KULA	77	53	24	0	0	100
3	KULA	77	53	24	0	0	100

Table 5- Number of training and test data modeled for the KULA region. The accuracy percentages obtained from the classification of the data set of the KULA station (Criteria 1: Ratio-C, 2: Ratio-logS, 3: Ratio-Duration) using the ANNs method are respectively 100%, 100% and 100%.

			Training Data Set*			Test Data Set**		
Criteria	**Station**	**Total Number of Data**	**Number of Data in the Training Set**	**Earthquake (E)**	**Quarry Blast (QB)**	**Number of Data in the Test Set**	**Earthquake (E)**	**Quarry Blast (QB)**
1	**KULA**	77	53	31	22	24	19	5
2	**KULA**	77	53	31	22	24	19	5
3	**KULA**	77	53	31	22	24	19	5

Training Data Set* = Training Set; Test Data Set ** = Test Set

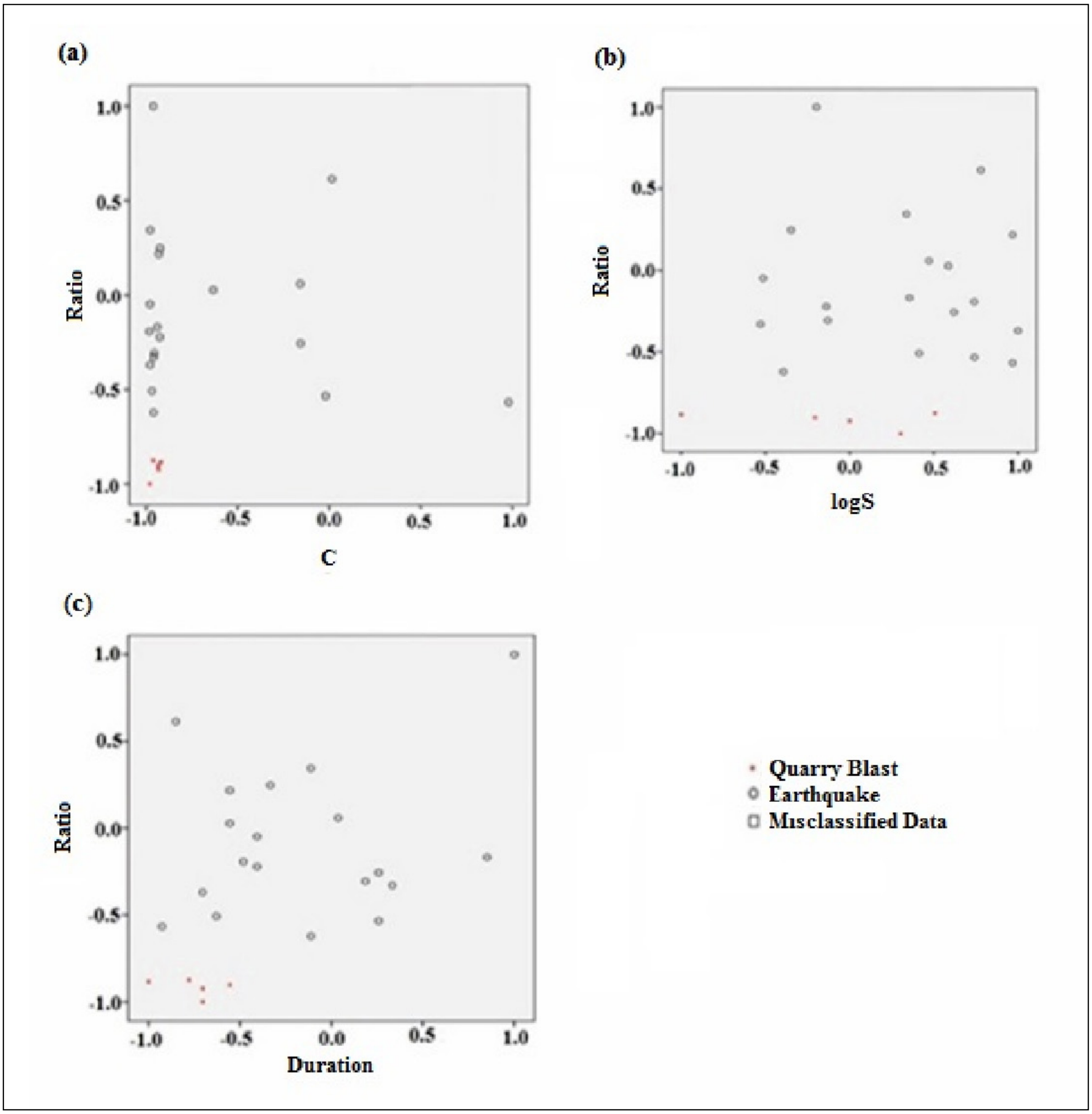

Figure 8- Accuracy percentage values obtained by ANNs method according to parameter pairs for KULA data. (a) 100% for ratio-C parameter pair; (b) 100% for ratio-logS parameter pair and (c) 100% for the Ratio-Duration parameter pair.

The accuracy percentage of the method was calculated by testing the data prepared with the help of MATLAB software (Matlab, 2011). ANNs method was applied for each parameter pair (C against Ratio, log S against Ratio and Duration against Ratio) and accuracy percentages were obtained for each. In addition, the number of neurons for Ratio versus C was taken as 10, for Ratio versus log S as 5, and for Ratio versus Duration, as 5. Accuracy percentages obtained from LDF and ANNs methods are given in table 6.

