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Artificial neural network to predict the health risk caused by whole body vibration of mining trucks

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Drivers of mining trucks are exposed to whole-body vibrations (WBV) and shocks during the various working cycles. These exposures have an adversely influence on the health, comfort and also working efficiency of drivers. Determination and prediction of the vibrational health risk of the mining haul trucks at the various operational conditions is the main goal of this study. To this aim, three haul roads with low, medium and poor qualities are considered based on the ISO 8608 standard. Accordingly, the vibration of a mining truck in different speeds, weights and distribution qualities of the materials in the dump body are evaluated for each haul road quality using the Trucksim software. An artificial neural network (ANN) is used to predict the vibrational health risk. The obtained results indicate that the haul road qualities, the truck speeds and the accumulation sides of material in the truck dump body have significant effects on the root mean square (RMS) of vertical vibrations. However, there is no significant relation between the material's weight and the RMS values. Also, the application of ANN revealed that there is a good correlation between the predicted and simulated RMS values. The performance of the proposed neural network to predict the moderate and high health risk are 88.11% and 93.93% respectively.

1. Introduction

Operators of all mobile machineries used in heavy industries such as mining are usually exposed to whole body vibrations (WBV). These vibrations reduce the efficiency of operators and have adverse non-ergonomic effects on their body [1].

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In the past, numerous studies have been done to explore the WBV exposure levels during the operation of mining equipment and machineries including haul trucks [2-5], load haul dumps (LHDs) [6, 7], shovels [8] and drilling machines [9, 10]. Among them, the haul trucks have been mostly studied due to their various working cycles including loading, transporting, dumping the load and returning to the loading area. Other vehicles are fixed or have a very short movement in their working place. Therefore, mining trucks are subject to the most dangerous vibrational health risk than the other vehicles.

Kumar [2] studied the WBV of two types of trucks; 240 t mechanical drive trucks and 320 t electric drive. In this research, the data were collected on smooth frozen roads. Results of this research showed that the frequency-weighed root mean square (RMS) of vertical vibration was between 0.30 and 2.72 m/s^2. Also, the unloaded travel cycles had the highest vibration accelerations. In another study, the WBV of 150 t haul trucks was measured by Eger et al. [11] using field data. The mean RMS of vertical accelerations was recorded between 0.28 and 0.37 m/s^2 for two trucks which indicates their low health risk level. Smets et al. [3] measured the WBV of eight haulage trucks with 35, 100 and 150 t capacities using field data. The obtained results revealed that the truck operators were typically exposed to moderate through high levels of WBV risk. Also, the truck type was found having no significant effect on the RMS of vertical vibrations which was consistent with Kumar's results. In the mentioned study, the interaction between speed, road roughness and the vibration magnitude and their effects on the WBV were not discussed.

Loading operation is one of the other causes of the vibrational health risk discussed in some researches. Frimpong et al. [4] studied vibrations in the high-impact shovel loading operations (HISLO) transmitted into cabin using a 3D dynamic model in MSC.ADAMS software. The results of this research showed that the maximum vibrations in the loading period occur at the first and second loading passes when the truck was empty. Therefore, they proposed that the vibration control in the first two passes of the loading operation is important. In a recent study, the WBV exposure of 32 haul trucks (with 136 to 290 t capacity) were measured [12]. The RMS of vertical accelerations for 20 trucks was in the moderate health risk level. However, the haul road conditions considered by field observations had a large effect on vertical vibration.

