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Noise Exposure Estimation of Surface-Mine- Heavy Equipment Operators Using Artificial Neural Networks

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Abstract

Ever inreasing demand to raw mineral production stimulates intense use of mining machinery and subsequently exposes mining machinery operators to high levels of continuous noise. Long-term exposure to high levels of continuous noise can cause Occupational Hearing Loss (OHL) on operators. In order to certify a good working environment, it is important to estimate real noise levels of opencast mining machines.
The aim of this study was to assess exposure levels to continuous noise using the test records of continouos noise emitted from mining machinery and recommend some actions to reduce it. Artificial neural networks (ANN) tool developed by MATLAB software has been used for these estimates.
During the study, consistent personal noise exposure levels emitting from 60 different opencast mining machinery was recorded. The lowest, highest, average and equivalent noise levels of the machines were recorded and possible exposure noise-levels ($L_{EX,8H}$) on operators were calculated.
Later, data obtained from tests were used to train the ANN multilayered model by forward-feed-fault-back circulation algorithm. During modeling of ANN; vehicle types, recording times, ambient temperature and pressure and relative humudity were determined as input parameters. By the help of the model, equivalent and momentary noise levels prior to maximum level were estimated. Following training and testing of the model, the obtained noise levels were examined by statistical analysis commonly used in ANN models. It was noticed that the designed model provided very close results to the actual test results and can be applied successfully.

Keywords: Noise exposure levels, mining industry, opencast mine vehicle operators, artificial neural networks, opencast mining

1.Introduction

Today, the rapidly developing technology brings serious changes in the mining sector as it is in every industrial field. In the opencast mining sector, excessive noise pollution is inevitable due to the use of heavy machinery. Numerous researches and studies have been carried out in the past regarding the noise levels of underground and surface mine machines [1-3], and reported that mine operators may experience hearing loss if they are constantly exposed to high levels of noise [4-8].

The noise-induced hearing loss is one of the most common occupational diseases in both developing and developed countries [9]. Joy and Middendorf [10] reported the coal mines patterns and trends in noise exposure in data collected by the Mine Safety and Health Administration (MSHA) inspectors in the United States from 1987 to 2004. The MSHA issued a new regulation about occupational noise exposure which is altered the regulatory requirements and enforcement policies during this time. The data were examined to identify the potential impacts of these changes. After the announcement of the new noise rule, this reduction in each group speeded-up dramatically. For instance, the overall annual noise median considering for surface coal mining dose declined 67 percent at the same time underground coal mining declined 24 percent too. It's proved that it has been hard to controlling noise exposure, accordingly noise-induced hearing loss (NIHL) still remains one of the leading risks in the mining industry [11]. Edwards et al. [12] presented a study in which he evaluated noise exposure levels in South African mining industries. In their study, the main issue addressed in the large-scale mining sector (underground gold, underground platinum, underground coal, and opencast coal mines) and small- to medium-scale sector mines (large underground diamond mines, small and large opencast diamond, ready-mix concrete, sand, and aggregate), of course, has been noise exposure. It was seen that on average, initial year 66.7 percent of the employees sampled, and following year 78.4 percent were exposed to noise levels of above the 85 dBA legislated occupational exposure level. Cinar and Sensogut measured the noise levels of various machines in four different mining sites in Turkey [13]. They rated the degree of discomfort of the employees from 0 to 5 according to depending on the severity of the noise they were exposed, and evaluated whether or not ear protection would be necessary. They also stated that machines should be maintained properly and personal protectors should be used.

Since the estimation of noise levels of the machine operators was influenced by many parameters and the large number of data to be used and the long time spent during works, led the researchers to develop different methods. Operators using heavy machinery in mines may be exposed to high levels of noise in working environment. İt has been an important issue for many researchers to predict noise levels accurately by analyzing the measurement data using appropriate models in order to protect the health of its employees and to ensure occupational safety. Artificial neural networks are one of the methods used for this purpose. ANN techniques are effective in complex and nonlinear models. On the other hand, ANN is preferred because of its speed, simplicity and success in learning from examples and not needing much data compared to traditional methods. Today in many areas of mining engineering, such as blasting wave propagation velocity, soil type estimation, [14-16], noise measurements estimation [17-18], long-term mining [19], methane ventilation estimation, soil collapse estimation [20], slope stability [21] the estimation of fuel consumption [22], to predict vibrational health risk[23] ANN has been successfully implemented by many researchers, designers, etc.. One of the undesirable effects caused by blasting operations in open-pit mines is the serious weakening of residential structures and livingquality in the surrounding area. To control and mitigate this situation, in the study used artificial neural networks to estimate the air blast overpressure (AOp) applied in the open-pit coal mine[24]. Blasting is one of the cheapest and most effective methods of breaking rock mass in open pit mines. However, side effects such as ground vibration (PPV), excessive air pressure, fly rock, fracture, dust and toxic are not trivial. Nguyen et al. [25] applied in their study, a series of artificial neural network models to predict PPV caused by the explosion in an open pit coal mine in Vietnam.