4. Results and Discussion

In this study, while LDF and ANNs methods were applied to the data in Manisa region for the first time, earthquakes and blasts were distinguished from each other. In order to distinguish earthquake and quarry blast events, 77 seismic events with $M_L \leq 3.5$ magnitude recorded at KULA station between May 2009 and June 2013 in the region between latitudes 38-39.30˚N and longitudes 28-29.30˚E were examined.

From the vertical component velocity seismograms recorded in the KULA station in the study area, parameters such as the ratio of the maximum S-wave amplitude to the maximum P-wave amplitude, the ratio of the strengths of the two time windows defined in the seismogram (C) and the signal duration (Duration) are determined, and their relationship with each other is examined by LDF and ANNs methods.

The results obtained by LDF and ANNs method for each parameter pair (Ratio-C, Ratio-logS and Ratio-Duration) of the data set belonging to KULA are given in table 6. In both methods, earthquakes and explosions were determined with high accuracy percentages.

As a result of the study, 39 (51%) of the 77 seismic events examined were determined as quarry blasts and 38 (49%) as earthquakes (Figure 9).

Table 6- Comparison of accuracy percentage values according to LDF and ANNs methods for the data set of KULA station (Criteria: 1. Ratio-C, 2. Ratio-logS, 3. Ratio-Duration).

Criteria	Method	Percentage of Accuracy (%)
1	LDF	94
	ANNs	100
2	LDF	93.5
	ANNs	100
3	LDF	89.6
	ANNs	100