In the above mentioned studies, the effect of truck type, driver gender, work cycle and loaded or unloaded truck dump body on the WBV have been investigated. There is not enough research considering the various mining operational conditions such as truck speed, weight and load geometry in the truck dump body. These parameters have influence on the vibration of small to medium mining trucks because of their light weights. In this paper, to compensate these deficiencies, an extensive range of operational conditions and their effects on the WBV of mining trucks are studied based on ISO 2631-1 standard. These operational conditions include the various haul road qualities, truck speeds and the materials' weights in the truck dump body. Also, distribution qualities of materials in the dump body are considered. To achieve the mentioned purposes, vibrational simulations are carried out using a comprehensive truck model in Trucksim software. An artificial neural network (ANN) is used for vibrational health risk prediction. A neural network is a powerful data model used to represent the complex relationship between the inputs and outputs of a system. Nowadays, ANNs have been successfully applied in the field of mining engineering such as prediction of blasting propagation velocity and ground vibration [13-15], prediction of methane ventilation in the longwall mining [16], localizing people in confined underground areas [17], ground subsidence prediction [18], prediction of slope stability [19], coal mine safety production [20] and prediction of fuel consumption of mining dump trucks [21].

The results of this paper provide guiding principles for truck operators to drive the vehicle with low vibrational health risk and suggest a new approach to predict the dangerous operational conditions. Therefore, these results will be helpful for the researchers and designers to present practical solutions for health risk reduction of mining trucks. Optimization of the vehicle suspension system, maintenance of the haul road, improvement of the loading quality and suggestion of the safe speed limits based on the haul road quality can reduce the health risk of operators.

The paper is organized as follows: In section 2, analysis of WBV and health risk level of vibrations are presented according to ISO 2631-1 standard. In section 3, artificial neural network is introduced and discussed. In section 4, a haul truck is firstly simulated by the TruckSim software and then the operational conditions including haul road quality, truck speed, weight and accumulation side of the materials in the truck dump body are described. The simulated truck is run at the above mentioned operational conditions and the risk levels of WBV at all operational conditions are discussed. Finally, in section 5, the artificial neural network is applied for health risk level prediction at various operational conditions.

2. Whole body vibration analysis

The most popular standard for measurement and evaluation of the human response to WBV is ISO 2631-1 standard. The two main criteria for describing acceleration amplitude in ISO 2631-1 are the frequency-weighted RMS (a_{wrms}) and the vibration dose value (VDV) [22]:

$$a_{wrms} = \sqrt{\frac{1}{T}\int_0^T a_w^2(t)\, dt} \tag{1}$$

$$VDV = \sqrt{\int_0^T a_w^4(t)\, dt} \tag{2}$$

where $a_w(t)$ is the frequency-weighted acceleration at time t and T is the measurement duration. Accordingly, the daily vibration exposure for 8 hours equivalent frequency-weighted RMS is calculated as follows [22]:

$$A(8) = a_w \sqrt{T/8} \tag{3}$$

where a_w is the frequency-weighted RMS and T is the exposure time in hour.

To evaluate the health risk level of vibrations, ISO 2631-1 defines “health guidance caution zone, (HGCZ)”. In practice, the exposures below, within and above the HGCZ are usually considered as low, moderate and high health risk respectively. For an 8 hour daily exposure, the upper and lower bounds of HGCZ are 0.47 m/s^2 and 0.93 m/s^2 respectively based on the RMS. The corresponding values for the VDV measure are 8.5 m/s$^{1.75}$ and 17 m/s$^{1.75}$ [23]. ISO 2631-1 defines the crest factor (CF) as the ratio of the maximum instantaneous peak value of the $a_w(t)$ to its RMS value [22]:

$$CF = \frac{\max(a_w(t))}{RMS\ (a_w)} \tag{4}$$

If the CF exceeds 9, vibration effects on the driver's body may not be estimated. In this condition, the VDV is used for evaluation and prediction of health risk.

3. Artificial neural networks

The artificial neural network (ANN) is an information processing tool used to simulate the human brain structure and functions. Neural networks (NN) resemble the human brain in two steps. At the first step, the knowledge for NN is required through learning and at the second step, the network knowledge is stored in the strengths of inter-neuron connections known as synaptic weights [24]. The most common NN model is the multilayer perceptron (MLP) which requires a desired output in order to learn. One of the supervised algorithms in MLP is the feed-forward back-propagation network which consists of one input layer, one or more hidden layer(s) and one output layer [25]. The input layer includes n neurons coding the n pieces of information $(X_1, \dots, X_n)$ at the entry of the system. The output layer comprises a single neuron corresponding to the value to be predicted. Each node of the output layer is linked to all nodes in the hidden layer and all hidden layer nodes are linked to all input layer nodes. All nodes are linked with each other by the weighted connection [24]. The weight of the first layer is coming from the input and the weight of each subsequent layer is coming from the previous layer. The summation of weighted input values in the neuron of hidden layer is calculated as follows [26]:

