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Development of a multi-layer perceptron artificial neural network model to determine haul trucks energy consumption

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ABSTRACT

The mining industry annually consumes trillions of British thermal units of energy, a large part of which is saveable. Diesel fuel is a significant source of energy in surface mining operations and haul trucks are the major users of this energy source. Gross vehicle weight, truck velocity and total resistance have been recognised as the key parameters affecting the fuel consumption. In this paper, an artificial neural network model was developed to predict the fuel consumption of haul trucks in surface mines based on the gross vehicle weight, truck velocity and total resistance. The network was trained and tested using real data collected from a surface mining operation. The results indicate that the artificial neural network modelling can accurately predict haul truck fuel consumption based on the values of the haulage parameters considered in this study.

1. Introduction

The reduction of energy consumption has gradually become more important worldwide since the rise of the cost of fuel in the 1970s. The mining industry annually consumes trillions of British thermal units (BTUs) of energy in operations such as exploration, extraction, transportation and processing. A large number of research studies and industrial projects have been carried out in an attempt to reduce energy consumption in mining operations [1–4]. Current investments in the improvement of mining equipment have resulted in a significant reduction of energy consumption [5,6]. A large amount of energy can also be saved by improving mining technologies and energy management systems [7,8]. Energy saving is also associated with the reduction of millions of tonnes of gas emissions because the major energy sources used in the mining industry are petroleum products: electricity, coal and natural gas [9,10]. The type of fuel used on a mine site is greatly dependent on the type of mining method and the equipment used. Most of the equipment used for the handling of materials in mining is powered by diesel engines [11], which are highly energy-intensive, accounting for 87% of the total energy consumed in material handling.

Service trucks, front-end loaders, bulldozers, hydraulic excavators, rear-dump trucks and ancillary equipment, such as pick-up trucks and mobile maintenance equipment, are examples of the diesel equipment used in mining operations. Trucks in surface mines are used to haul ore and overburden from the pit to the stockpile, the dumpsite or to the next stage of the mining process. They are used in combination with other equipment, such as excavators, diggers and loaders, according to the production capacity and the site layout. The trucks used in the haulage operations of surface mines use a great amount of energy and this has encouraged truck manufacturers and major mining corporations to carry out a number of research projects on the energy efficiency of haul trucks [12–16].

The study conducted by Antoung and Hachibli [13] is concerned with the implementation of power-saving technology to improve the motor efficiency of mining equipment. The focus of their study is on the technical performance of motor components and how they contribute to the reduction of friction and the improvement of the motor efficiency. Beatty and Arthur [14] investigate the effect of some general parameters, such as cycle time and mine planning, on the energy used by haul trucks. They determine the optimum values of these parameters to minimise fuel consumption in hauling operations, but they do not consider the three technical key parameters of gross vehicle weight (GVW), total resistance (TR) and truck velocity (V). The research presented by Carmichael et al. [15] is concerned with the effects of haul truck fuel consumption on costs and gas emissions in surface mining operations; however, the simulation used in their research does not include the pertinent factors affecting the fuel consumption.

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Chingooshi et al. [16] study the smart energy mining strategy and identify the effective key parameters involved in energy efficiency opportunities in the mining industry as a whole; however, their research excludes the technical aspects of the parameters that affect fuel consumption for haul trucks. The scope of the present paper differs from the above-mentioned studies because it aims to determine how the fuel consumption of a haul truck varies with the truck payload, truck tyre rolling resistance (RR) and the haul grade resistance (GR) when the truck is travelling with the best engine performance.

The understanding of the energy efficiency of a haul truck is not limited to the analysis of vehicle-specific parameters and mining companies can often benefit by expanding the analysis to include other factors that affect the energy use of trucks, such as payload distribution; however, reasonable progress has not yet been made in this field of research due to the complexity of the parameters involved. There are a number of key parameters that influence the energy used by trucks in a mine fleet, all of which need to be taken into account simultaneously for the optimisation of fuel consumption.

Artificial neural networks (ANNs) can be used to determine fuel consumption by taking into consideration a number of parameters that influence the fuel consumption of trucks. ANNs have been used in many engineering disciplines, such as materials, biochemical engineering, medicine and mechanical engineering [17–30]. ANNs are desirable solutions for complex problems as they can interpret the compound relationships between the multiple parameters involved in a problem. One of the main advantages of the ANNs is that they can simulate both linear and nonlinear relationships between the parameters using the information provided to train the network. This paper presents the development of a multi-layer perceptron artificial neural network model to determine the fuel consumption of haul trucks in surface mines.

2. Haul truck fuel consumption

Haul truck fuel consumption is a function of various parameters, the most significant of which have been identified and categorised into seven main groups (Fig. 1). The key parameters that affect the energy consumption of haul trucks include the payload management, the model of the truck, GR and RR, according to a study conducted by the Department of Resources, Energy and Tourism. That study examines the best truck ratio (BTR) and the diesel consumption for a fixed production of 20 million tonnes of moved material and finds an optimal payload associated with the minimum BTR and diesel consumption. The BTR is defined as the ratio of actual consumed energy to the theoretical best use of energy by haul trucks. It is also shown that the model of the truck and the haul road condition affects the BTR and the diesel consumption.