At present, widespread capacity of labor force and very large areas opened for mining boomed the use of excavating machinery in Turkey. In this study, noise readings of hauling and excavating machine of three opencast lignite mines at the western region of Turkey were assessed and the necessary measures suggested to ease the effect of continuous machine-noise on operators have been highlighted. In line with the study, heavy mining machinery regularly in operation within normal working hours was determined and, personal noise exposure measurements of 60 machine operators were recorded regularly in accordance with international standards. Then the equivalent noise levels of all machines were calculated. Furthermore, the noise exposure levels ($L_{EX,8H}$) of the operators using the machines were determined and the results were evaluated according to the noise regulation of the Ministry of Labor and Social Security. The results obtained during the study were presented and critical values for further works to reduce the noise exposures of machine operators down to below the legal exposure limits were recommended.

Then, the noise exposures levels of heavy machinery operators in open pit mines were trained through artificial neural networks using forward-feed-fault-back circulation algorithm, and the network that best predicts experimental results was formed. The results obtained from ANN were compared with the real-time recorded noise data showed that the model has a high sensitivity and the model can perform real time recalculations with high precision.

2. Noise Control Methodology

2.1. Regulations

Several rules have been introduced in many countries as acts, regulations, standards and directives regarding control of occupational noise effects. The common purpose of rules under different names is to limit the impact of noise and protect environment and the people living in from the negative effects of it. Turkish Standards Institute published TS 2607 ISO 1999 (2005) standart for determination of occupational noise exposure caused by machinery and equipment and estimation of noise-induced hearing impairment in order to be assessed whether employees' noise levels are within the legal limits. These are daily and weekly noise impact levels. The daily noise impact level (LEX, 8h) is defined as the time-weighted average of all noise impact levels, including instantaneous pulsed noise, during an eight-hour working day. The weekly noise impact is the time-weighted average of five over eight hours of daily, noise-affected levels measured during a week. The minimum exposure action values in this regulation are 80 dBA and 135 dBC; the highest exposure action values are 85 dBA and 137 dBC while the exposure limit values are 87 dBA and 140 dBC, correspondingly. In addition, determination of daily and weekly noise impact levels, measuring principles and evaluating the noise experienced in the working environment are given in TS EN ISO 9612 (2009) titled as "Determination of Acoustic-Professional Noise Exposure-Engineering Method".

2.2. Noise Measurements

In the mining sector, there are many noise sources which cover all the stages of mining work. The noise that occurs in each of these stages is different. The noise exposure measurements in this study are performed in accordance with TS EN ISO 9612-2009 "Determination of Acoustic-Occupational Noise Exposure-Engineering Method" and TS 2607 ISO 1999 "Acoustic - Determination of Exposed Noise at Work and Estimation of Hearing Loss Caused by this Noise" standards. Noise measurements were obtained from three separate coalmine site operating in the western part of Turkey.The measurements were taken in the following workplaces of machineries namely: earthmoving truck, hydraulic excavator, crawler dozer, grader and hydraulic hammer-drill (Table 2.1).

Personal exposure measurements were made on a nominal day, including operator periods and break times. Before the measurements were started, the information about the duration of the work, sources of exposure, process steps affecting the work, exposure time, work station status, number of employees and rest periods were recorded. Operators work on average 8 hours per day, 5 days per week and 210 days per year on average.

The measurements were carried out using a high precision noise level meter suitable for all noise measurements mentioned in the "Regulation on Assessment and Management of Environmental Noise" of the Ministry of Environment and Urbanization (SVANTEK). The noise meter measures the results of SPL, Leq, SEL, Ln (L1-L99) and so on.
When operators are assumed to carry out their work for one full shift, the equivalent noise level of 8 hours according to TS EN ISO 9612 (2009) is determined as $L_{EX,\ 8h}$, Equation (2.1 and 2.2). Assuming that operators continue their work in one full shift, equivalent noise level for 8 hours exposure period is determined by $L_{EX,8h}$ corresponding to TS EN ISO 9612 (2009) standart.