$$a_j = \sum_{i=1}^{n} X_i \cdot W_{ij} \tag{5}$$

where X_i is the input value, W_{ij} is the weight of the connection for the i^{th} input in the input layer with the j^{th} neuron of the hidden layer and n is the number of input variables.

Response of the neurons in the back-propagation method is quantified using transfer functions. There are different types of linear and non-linear transfer functions such as purely linear (Purlin), positive linear (Poslin), tangent sigmoid (Tansig) and logarithmic sigmoid (Logsig). Generally, the non-linear and linear transfer functions are used, respectively, in the hidden and output layers [27]. Logsig is the most common non-linear transfer function in the back-propagation NN:

$$Logsig(a_j) = \frac{1}{1 + \exp(-a_j)} \tag{6}$$

The error signal (e_k) between the input t_k and the output y_k of layer k used to calculate the weight updates is defined as follows:

$$e_k = t_k - y_k \tag{7}$$

The error signal represents the network power in the knowledge learnt. Accordingly, to recognize the optimum network, different network architectures are tried by calculating the mean square of error (MSE) as the total error function:

$$MSE = \frac{1}{2} \sum_{k=1}^{n} (t_k - y_k)^2 \tag{8}$$

4. Mechanical simulation of vibrations

In this section, TruckSim as a powerful software for simulating the behavior of heavy trucks is used for simulation studies. A three-axle truck shown in Fig. 1 with the parameters of Table 1 is used for the simulation study [28]. Such trucks are popular in mining activities due to their high maneuverability and compatibility in various operational conditions. Operational conditions are described at the following sub-section.

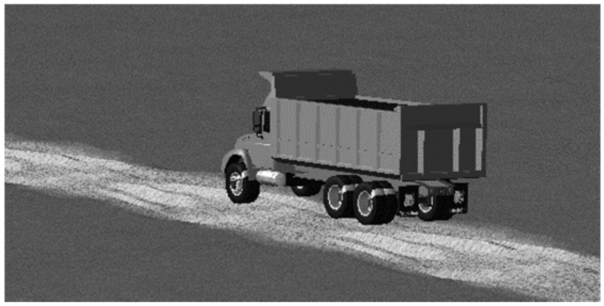

Fig. 1. Truck used for the simulation study [28]

Table 1. Parameters of the case study truck [28]

Parameter	**Value**
Sprung mass (kg)	6500
Front unsprung mass (kg)	600
Rear unsprung mass (kg)	1600
Mass of seat and driver (kg)	100
Stiffness of front suspensions (N/m)	400000
Stiffness of rear suspensions (N/m)	2500000
Tire stiffness (N/m)	1350
Seat stiffness (N/m)	57600
Damp coefficient of front suspensions (N·s/m)	20000
Damp coefficient of rear suspensions (N·s/m)	30000
Damp coefficient of seat (N·s/m)	400
Dump body dimensions; long× width× height (m)	5×2.4×2

4.1. Operational conditions

The operational conditions for the simulation studies are given in Table 2. The truck speed is in the range of 40 to 70 km/h with 5 km/h intervals. The weight of materials in the truck dump body is 24 to 30 t with 2 t intervals. To consider materials distribution qualities, the materials gravity center is moved around the area center of the truck dump body. Also, the uniformly distributed case is considered.