In the present study, the effects of the GVW (representing the sum of the empty truck weight and the payload), the maximum truck velocity (V_{max}, representing the truck model at a fixed payload) and the TR (representing the haul road condition) on the energy consumption of the haul trucks were examined. The TR is equal to the sum of RR and GR when the truck is moving against the grade of the haul road.

$$\mathrm{TR} = \mathrm{RR} + \mathrm{GR} \tag{1}$$

The RR depends on the tyre and hauling road surface characteristics and is used to calculate the rolling friction force, which is the force that resists the motion when the truck tyre rolls on the haul road (Fig. 2).

For typical haul roads, the RR is 2% if the road is hard and well-maintained; on the bench and close to the dump end, the road quality deteriorates and the RR is expected to increase to 3%; during wet periods when the road conditions are worsened, the RR might increase to 4%; finally, under very poor conditions, the RR may rise to 10–16%, however, this would only be over very small sections of the haul road and for short periods of truck operations. In this study, the haul road is considered to have the same conditions as the dirt-dry, but not firmly packed, road and, therefore, a RR of 3% is used in the analysis. The typical values for RR are presented in Table 1.

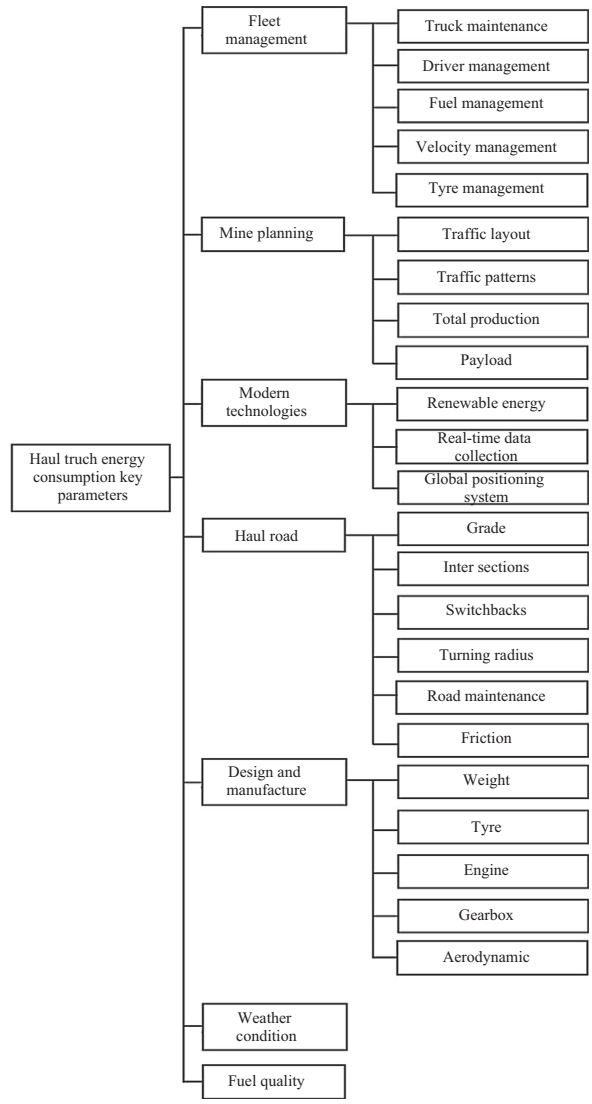

Fig. 1. Haul truck energy consumption key parameters.

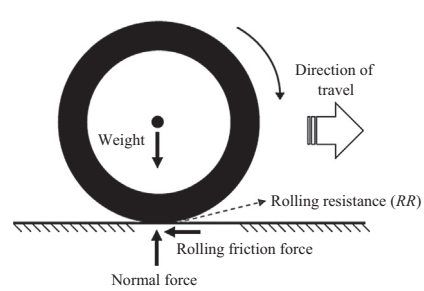

Fig. 2. A schematic diagram of a truck tyre showing the force.

Table 1
Typical values for rolling resistance (RR) (%).

Road condition	Rolling resistance
Bitumen, concrete	1.5
Dirt-smooth, hard, dry and well maintained	2.0
Gravel-well compacted, dry and free of loos material	2.0
Dirt-dry but not firmly packed	3.0
Gravel-dry not firmly compacted	3.0
Mud-with firm base	4.0
Gravel or sand-loose	10.0
Mud-with soft spongy base	16.0

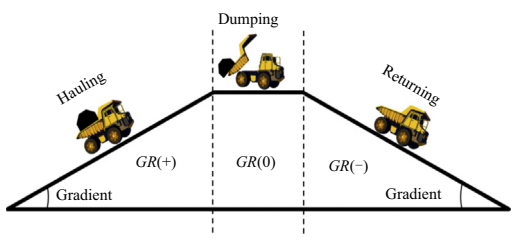

Fig. 3. Grade resistance (GR).