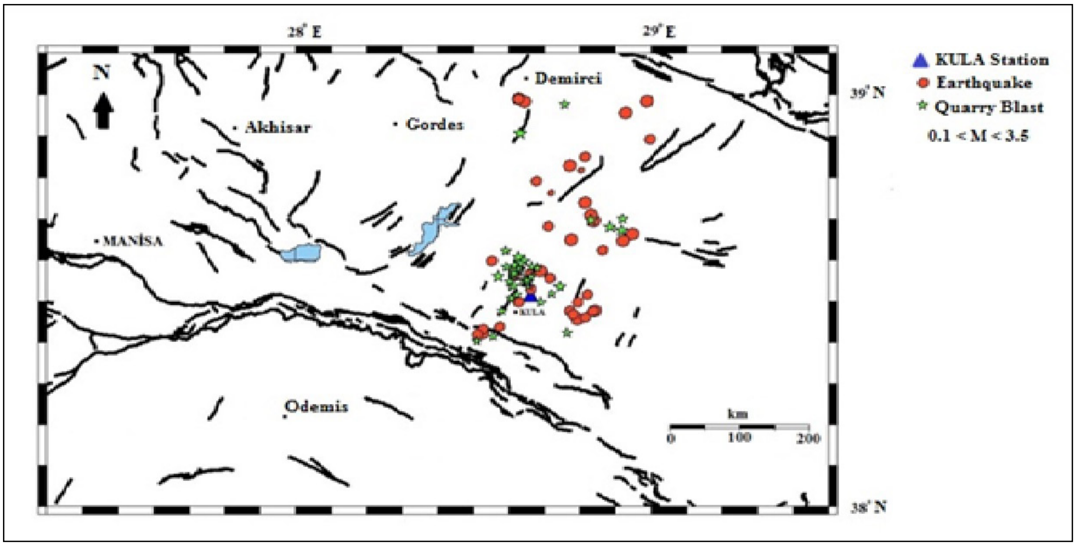

Figure 9- Earthquakes and blasts, $M_L \leq 3.5$, occurred in the study area between May 2009 and February 2014. The KULA station is marked with a blue triangle (KRDAE, BDTIM).

In this study, it was understood that the number of neurons is a very important criterion for ANNs. The reason for this is that the number of neurons directly affects the results in the creation of the artificial neural network topology. This shows that if the number of neurons is correctly decided during the preliminary study before the ANNs method is applied, the accuracy percentage value will be higher. In addition, when the ANNs method is applied, when the determination coefficient (R^2) value approaches 1 during training, the training is stopped and then, the test is started and information about the learning process is provided. In other words, the determination coefficient is a stopping criterion.

Comparing the differentiation accuracy percentages obtained by LDF and ANNs for different parameter pairs, it is seen that both methods are successful in distinguishing earthquakes and blasts from each other, but the ANNs method is more successful than the LDF method (Figure 5a, b, c, figure 7a, b, c; table 6).

In addition, when international and Turkish scientific studies are examined, it is seen that LDF and ANNs methods are frequently used to distinguish blasts from earthquakes in different study regions. Ceydilek and Horasan (2019) used the LDF method at four stations (AKHS, BLN, CAM and KTT) to distinguish earthquakes and explosions in the Manisa region. The accuracy percentages for the Ratio-logS parameter pair obtained from the events recorded by each of the AKHS, BLN, CAM and KTT stations are 94.4%, 95.8%, 90.0%, 93.2%, respectively. The accuracy percentages for the Ratio-Duration parameter pair obtained from the events recorded by the same stations are 91.2%, 89.6%, 91.4%, 88.6%, respectively. In this study, 94%, 93.5% and 89.6% accuracy values were obtained with the LDF method for Ratio-C, Ratio-logS and Ratio-Duration parameter pairs, respectively. It is seen that the results obtained from this study are compatible with the results obtained by Ceydilek and Horasan (2019) in Manisa region.

In addition, the LDF method is one of the most popular and successful methods used in earth sciences to distinguish between natural and artificial seismic events. Horasan et al. (2009) obtained the accuracy percentage values with the Ratio-logS parameter pair for İstanbul-Gaziosmanpaşa, Çatalca, Gebze-Hereke, and İstanbul-Ömerli regions as 98.6%, 93.8%, 97.7% and 95.8%, respectively. Yılmaz et al. (2013) defined the accuracy percentage values as 96.3%, 89.3%, 100%, 100%, 96.5% and 100% for KTUT, ESPY, BAYT, PZAR, GUMT and BCA stations in Trabzon, respectively. Badawy et al. (2019) applied the LDF method to the Ratio versus logS values in Egypt, and the accuracy percentages for AYT, MYD and GLL stations were 91.7%, 83.7% and 83.2%, respectively. By applying the same method to Spectral Ratio values against C for the same study, Badawy et al. (2019) obtained the accuracy percentages as 95.7%, 98% and 98.4% for AYT, MYD and GLL stations, respectively. These values show that the method gives successful results. The accuracy percentages of the parameters may vary depending on the number of data, geological features and local ground effects.