Table 2. Operational conditions for the simulated truck

Parameter	Range	No. of states
Speed (km/h)	[40:5:70]	7
Materials weight (t)	[24:2:30]	4
The accumulation sides of materials in the dump body (load geometry)	100, 200 and 300 mm to left (driver)	3
	100, 200 and 300 mm to right	3
	100, 200 and 300 mm to front	3
	100, 200 and 300 mm to rear	3
	Uniformly distributed materials	1

In this paper, for definition of the haul road quality, road classification based on the ISO 8608 standard is used. In this classification, road roughness has been classified using the Power Spectral Density (PSD) values at the spatial frequency of 1/2π cycles/m. In ISO 8608 classification, the relationship between the PSD and the spatial frequency on logarithmic scale is considered for the road classification as shown in Fig. 2 [29].

Ranges of the PSD values at the spatial frequency $\Omega_0 = 1/2\pi$ cycle/m, $Sg(\Omega_0)$, for different classes of road are given in Table 3. In this study, as shown in Fig. 3, three roads in the classes of good (B), medium (C) and poor (D) are created based on the ISO classification for the truck constant speed of 65 km/h.

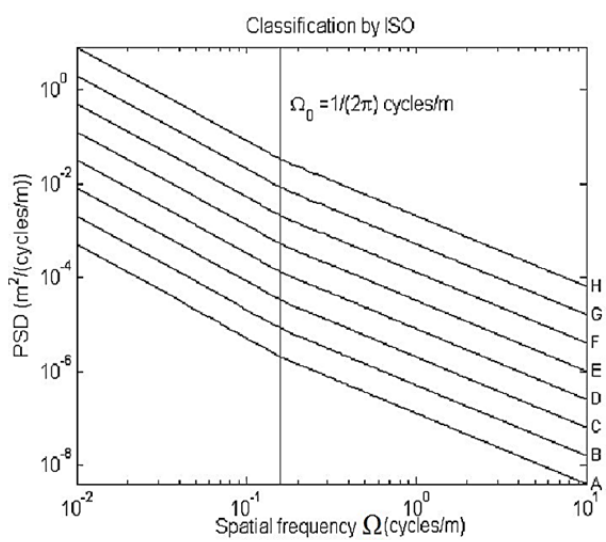

Fig. 2. Classification of the road roughness by ISO 8608 [29]

Table 3. Classification of the road roughness in ISO 8608 [29]

Class of the road	Degree of roughness ($Sg(\Omega_0)\times10^{-6}$ m^3/Cycle) Range	Geometric mean
A (Very good)	< 8	4
B (Good)	8 – 32	16
C (Average)	32 – 128	64
D (Poor)	128 – 512	256
E (Very Poor)	512 – 2048	1024
F	2048 – 8192	2048
G	8192 – 32768	4096
H	> 32768	16384

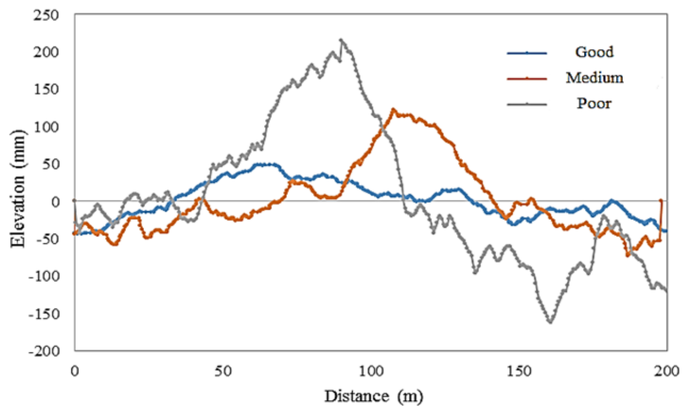

Fig. 3. Three roads created in the good, medium and poor classes

4.2. Vibrational simulation outputs and discussions

In this section, simulation studies are carried out to show the health risk level of vibrations at the various operational conditions. Regarding all states defined in Table 2 together with the three haul road qualities, the simulated truck is run in all (7×4×13×3=) 1092 operational conditions. The 8 h equivalent frequency-weighted RMS ($A(8)$) of the driver which is in the left (driver) side of the truck cabin at all 1092 conditions are obtained from MATLAB software. It is noted that, in each trial, it is assumed that the truck operates only 7 h in each 8 h working cycles. For example, Fig. 4 represents the vibration signal in time and frequency domains corresponding to 30 t uniformly distributed materials at good haul road condition and the speed of 40 km/h.