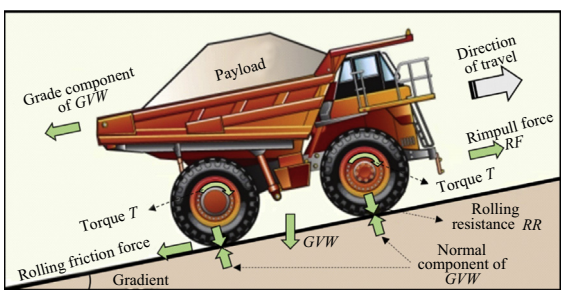

Fig. 4. A schematic diagram of a typical haul truck and effective key factors on truck performance.

The GR is the slope of the haul road, it is measured as a percentage and is calculated as the ratio between the rise of the road and the horizontal length (Fig. 3). For example, a section of the haul road that rises at 10 m over 100 m has a GR of 10%. The GR is positive when the truck is travelling up the ramp and is negative when it travels down the ramp. The GR is positive for all the test conditions considered in this study, as the truck carrying the payload is travelling against the grade of the haul road.

Fig. 4 presents a schematic diagram of a typical haul truck and the key factors that affect the performance of the truck, such as the GVW, RR, gradient, friction force and rimpull force (RF).

RF is the force available between the tyre and the ground to propel the machine (Fig. 5). It is related to the torque (T) that the machine is capable of exerting at the point of contact between its tyres and the ground and the truck wheel radius (r).

$$\mathrm{RF} = \frac{T}{r} \tag{2}$$

Caterpillar trucks are the most popular vehicles of the different brands used in the mining industry. Based on the power of vehicle, mine productivity, haul truck capacity and other key parameters, CAT 793D (Table 2) was selected for the analysis presented in this study.

Fig. 6 presents the rimpull-speed-grade ability curve extracted from the manufacturer's catalogue.

This curve was used to determine the rimpull (R) and the V_{max} based on different values of TR for the real values of GVW in the mine site dataset. This dataset was collected from a surface coal mine in central Queensland, Australia for a CAT 793D truck and includes the following information: date, payload (tonne), V (km/h), cycle time (hh:mm:ss), cycle distance (km), RR (%), GR (%), TR (%) and truck fuel consumption (L/h). A sample of the dataset is presented in Table 3.

The cycle time, presented in Table 3, is the round trip time for the hauling truck and is calculated based on the fixed, travel and wait time: the fixed time is the sum of loading, manoeuvring, dumping and spotting; the travel time is the sum of the hauling and returning time; and the wait time is the queueing time for dumping and loading (Fig. 7) [31]. The rate of fuel consumption for the CAT 793D truck was determined based on the values of GVW in the collected dataset and the calculated power.

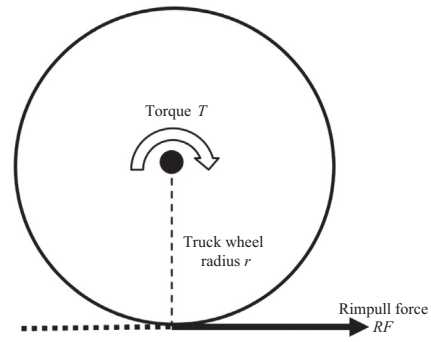

Fig. 5. Schematic of the wheel showing the rimpull force (RF).

Table 2
CAT 793D Mining truck specifications.

Specification	Value
Engine	
Engine model	CAT 3516B HD
Gross power (kW)	1801
Net power (kW)	1743
Weights-approximate	
Gross weight (tonnes)	384
Nominal payload (tonnes)	240
Body capacity	
Struck (m^3)	96
Heaped (m^3)	129

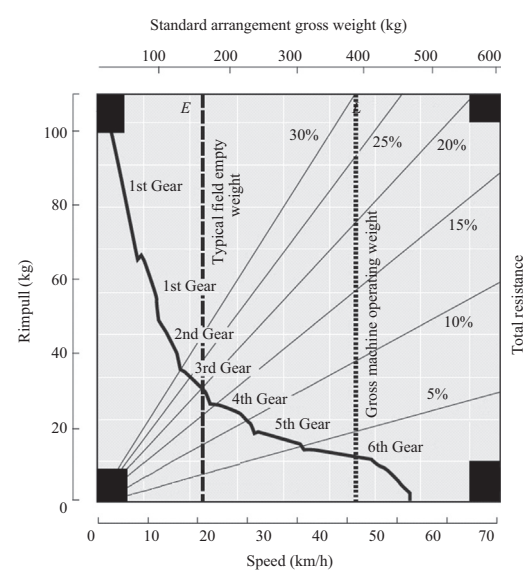

Fig. 6. Rimpull-speed-grade ability curve for Truck CAT 793D.

Table 3
A sample of dataset collected from a surface coal mine in central Queensland, Australia (CAT 793D).