Table 2.1 Machines and their specifications working at opencast mining sites.

Machine Types	Machine Models	Average Power	Capacity	Numbers of Machines	Field of Usage
Truck	KOMATSU 630 ES	1600 HP	170 ton	2	Earthmoving Truck used in ore or overburden transport
	KOMATSU HD 785	875 HP	85 ton	5	
	KOMATSU HD 465	702 HP	50 ton	15	
Electric Excavator	MARION 191M	1250kW	17yd^3	6	Excavator and loader used in ore or overburden excavation and loading
Hydraulic Excavator	KOMATSU PC1100	623 HP	6,5 yd^3	5	
	HITACHI EX 1200	655 HP	5m^3	1	
Loader	CAT 992	690HP	12,5 yd^3	5	
Dozer	KOMATSU D155	320HP	-	3	Crawler dozer and paydozer powerful tracked machines that is used for ground leveling, to move material and short distance excavation or support operations in open-pit mining) use a variety of front mounted blades. Large dozers often do pioneering work, such as moving dirt in preparation
	KOMATSU D275	446HP	-	5	
	KOMATSU D355	410HP	-	2	
Paydozer	KOMATSU WD600	448HP	-	1	
Grader	KOMATSU GD 705R	180HP		2	Grader is a construction machine with a long blade used to prepare the base course to create a wide flat surface upon which to place the road surface.
	KOMATSU GD 825A	280HP	-	3	
Hydraulic breaker and drill	ING. RAND	455HP	9,5inch	3	Hydraulic breakers and drills are used in blasting hole drilling operations in open mining operations
	REEDRILL	400HP	9,9inch	2	

Conceptual constant sound level (dB) containing the same amount of energy for the same duration as the acoustic energy of the A-weighted wavy sound measured over a specified period of time

$$L_{Aeq} = 10log\left[\left(\frac{1}{n}\sum_{i=1}^{n} 10^{L_i/10}\right)\right] \quad (2.1)$$

$$L_{Ex,8h} = L_{Aeq} + 10\log\left[\frac{T_e}{T_o}\right] \quad (2.2)$$

Where:
L_{Aeq} : A-weighted equivalent continuous sound level (dB), equivalent to the total sound energy measured over a stated period of time and is also known as the time-average sound level
$L_{EX,8h}$: the time-average, A-weighted noise level for a nominal 8-hour working day, also known as $L_{EP,d}$ (dB)

T_e: Total continuous sound exposure time for the working day (7½ hours)
T_o: Maximum continuous sound exposure duration (8 hours)
n : Number of measurements
L_i : Sound measurement values (dBA)

Table 2.2 shows the LAeq, $L_{EX,\ 8H}$ values measured according to equations 1.1 and 1.2 in the operator cabin of 2018 for a total of 60 work machines operating in three separate opencast mine operations. Figure 2.1 shows the range and average noise level of the noise measurements made for construction machinery. In approximately 27% of these measurements, values equal to or greater than the 87 dBA exposure limit value specified in Noise Regulation were determined. The average noise levels for these groups ranged from 81.24 to 91.08 dBA. The lowest noise level was measured during the operation of the excavator operator at 74.5 dBA and the maximum noise level at the operation of the dozer operator at 98 dBA. In Figure 2.1, it can be seen that the noise exposure of the dozer machine operator which is one of the five different machines, is above the exposure limit value of 87dB (A), and the noise explosure level of two machines (grader and hydraulic hammer) operators are 85dB (A) which is the highest exposure action value. Mining is a characteristic constantly changing process. Factors such as driver's influence, uneven and rough terrain, intensity of work, exposure time, vehicle tire pressure affect the noise levels. In addition, noise exposures vary according to the types of machines used. Operation of the machine with diesel or electricity changes the noise values considerably.

Table 2.2 Noise levels of all measuring machines (dBA).