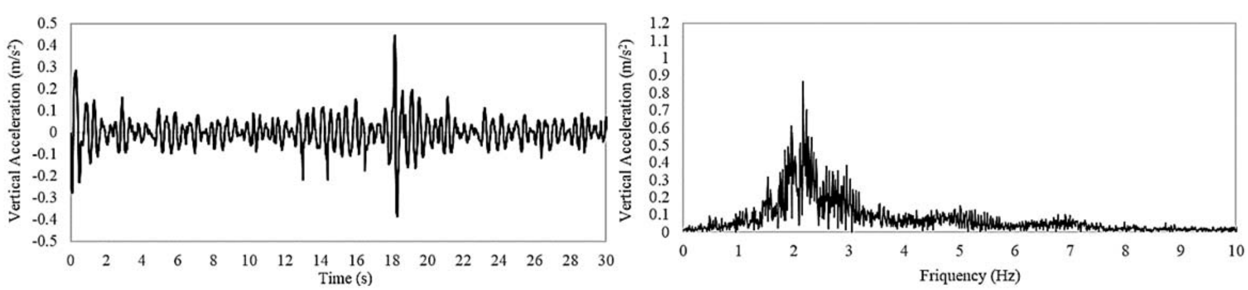

Fig. 4. Vibration signal for 30 t uniformly distributed materials at good quality haul road in the time and frequency domains (speed 40 km/h)

According to Fig. 4, the RMS of vertical vibration is 0.642 m/s^2 which indicates the moderate health risk. Also, the high vibrational energy is observed at 2.21 Hz in the frequency domain. For the same condition, the RMS of signal for the medium and poor quality haul roads are calculated as 0.793 m/s^2 and 1.074 m/s^2 respectively. The results indicate that, deterioration of the haul road quality from good to medium and poor respectively, increases the RMS values by 23.52% and 67.29%.

In the following, the mean RMS values are compared in the different operational conditions and their effects on the mean RMS are analyzed statistically. To achieve this aim, analysis of the variance (ANOVA) is used. ANOVA is applied for determination of the independent variable(s) effects on the dependent variables. In ANOVA, the absence of a difference between the means of independent variable(s) and dependent variables is defined as the null hypothesis. In other words, the null hypothesis in ANOVA is that the means of two groups of variables are equivalent. The p value is used to accept or reject the null hypothesis. Small p value, for example smaller than 0.05 at 5% significant level, indicates that there is a strong evidence to reject the null hypothesis and vice versa [30]. In this paper, the multivariate analysis of variance is done at 5% significant level using SPSS.22 software and the results are given in Table 4. Based on the results presented in Table 4, the road conditions, the truck speeds and the materials' distribution qualities are the most effective parameters on the RMS values ($p< 0.001$). The materials' weight has no significant effect on the RMS values ($p> 0.05$).

Table 4. Results of the ANOVA at 5% significant level

Variable	***df***	***F*- Value**	**Significant**
Haul road quality	2	1152.772	< 0.001
Speed	6	43.120	< 0.001
Materials weight	3	0.550	0.648
Load geometry	12	4.847	< 0.001
Two-way interaction			
Haul road quality × Load geometry	24	54.800	< 0.001
Haul road quality × Speed	12	560.361	< 0.001
Load geometry × Speed	72	44.622	< 0.001
Three-way interaction			
Speed × haul road quality × Load geometry	144	11.974	< 0.001

At the remaining of this section, the effect of the various haul road qualities, the truck speeds and also the distribution qualities of materials on the RMS values is studied. To achieve this aim, Scheffe's Post Hoc Test is used. The Scheffe's Post Hoc Test is the mean comparison test used for finding relationships between the sub-groups of the significant parameters [30]. Results of the Scheffe test are given in Table 5. In this Table, there is no significant difference between each subgroup of the operational conditions which have the same symbol ($p> 0.05$). Scheffe test reveals that there is a significant difference between all haul road qualities. The materials' weight levels have no significant effect on the RMS values (with the same symbol). Moreover, the accumulation of the materials on the rear sides has the lowest effect on the RMS values.