Date	Payload (tonne)	Truck velocity (km/h)	Cycle time (hh:mm:ss)	Cycle distance (km)	Rolling resistance (%)	Grade resistance (%)	Total resistance (%)	Fuel consumption (L/h)
23/01/2013	218.6	8.49	00:25:35	4.989	3.0	11.6	14.6	84.44
15/02/2013	219.4	11.39	00:16:17	5.150	3.0	8.7	11.7	90.26
13/03/2013	168.2	11.17	00:11:12	2.414	3.0	10.7	13.7	89.90
29/03/2013	158.9	14.04	00:17:42	5.150	3.0	9.1	12.1	93.78
22/04/2013	216.5	10.36	00:19:17	5.311	3.0	9.6	12.6	88.48
08/05/2013	202.1	12.06	00:18:45	5.311	3.0	9.4	12.4	91.28
25/06/2013	185.5	11.53	00:16:24	4.023	3.0	10.1	13.1	90.49
16/08/2013	175.9	11.94	00:18:48	4.667	3.0	10	13	91.10
07/10/2013	147.6	13.27	00:22:23	5.311	3.0	10.3	13.3	92.90
19/12/2013	214.3	11.58	00:17:55	5.150	3.0	8.9	11.9	90.56

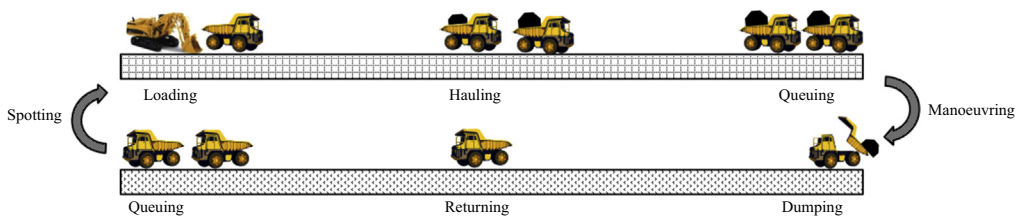

Fig. 7. Hauling truck operations in a round trip [31].

Table 4
Typical values of load factors (LF).

Operating conditions	LF (%)	Conditions
Low	20–30	Continuous operation at an average GVW less than recommended, No overloading
Medium	30–40	Continuous operation at an average GVW recommended, minimal overloading
High	40–50	Continuous operation at or above the maximum recommended GVW

The truck fuel consumption can be calculated from Eq. (3) (Filas [32]):

$$FC = \frac{SFC}{FD}(LF \cdot P) \tag{3}$$

where SFC is the engine specific fuel consumption at full power (0.213–0.268 kg/(kW h)) and FD is the fuel density (0.85 kg/L for diesel). The simplified version of Eq. (3) is presented by Rung [33]:

$$FC = 0.3(LF \cdot P) \tag{4}$$

where LF is the engine load factor and is defined as the ratio of average payload to the maximum load in an operating cycle [2]. The typical values of LF are presented in Table 4. P is the truck power (kW). For the best performance of the truck operation, P is determined by:

$$P = \frac{1}{3.6}(RF \cdot V_{max}) \tag{5}$$

where RF is calculated by the product of rimpull (R) and the gravitational acceleration (g). V_{max} is calculated by Eq. (6), which is based on the relationship between R and V_{max} as presented in Fig. 6 (Soofastaei [34]).

$$V_{max} = a - b \times \exp(-c \times R^d) \tag{6}$$

where a = 53.867, b = 54.906, c = 37.979 and d = −1.309.

DataThief 5.6 and Curve Expert 2.1 were used to find an equation for R as a function of TR and GVW based on the rimpull-speed-grade ability curve (Fig. 6).

$$R = 0.183GVW(0.006 + 0.053TR) \tag{7}$$

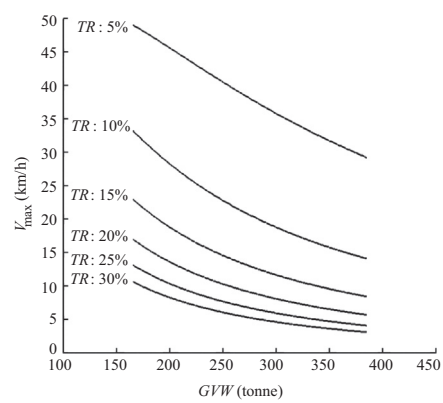

Fig. 8. Variation of V_{max} with GVW for different TR.

The relationship between V_{max} and GVW for six values of TR is illustrated in Fig. 8. The results show that, for any value of TR, V_{max} decreases as GVW increases (this is due to the increased payload that causes R to increase and, consequently, V_{max} to decrease). The results also show that, for a fixed GVW, V_{max} decreases as TR increases.

Table 5 presents FC for different values of GVW obtained from the real mine dataset in the range of 165 tonnes (empty truck) to 385 tonnes (fully loaded truck). TR = 10% ± 0.1. FC was calculated based on Eq. (4) and by using the values of R and V_{max}. For other values of TR in the range of 1–30%, FC was calculated versus GVW, as presented in Fig. 9. The results generally show that, for all values of TR, FC increases as GVW increases. It can also be seen that, for a fixed GVW, FC increases as TR increases.