Work machine	**Number**	**L_{Aeq} (Average)**	**L_{Aeq} (min)**	**L_{Aeq} (max)**	**L_{EX-8h} (Average)**	**L_{EX-8h} (min)**	**L_{EX-8h} (max)**
Truck	22	84,75	77,8	**94,9**	84,46	77,52	**94,62**
Excavator	17	81,24	74,5	**90,6**	80,96	74,22	**90,32**
Grader	5	86,56	82,2	**95**	86,28	81,92	**94,72**
Dozer	11	**91,08**	82,4	**98**	**90,8**	82,12	**97,72**
Drill	5	85,46	81,5	**89,9**	85,18	81,22	**89,62**

Indicated in bold are noise levels above the 87 dB(A) limit

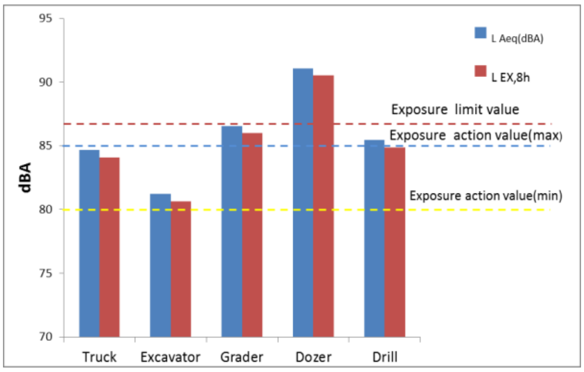

Figure 2.1. Noise levels of different machines during production.

3. Artificial Neural Network

Artificial Neural Network (ANN) is a kind of intelligent computing system that simulates biological neural network. It has features such as self-learning, self-organizing, non-linear dynamic process and high fault tolerance a large number of inputs and outputs are required for the ANN to train and reach the target outputs. These data sets are called "training" and "test". After the learning process, "test" is performed to see how the designed network is using the "test" data. In the learning process, the system, which regulates the weights of ANN in the network to produce the desired outputs, is called the learning algorithm. The training process continues until the targeted output value is achieved. The error resulting from the difference between the desired output and the resulting output value in the network is minimized by changing weights.

There are many ANN architectures in the literature. In this study, a backward-spread forward-feed multi-layer learning mechanism suitable for engineering applications was used for prediction. In the ANN model, the noise measurements test data of heavy machinery operators in surface coal mining were usedMATLAB program was used in the design and training of ANN model for estimation of risk levels of noise exposures in mining enterprises. Not all data are used in the education of ANN models, preferably 70 to 90% of the data allocated for training and 30 to 10% of the test data. In this study, 48 of the 60 data obtained from the measurement results were randomly used for training and 12 of them were used for testing and verification process, and our database was divided into 80% training and 20% test data. Training and test data were determined for the analysis of the random network to represent each set of inputs. Within the scope of the study, vehicle type, measurement times, ambient temperature, pressure and relative humidity were determined as input parameters for the applied neural network, equivalent noise level and maximum value of instantaneous noise pressure were determined as output parameters. Different normalization techniques have been tried for these parameters and it has been found that using the equation (3.1), normalizing technique between 0.1 and 0.9 gives more realistic results.

$$x_N = 0{,}8\left(\frac{x_i - x_{min}}{x_{max} - x_{min}}\right) + 0{,}1 \qquad \textbf{(3.1)}$$

In this equation parameters refers to;

x_N : The normalized data
x_i : The actual value in a parameter
x_{min} : The minimum value in a parameter
x_{max} : The maximum value in a parameter

The data used for testing for the stable structure of ANN’s were not used during the training phase of the network.

4. Results and Discussion

4.1. The noise level to which operators using construction machinery are exposed

In this study, it is aimed to determine the noise level exposed to the operators using the construction machinery in the open mine operations and daily personal noise measurements from 60 different construction operators are carried out in accordance with the standards. Noise may be generated during operations such as loading-unloading, digging drilling while many mining machines are operating at the same time. This affects all operators operating at the same time. According to the noise measurement results in different units of the enterprise, there are some workplaces with noise levels between 74.5-98 dB. Approximately 85% of the noise measurements were 80 dBA and 27% were higher than 87 dBA. Between the all machines, crawler dozer operators are exposed to noise above the exposure action value. In the study, the average equivalent noise level (L_{Aeq}) was calculated as 91.08 dBA. The equivalent noise level of 8 hours ($L_{EX\text{-}8h}$) is 90.8 dBA. Tracked dozers are the highest noise level vehicles among the sampled work machines and the measurement results are very close to the exposure limit value of 87 dBA. The noise level of earthmoving truck, hydraulic excavator, grader and hydraulic hammer-drills is equal to or higher than the limit of 80.0 dBA, which is the limit of precaution.

4.2. Artificial Neural Networks Results

In this study, it is aimed to obtain a reliable noise risk level estimation with ANN in open pit mine operation conditions. Nowadays, ANN is more economical and faster than experimental studies and can be used successfully in many engineering applications. An artificial neural network model was developed to predict noise measurements of heavy machinery operators. The input data for ANN are normalized to be between 0.1 and 0.9 . Many different models established on MATLAB have been tried and the most successful model has reached 5000 acceptable iterations and the network has been completed. The average error rate of the training phase was found to be 1.74% for the equivalent noise level and 1.24% for the maximum value of the instantaneous noise pressure.