Table 5. The results of the Scheffe's Post Hoc Test

Haul road quality			Speed (km/h)							Materials' weight (t)			
Poor	Medium	Good	70	65	60	55	50	45	40	24	26	28	30
1.486[a]	1.067[b]	0.823[c]	1.336[a]	1.276[b]	1.209[c]	1.134[d]	1.065[e]	0.972[f]	0.886[g]	1.142[a]	1.131[a]	1.120[a]	1.109[a]

Material accumulation side												
300 mm to left	200 mm to left	100 mm to left	300 mm to right	300 mm to front	200 mm to front	100 mm to front	Uniform	300 mm to rear	200 mm to right	100 mm to rear	200 mm to rear	100 mm to right
1.280[a]	1.250[b]	1.173[c]	1.132[d]	1.128[d]	1.114[d]	1.094[e]	1.071[f]	1.068[f,g]	1.056[f,g,h]	1.051[g,h]	1.046[h]	1.021[i]

5. Prediction of the health risk level using ANN

In this section, the artificial neural network is applied to predict the vibrational health risk level at various operational conditions. To achieve this aim, firstly, the neural network with the best performance is architected. Then, the performance of the proposed ANN is evaluated.

5.1. Neural network architecture

For the implemented neural network, the input layer data is composed of four parameters; haul road quality, truck speed, weight and accumulation side of the materials in the truck dump body. The output layer is composed of a single parameter; the RMS of vertical acceleration. The first data set consists of about 90% of mechanical simulation data and the other data, selected randomly, are used for evaluation analysis of the network. The numerical codes, considered for each operational parameter are given in Table 6.

A feed-forward back-propagation network, described in section 3, is selected for this study. Logsig and Purlin, respectively, are applied as transfer functions for the hidden and output layers. Also, training of the network is implemented by the Levenberg-Marquardt algorithm. To select the best network, several networks with different architectures are created using the back-propagation algorithms available in MATLAB software. The best results, given in Table 7, are obtained by different neuron and layer numbers. It is obvious from Table 7 that the best values of correlation coefficient for training and validation are 99.90% and 99.70% respectively. Therefore, the 9-9-1 network architecture is selected as the final network for prediction of the health risk level.

Table 6. Numerical codes which were used as each operational condition

Haul road quality		**Truck Speed (Km/h)**		**Load geometry**				**Materials weight (t)**	
Parameter	Code	Parameter	Code	Parameter	Code	Parameter	Code	Parameter	Code
Good	1	40	1	Uniform	1	100 mm to front	8	24	1
Moderate	2	45	2	100 mm to left	2	200 mm to front	9	26	2
Poor	3	50	3	200 mm to left	3	300 mm to front	10	28	3
		55	4	300 mm to left	4	100 mm to rear	11	30	4
		60	5	100 mm to right	5	200 mm to rear	12		
		65	6	200 mm to right	6	300 mm to rear	13		
		70	7	300 mm to right	7				

Table 7. The best results obtained from different neuron and layer numbers

Neural network architecture	*MSE*	Best training performance	Best epoch	Training correlation	Validation correlation	Test correlation
8-9-1	0.0161	0.0162	12	0.940	0.933	0.960
9-9-1	**0.0006**	**0.0003**	**68**	**0.999**	**0.997**	**0.997**
7-8-1	0.0156	0.0131	7	0.949	0.945	0.941
7-7-1	0.0089	0.0125	17	0.947	0.960	0.952
6-6-1	0.0221	0.0140	13	0.947	0.931	0.949
9-1	0.0035	0.0035	78	0.987	0.987	0.986
8-1	0.0137	0.0063	46	0.976	0.959	0.973
6-1	0.0140	0.0107	50	0.949	0.960	0.935

5.2. Performance analysis of the proposed network

For validation analysis of the selected network, 102 random actual data from mechanical simulation are compared with the estimated data from the proposed 9-9-1 network. The data used for the network performance analysis are given in Table 8. Regarding to the validation results illustrated in Fig. 5, there is 99.34% correlation between the actual and estimated RMS values.