It must be noted that, up to this point, the truck fuel consumption has been calculated based on the best truck performance recommended by the manufacturer using the values of V_{max} presented in the rimpull-speed-grade ability curve (Fig. 6); however, in real mining operations, the haul trucks travel at speeds that are normally lower than the V_{max}. The relationship between the truck fuel consumption, payload, TR and actual V is generally complex and requires an artificial intelligence method to determine the

Table 5
Fuel consumption (FC) by CAT 793D for TR = 10% ± 0.1 (sample).

GVW* (tonne)	Rimpull (tonne)	Truck velocity (km/h)	Power (kW)	LF	Fuel consumption (L/h)
166.3	16.46	33.03	1482.77	0.21	94.93
172.8	17.10	32.02	1493.49	0.21	98.64
185.1	18.32	30.21	1509.64	0.22	102.96
192.4	19.04	29.21	1516.99	0.23	106.59
202.3	20.02	27.92	1524.71	0.23	110.29
214.9	21.27	26.40	1531.34	0.24	113.93
235.4	23.30	24.17	1536.00	0.25	117.45
254.7	25.21	22.33	1535.09	0.25	120.56
286.4	28.35	19.74	1525.83	0.26	122.98
297.1	29.41	18.97	1521.11	0.27	125.75
306.5	30.34	18.33	1516.46	0.27	128.49
308.7	30.55	18.19	1515.31	0.28	131.53
312.4	30.92	17.95	1513.32	0.29	134.48
321.9	31.86	17.35	1507.97	0.29	137.12
336.2	33.28	16.52	1499.30	0.30	139.43
342.6	33.91	16.17	1495.21	0.31	142.14
356.4	35.28	15.45	1486.05	0.31	144.34
368.7	36.49	14.85	1477.53	0.32	146.57
371.4	36.76	14.72	1475.62	0.33	149.43
375.6	37.18	14.53	1472.63	0.33	152.17
381.5	37.76	14.26	1468.38	0.34	154.77
384.2	38.03	14.14	1466.42	0.35	157.59

Note: *GVW = Payload + Empty truck weight.

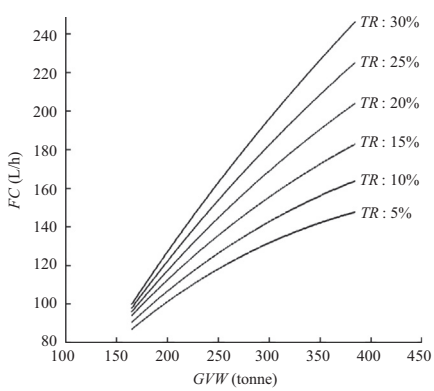

Fig. 9. Variation of FC with GVW for different TR.

relationship. In the next section of this paper, the details of an ANN model, that was developed to determine how the truck fuel consumption varies with the variation of payload, TR and *V*, are presented.

3. Artificial neural network

3.1. Background

ANNs, also known as neural networks (NNs), simulated neural networks (SNNs) or 'parallel distributed processing', are the representation of methods that the brain uses for learning [35]. ANNs are series of mathematical models that imitate a few of the known characteristics of natural nerve systems and sketch on the analogies of adaptive natural learning. The key component of a particular ANN paradigm could be the unusual structure of the data processing system. A typical neuronal model is thus comprised of weighted connectors, an adder and an activation function (Fig. 10).

ANNs are utilised in various computer applications to solve complex problems. They are fault-tolerant and straightforward models that do not require information to identify the related factors [36] and do not require the mathematical description of the phenomena involved in the process.

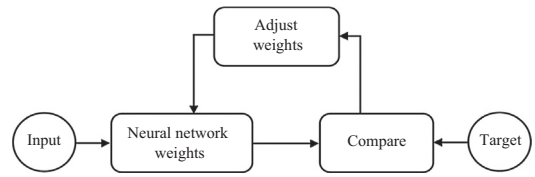

Fig. 10. A typical procedure of an artificial neural network.

3.2. Neural network structure, training and development

The main part of a neural network structure is a 'node'. Biological nodes generally sum the signals received from numerous sources in different ways and then carry out a nonlinear action on the results to create the outputs. Neural networks typically have an input layer, one or more hidden layers and an output layer. Each input is multiplied by its connected weight and in the simplest state, these quantities and biases are combined; they then pass through the activation functions to create the output (see Eqs. (8)–(10)). Fig. 11 shows the data treatment in a node (it should be noted that the hidden layer nodes may use any differentiable activation function to generate their output).

$$E_k = \sum_{j=1}^{q} (w_{i,j,k} x_j + b_{i,k}) \quad k = 1, 2, \ldots, m \tag{8}$$

where x is the normalised input variable, w is the weight of that variable, i is the input, b is the bias, q is the number of input variables, and k and m are the counter and number of neural network nodes, respectively, in the hidden layer.