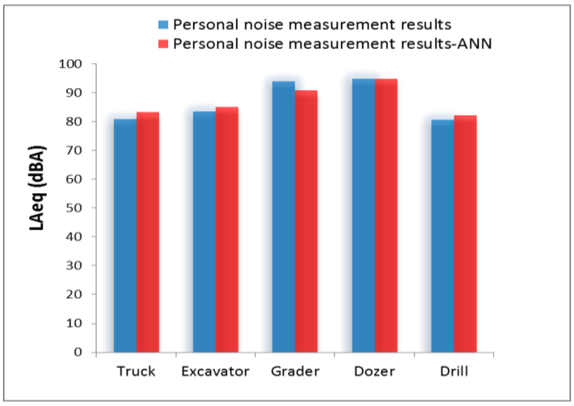

Figure 4.1. Comparison of equivalent noise level measurement results and ANN results for all mining machines during the training phase.

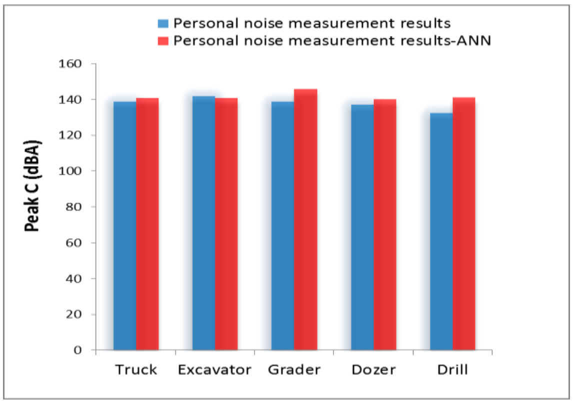

Figure 4.2. Comparison of the maximum value of the instantaneous noise pressure and the ANN results in the training phase for all mining machines.

When the graphs given in Figures 4.1 and 4.2 are taken into consideration, it is clear that the experimental results and the values obtained from ANN are very close.

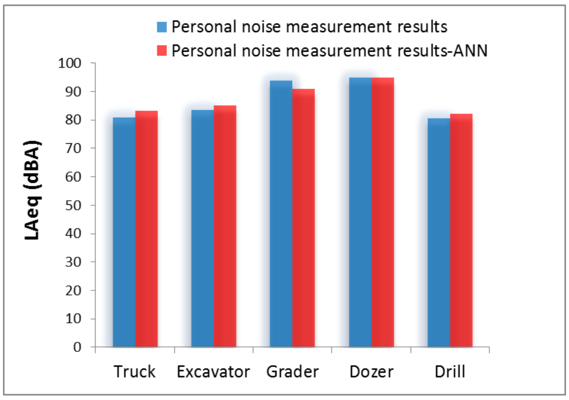

Figure 4.3. Comparison of the equivalent noise level measurement results and the ANN results in the test phase for all mining machines.

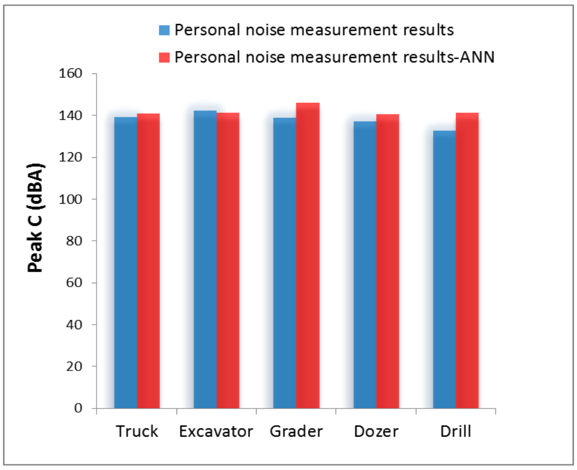

Figure 4.4. Comparison of the maximum value of the instantaneous noise pressure and the ANN results in the test phase for all mining machines.

After reaching the required error limit in ANN training, the test procedure of ANN was started. In order to test the performance of the network, 12 values that were not used in the training set were presented to the network and the results were compared with the experimental results. The relationship between actual test data and calculated values using ANN method is shown in Figure 4.3-4.4.