Moreover, the network is validated by comparison of the estimated and the actual health risk level of the dataset used for the network performance analysis. The results are given in Table 9. According to Table 9, the performance of the proposed ANN for prediction of the moderate and high health risk levels are 88.89% and 93.93%, respectively. These results show that the proposed network is an effective tool for vibrational health risk prediction.

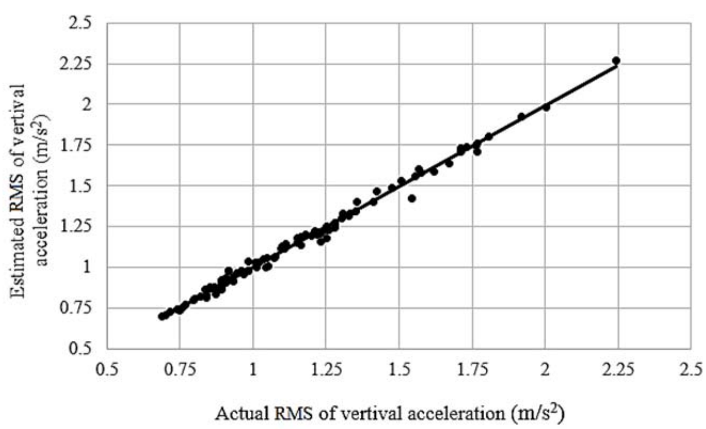

Fig. 5. Correlation between the actual and predicted RMS values of vertical vibration

Table 8. Dataset used for performance analysis of the network

No.	Haul road quality	Truck speed	Materials' weight	Load geometry	RMS	Risk level	No.	Haul road quality	Truck speed	Materials' weight	Load geometry	RMS	Risk level
1	2	3	1	11	1.092	High	**52**	2	5	4	5	1.076	High
2	2	1	1	11	0.895	Moderate	**53**	1	5	2	4	1.151	High
3	1	1	3	10	0.754	Moderate	**54**	1	6	2	6	0.891	Moderate
4	2	5	2	9	1.221	High	**55**	2	4	2	11	1.164	High
5	2	5	4	1	1.151	High	**56**	3	1	3	2	1.240	High
6	1	1	3	5	0.687	Moderate	**57**	3	2	2	8	1.302	High
7	2	1	3	4	0.927	High	**58**	2	5	3	2	1.279	High
8	1	6	3	5	0.887	Moderate	**59**	1	4	2	6	0.840	Moderate
9	1	3	4	9	0.889	Moderate	**60**	1	2	3	11	0.835	Moderate
10	2	4	3	2	1.219	Moderate	**61**	1	4	4	1	0.889	Moderate
11	2	7	3	4	1.551	High	**62**	3	6	1	4	2.242	High
12	3	3	1	3	1.620	High	**63**	2	1	3	12	0.867	Moderate
13	2	7	2	11	1.353	High	**64**	1	1	4	9	0.740	Moderate
14	1	3	2	1	0.867	Moderate	**65**	1	2	3	7	0.795	Moderate
15	2	3	1	8	1.073	High	**66**	1	7	2	11	1.022	High
16	1	3	2	13	0.835	Moderate	**67**	2	6	3	3	1.425	High
17	1	4	1	9	0.970	High	**68**	1	2	4	13	0.759	Moderate
18	2	7	4	14	1.181	High	**69**	3	4	2	3	1.707	High
19	2	1	2	8	0.888	Moderate	**70**	2	2	4	3	1.044	High
20	3	5	2	1	1.666	High	**71**	1	4	3	5	0.819	Moderate
21	3	6	2	1	1.763	High	**72**	1	5	3	3	1.095	High
22	2	6	3	6	1.165	High	**73**	2	2	1	1	0.980	High
23	3	5	3	2	1.809	High	**74**	2	6	4	11	1.300	High
24	1	3	1	10	0.904	Moderate	**75**	2	5	4	2	1.249	High
25	3	2	1	5	1.330	High	**76**	3	3	3	9	1.543	High
26	1	7	1	12	0.960	High	**77**	2	1	4	12	0.867	Moderate
27	1	7	1	6	0.929	High	**78**	1	1	3	11	0.749	Moderate
28	1	4	2	2	1.040	High	**79**	1	4	1	6	0.871	Moderate
29	2	7	1	8	1.309	High	**80**	1	3	2	14	0.853	Moderate
30	1	3	1	11	0.911	High	**81**	1	6	3	14	0.909	High
31	3	6	1	7	2.005	High	**82**	1	5	3	14	0.893	Moderate
32	2	3	1	6	1.011	High	**83**	2	6	2	7	1.279	High
33	1	6	3	1	0.945	High	**84**	3	2	4	4	1.411	High
34	1	7	2	5	0.887	Moderate	**85**	3	7	4	6	1.733	High