In general, the activation functions consist of both linear and nonlinear equations. The coefficients associated with the hidden layer are grouped into matrices $W_{i,|,j,k}$ and $b_{i,k}$. Eq. (9) can be used as the activation function between the hidden and the output layers (in this equation, f is the transfer function).

$$F_k = f(E_k) \tag{9}$$

The output layer computes the weighted sum of the signals provided by the hidden layer and the associated coefficients are grouped into matrices $W_{o,k}$ and b_o. Using the matrix notation, the network output can be given by Eq. (10).

$$\text{Out} = \left(\sum_{k=1}^{m} w_{o,k} F_k \right) + b_o \tag{10}$$

Network training is the most important part of neural network modelling and is carried out using two methods: controllable and uncontrollable training. The most common training algorithm is

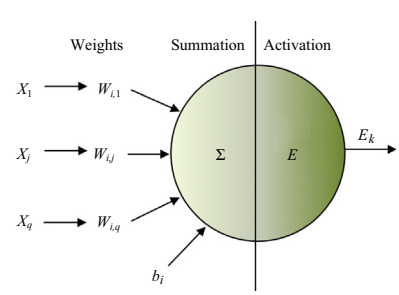

Fig. 11. Data processing (treatment) in a neural network cell (node).

that of back-propagation. A training algorithm is defined as a procedure that consists of adjusting the coefficients (weights and biases) of a network to minimise the error function between the estimated network outputs and the real outputs.

This paper presents a study in which different types of algorithms were examined in order to determine the best back-propagation training algorithm. In comparison to other back-propagation algorithms, the Levenberg–Marquardt (LM) back-propagation training algorithm has the minimum mean square error (MSE), root mean square error (RMSE) and correlation coefficient (R^2).

In addition, network training with the LM algorithm can run smoothly with the minimum expanded memory specification (EMS) and a fast training process. MSE, RMSE and R^2 are the statistical criteria utilised to evaluate the accuracy of the results according to following equations [36,37]:

$$\mathrm{MSE} = \frac{1}{p}\sum_{r=1}^{p}(y_r - z_r)^2 \tag{11}$$

$$\mathrm{RMSE} = \left(\frac{1}{p}\sum_{r=1}^{p}(y_r - z_r)^2\right)^{\frac{1}{2}} \tag{12}$$

$$R^2 = 1 - \frac{\sum_{r=1}^{p}(y_r - z_r)^2}{\sum_{r=1}^{p}(y_r - \bar{y})^2} \tag{13}$$

where y is the target (real), z is the output (estimated) of the model, $\bar{y}$ is the average value of the targets and p is the number of the network outputs.

In this project, the MSE and R^2 methods were applied to examine the error and performance of the neural network output and the LM optimisation algorithm was utilised to obtain the optimum weights of the network.

4. Proposed model

4.1. Network structure

The structure of the proposed ANN model for function approximation is a feed-forward multi-layer perceptron neural network with three input variables and one output. The feed-forward network frequently has one or more hidden layers of sigmoid nodes tracked by an output layer of linear nodes. Multiple layers of nodes with nonlinear activation functions allow the network to learn the linear and nonlinear connections between the input and output vectors. The linear output layer allows the network to create values outside the $[-1, +1]$ range.

The activation functions in the hidden layer (f) are the continuous differentiable nonlinear tangents sigmoid presented by Eq. (14).

$$f = \tan\mathrm{sig}(E) = \frac{2}{1 + \exp(-2E)} - 1 \tag{14}$$

where E can be determined by Eq. (8).

In order to find the optimal number of nodes in the hidden layer, MSE and R^2 were calculated for different numbers of nodes in the hidden layer. The minimum MSE and the maximum R^2 (best performance) were found for 15 nodes in the hidden layer (as shown in Table 6 and Fig. 12).

The schematic structure of the designed neural network based on three input variables, fifteen nodes in the hidden layer and one output is shown in Fig. 13.

The statistical features of the input and output variables used for the network synthesis, showing the variation range and the standard deviation of each variable, are given in Table 7.

Table 6
Values of MSE and R^2 for different numbers of nodes in the hidden layer.

Number of nodes in hidden layer(s)	MSE	R^2
1	248.0580	0.988211
2	37.22722	0.998248
3	0.998305	0.999953
4	0.228053	0.999989
5	0.031135	0.999999
6	0.145217	0.999993
7	0.026266	0.999999
8	0.019214	0.999999
9	0.011070	0.999999
10	0.019934	0.999999
11	0.021152	0.999999
12	0.001974	1.000000
13	0.022326	0.999999
14	0.010901	0.999999
15	0.001716	1.000000
16	0.005223	1.000000
17	0.002423	1.000000
18	0.003433	1.000000
19	0.010185	1.000000
20	0.003890	1.000000

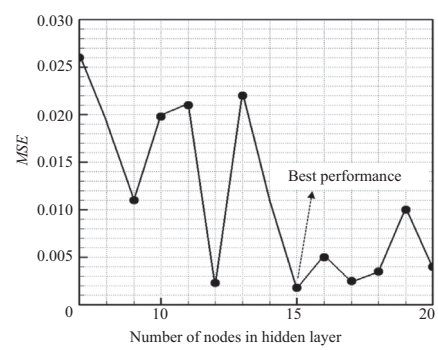

Fig. 12. Performance of the network at different hidden nodes using LM algorithm.