When the results obtained from the test set were compared with the experimental results, it was found that the network found sufficient accuracy and the error rate in the test phase was 2.82% for the equivalent noise level and 2.66% for the maximum value of the instantaneous noise pressure. In Figure 4.5, Scatter diagrams are drawn between equivalent noise measurement values and calculated values using ANN method. The correlation coefficient was found to be 0.9914 (Figure 4.5-a) for the equivalent noise level (L_{Aeq}) in drilling machines and the maximum value of instant noise pressure in the grader (Peak) was 0.9924 (Figure 4.5-b). The results of the study show that ANN method can be used very successfully in estimating equivalent noise measurement values.

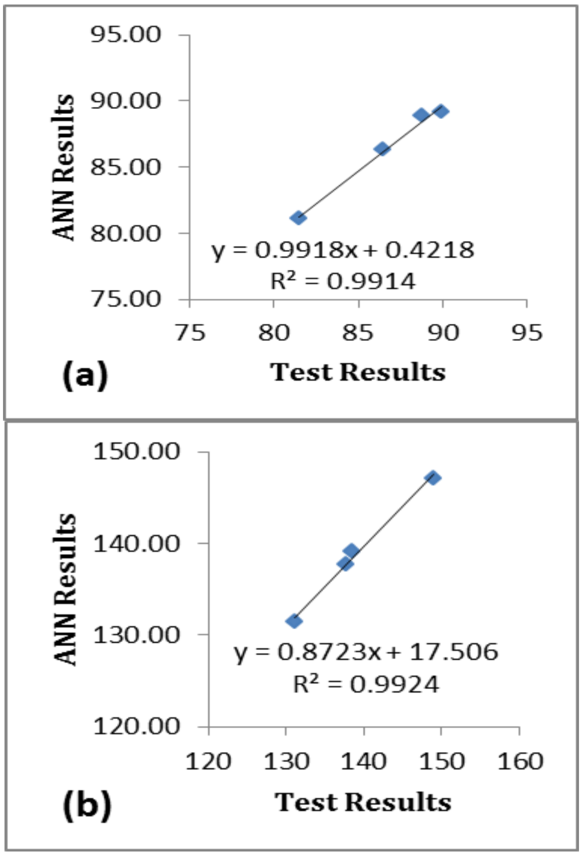

Figure 4.5. Scatter diagrams of equivalent noise measurement values (R^2: coefficient of determination).

5. Results

Preventive engineering measures should be taken in the workplaces in order to reduce the noise exposure of operators using heavy machinery and to minimize the risks that may occur as a result of these exposures. Assessing the noise levels of mining sites will help to control the risk of noise-related hearing loss among workers. Measures that can be taken to reduce the exposure are as follows;

- Many parts of the machine will loosen over time due to uneven and rough roads. If these loosening parts are not installed properly, it will cause noise and operators will be adversely affected. Periodic maintenance of machinery and special parts and regular lubrication of moving parts will reduce noise levels.

- Every personnel who will work in places with a noise level of 80 dB (A) and more, before starting work; training should be given, emphasizing the benefits and importance of personal protective equipment, including possible effects of noise on hearing, the purpose of ear protectors and their proper and regular usage, identification of the appropriate type of protection and their maintenance and cleaning. Posters regarding noise hazards and the importance of using personal protective equipment should be posted where workers can see them. Also, employers should provide employees with healthy and appropriate conditions of working. On the other hand, the workers should all the time to consider the effects of noise and consequential damages, and use personal protective equipment.
- It is necessary to keep the doors and windows of the machine closed to prevent noise in the cabin. Noise formation can be controlled by using insulation material in the cabin.

In addition, ANN-based mathematical model developed to estimate the data obtained from noise measurements of heavy machinery operators in opencast mine. The values obtained after training and testing of ANN were examined and the following basic results were obtained:

- The results of the study showed that the results obtained during the ANN training and the testing phase give close values to the actual results and show that it is possible to estimate the noise measurements of the machine operators in a healthy way.
- Designed with five inputs and two outputs, the network structure provides high accuracy estimates.

- Due to the low error rate of the training phase, the value selected for the test phase in the ANN was very close to the actual test result.

- In the estimation of the equivalent noise level and the maximum value of the instantaneous noise pressure in the construction machinery operators, it has been concluded that the mathematical model can be formed with ANN.

- With this study, it is seen that the risk level can be estimated in mining enterprises by ANN without the need for classical methods that cause time and cost loss.

Author Contributions

Ayla Tekin: wrote the manuscript.

Ethics

There are no ethical issues after the publication of this manuscript.

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