35	2	6	2	11	1.326	High
36	1	7	3	10	1.011	High
37	3	5	1	3	1.917	High
38	3	6	4	6	1.706	High
39	2	3	4	1	1.032	High
40	2	4	1	1	1.113	High
41	1	1	1	1	0.716	Moderate
42	1	7	4	12	0.910	High
43	2	7	2	14	1.212	High
44	1	5	2	12	0.907	High
45	1	1	3	9	0.745	Moderate
46	1	3	2	3	1.010	High
47	2	5	3	11	1.253	High
48	1	1	2	13	0.702	Moderate
49	3	1	4	6	1.248	High
50	2	4	1	4	1.346	High
51	1	4	2	4	1.107	High
86	2	2	3	9	0.979	High
87	3	6	1	1	1.761	High
88	1	4	1	2	1.053	High
89	3	4	1	5	1.567	High
90	1	3	3	1	0.862	Moderate
91	1	4	4	5	0.801	Moderate
92	3	1	2	5	1.231	High
93	2	1	2	14	0.904	High
94	3	5	4	9	1.765	High
95	1	6	1	1	0.976	High
96	3	3	3	2	1.475	High
97	2	7	3	13	1.198	High
98	1	3	4	8	0.877	Moderate
99	1	6	1	5	0.904	High
100	2	7	2	4	1.574	High
101	1	6	4	14	0.895	Moderate
102	2	3	4	7	0.982	High

Table 9. Prediction of the health risk level based on the proposed neural network

	Number of cases	
Health Risk level	Real data	**ANN prediction**
Moderate	36	**32**
High	66	**70**
Total	102	**102**

6. Conclusion

Driving trucks in various mining operational conditions generate dangerous health risk of vibrations that needs special attentions. In this paper, haul road quality, truck speed, weight and load geometry in the truck dump body are considered as the main controllable mining operational conditions. The RMS value of vertical vibration at the driver side of a three-axle truck cabin is obtained using the Trucksim software at all operational conditions. The vibrational heath risk levels are evaluated according to ISO 2631-1 standard. The feed-forward back-propagation artificial neural network (ANN) is used to predict the health risk levels. Results of this study show that mining truck drivers are exposed to moderate to high vibrational health risk. There is a significant difference between the haul road quality, the truck speed and the materials distribution in the truck dump body in the RMS of vibrations. The materials' weight has no considerable effect on the RMS value of vibration. To reduce the vibrational health risk, it is proposed that the loader operators attempt to accumulate the materials uniformly or near to the rear side of the dump body as much as possible. Application of the proposed ANN shows that there is a good agreement between the observed and predicted RMS values (R^2= 99.34%). Therefore, the proposed ANN could be used as a helpful tool for health risk prediction. These results provide practical guidelines for the operators to drive the trucks with low health risk.

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