4.2. Network training

In order to train the ANN model, 4600 pairing data were randomly selected from the 6630 values of the collected site data. From the selected site data, the values of payload, V_{max} and TR were used to calculate the fuel consumption and used to train the ANN model. Based on the network structure presented earlier, the normalised fuel consumption can be determined by Eq. (15):

$$\mathrm{FC}_n = \sum_{k=1}^{m}\left[w_{o,k}\left(\frac{2}{1 + \exp\left(-2\left(\sum_{j=1}^{q}(w_{i,j,k}x_j) + b_{i,k}\right)\right)} - 1\right)\right] + b_o \tag{15}$$

where m is the number of nodes in the hidden layer ($m = 15$), q is the number of inputs ($q = 3$) and w and b are weight and bias, respectively. In this equation, i is the input, o is the output and FC_n is the normalised fuel consumption. The results of the network training, in terms of the values of the adjustable weight (w) and bias (b) used in Eq. (15), are presented in Table 8.

Fig. 14 shows the variation of *MSE* during the network training: it can be seen that the error approaches zero after 25 epochs, indicating that the desired network convergence was obtained during the training.

4.3. Network application

The developed ANN model, after being trained, was used to calculate the haul truck fuel consumption as a function of GVW(x_1), TR(x_2) and V_{max}(x_3), based on the following steps:

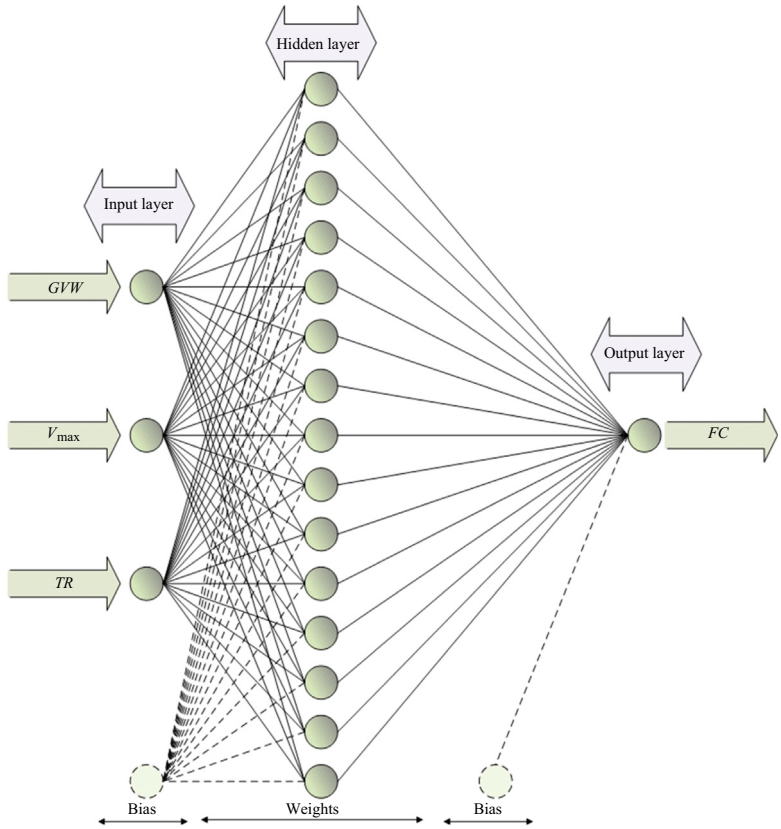

Fig. 13. Schematic illustration of the designed neural network structure.

Table 7
Input and output variables statistical features.

Statistical features	Gross weight (tonne)	Total resistance (%)	Maximum velocity (km/h)	Fuel consumption (L/h)
Maximum	385	30	53.87	237.92
Minimum	165	1	3.13	13.61
Mean	275	15.5	19.57	32.53
Median	275	15.5	13.46	140.82
STDEV	63.79	8.65	15.15	41.42
Size	6630	6630	6630	6630

Step 1: Normalising the input parameters between −1 and +1

$$x_n = \left(\frac{x - x_{min}}{x_{max} - x_{min}} \times 2\right) - 1 \tag{16}$$

Step 2: Calculating the E parameter for each hidden node

$$E_k = \sum_{j=1}^{q}(w_{i,j,k}x_j + b_{i,k}) \quad k = 1, 2, \ldots, 15 \tag{17}$$

Step 3: Calculating the F parameters

$$F_k = \frac{2}{1 + \exp(-2E_k)} - 1 \quad k = 1, 2, \ldots, 15 \tag{18}$$

Step 4: Calculating the normalised fuel consumption FC_n

$$\mathrm{FC}_n = \left(\sum_{k=1}^{15} w_{o,k}F_k\right) + b_o \tag{19}$$

Step 5: Denormalising the fuel consumption

$$\mathrm{FC} = 13.61 + \frac{(\mathrm{FC}_n + 1)(237.92 - \mathrm{FC}_n)}{2} \tag{20}$$

Table 8
Adjustable parameters obtained (weights and bias) in the proposed model m = 15 (k = 1, 2, . . . , 15), q = 3 (j = 1, 2, 3).