ANNs method has also been used for about the last decade to distinguish natural and artificial seismic events from each other. Yıldırım et al. (2011) used three methods to distinguish natural and artificial seismic events in and around İstanbul. They achieved 99% accuracy with Back Propagation - Feed Forward ANNs (BPNNs), 97% accuracy with Probabilistic Artificial Neural Networks (PNN) and 96% accuracy with Fuzzy Logic Systems (ANFIS). In this study, the accuracy percentage values obtained by using the BPNNs learning algorithm with the ANNs method applied for the KULA station and its vicinity is 100% for each pair of parameters. In other words, accuracy percentage values close to each other were obtained. In this study, the BPNNs learning algorithm preferred in the ANNs method has been quite successful in distinguishing seismic events from each other.

In addition, the determination coefficient (R^2) values corresponding to the number of neurons (Nn), which are important in the ANNs method - 0.96 and 1 for the Ratio-C parameter pair, 0.93 and 1 for the Ratio-logS parameter pair, and 1 for the Ratio-Duration parameter pair - was obtained at different value ranges for all neuron count values ranging from 25 to 5 increments (Table 3). This situation indicates that the BPNNs learning algorithm used in the artificial neural network architecture created in this study is successful on these parameters.

In addition, if we compare the results obtained with LDF and ANNs methods with each other, 94% in LDF method and 100% in ANNs method for Ratio-C parameter pair; for the ratio-logS parameter pair, 93.5% in the LDF method and 100% in the ANNs method; for the Ratio-Duration parameter pair, 89.6% accuracy was obtained in the LDF method and 100% in the ANNs method.

In the LDF method, 39 of the 39 quarry blast events were determined as quarry blast in Table 1 for the Ratio-C parameter pair. Of the 38 events defined as earthquakes, 33 of them were earthquakes and 5 of them were quarry blasts. Thus, earthquakes and explosions were distinguished from each other with 94% accuracy with the LDF method. For the ratio-logS parameter pair, 39 of 39 blasts were determined as blasts with the LDF method. Of the 38 events defined as earthquakes, 33 were determined as earthquakes and 5 were quarry blasts (Table 1). The accuracy percentage in the LDF method for this parameter pair is 93.5%. For the Ratio-Duration parameter pair, the accuracy percentage value obtained by the LDF method is 89.6%. These accuracy percentage values show that the method is successful.

Accuracy percentage was evaluated by using only test data with ANNs method. The reason for this is to test the success of the learning algorithm used on the artificial neural network model. Accordingly, 19 of the 24 test data for each parameter pair were correctly identified as earthquakes and the remaining 5 as quarry blast. Thus, earthquakes and explosions were distinguished from each other with 100% accuracy by ANNs method. These results show that the ANNs method distinguishes earthquakes and explosions with high accuracy. Comparing the two methods with each other, both methods are very successful in distinguishing earthquakes and explosions from each other. In this application, it is seen that the ANNs method is more successful than the LDF method.

Studies to distinguish earthquakes and blasts from each other are important for seismicity studies in seismology. By correctly distinguishing earthquakes and blasts, it will contribute to the preparation of seismic catalogs with only earthquakes and therefore to more accurately determining active faults and seismic risk studies in the region. As in the relation proposed by Gutenberg and Richter (1949) given below,

$$\log N = a - bM \tag{7}$$

coefficients a and b can be found. In this relation, a and b are constant coefficients. While b-value is the slope of the line obtained by plotting the logarithm of the number corresponding to the magnitude, the coefficient a is where the line intersects the LogN axis (Bayrak et al., 2013). With the help of these coefficients, the correct determination of the linear relationship between the numbers and magnitudes of earthquakes occurring in a certain area will provide correct results. In fact, by applying the linear regression method to calculate the Gutenberg-Richter (1949) relation for each seismic source zone in Kızılbuğa (2016) study, a and b parameters were obtained in the study area. Thus, by estimating the maximum acceleration values of earthquakes that may occur in that region, the earthquake hazard map of the region was obtained. Therefore, in the light of our study, parameters a and b, which will be determined correctly, will contribute to the preparation of earthquake hazard maps of a region.

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