Weight				Bias	
$w_{i,j,k}$			$w_{o,k}$	$b_{i,k}$	b_o
$w_{i,1,1}$	$w_{i,2,1}$	$w_{i,3,1}$	$w_{o,1}$	$b_{i,1}$	b_o
0.1665	0.7960	−0.6736	1.2290	0.0446	−2.2715
$w_{i,1,2}$	$w_{i,2,2}$	$w_{i,3,2}$	$w_{o,2}$	$b_{i,2}$	
0.1203	1.2317	−0.4215	1.0472	1.3500	
$w_{i,1,3}$	$w_{i,2,3}$	$w_{i,3,3}$	$w_{o,3}$	$b_{i,3}$	
0.2995	−0.0739	−0.6099	1.2477	0.2680	
$w_{i,1,4}$	$w_{i,2,4}$	$w_{i,3,4}$	$w_{o,4}$	$b_{i,4}$	
−0.4642	2.2158	−1.2879	3.5790	4.3941	
$w_{i,1,5}$	$w_{i,2,5}$	$w_{i,3,5}$	$w_{o,5}$	$b_{i,5}$	
0.4443	0.8145	−0.1406	1.0073	−0.2283	
$w_{i,1,6}$	$w_{i,2,6}$	$w_{i,3,6}$	$w_{o,6}$	$b_{i,6}$	
0.6018	0.7676	0.6249	0.6943	−0.6287	
$w_{i,1,7}$	$w_{i,2,7}$	$w_{i,3,7}$	$w_{o,7}$	$b_{i,7}$	
−0.2136	−0.3001	0.1248	0.8841	0.4164	
$w_{i,1,8}$	$w_{i,2,8}$	$w_{i,3,8}$	$w_{o,8}$	$b_{i,8}$	
−0.6371	−0.5198	−0.6359	0.7212	0.6409	
$w_{i,1,9}$	$w_{i,2,9}$	$w_{i,3,9}$	$w_{o,9}$	$b_{i,9}$	
0.0703	0.7174	−1.4252	1.2914	2.3359	
$w_{i,1,10}$	$w_{i,2,10}$	$w_{i,3,10}$	$w_{o,10}$	$b_{i,10}$	
−0.1585	−0.3657	0.1386	0.8588	0.4348	
$w_{i,1,11}$	$w_{i,2,11}$	$w_{i,3,11}$	$w_{o,11}$	$b_{i,11}$	
−0.2491	0.4677	0.3727	0.5701	0.0008	
$w_{i,1,12}$	$w_{i,2,12}$	$w_{i,3,12}$	$w_{o,12}$	$b_{i,12}$	
0.1959	−0.9730	0.7279	1.7479	−1.2233	
$w_{i,1,13}$	$w_{i,2,13}$	$w_{i,3,13}$	$w_{o,13}$	$b_{i,13}$	
−0.4013	−0.9377	−0.7644	1.3130	−0.9649	
$w_{i,1,14}$	$w_{i,2,14}$	$w_{i,3,14}$	$w_{o,14}$	$b_{i,14}$	
0.2715	−0.1492	1.0988	2.0026	0.6752	
$w_{i,1,15}$	$w_{i,2,15}$	$w_{i,3,15}$	$w_{o,15}$	$b_{i,15}$	
0.4799	0.9377	2.1059	2.6285	−1.8993	

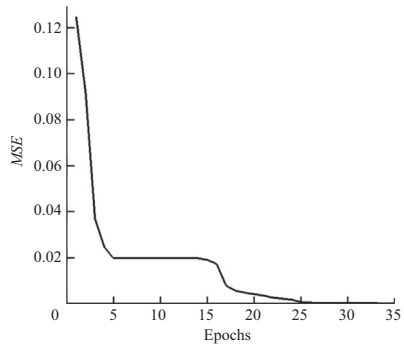

Fig. 14. Neural network error diagram (MSE) during network training.

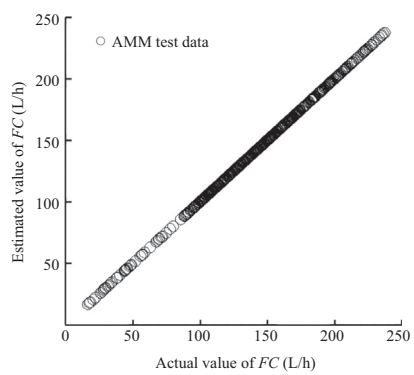

Fig. 15. Comparison of actual values with network outputs for test data (first quarter bisector).

Table 9
Sample values for estimated (ANN) and independent (tests) fuel consumption.

Estimated value of FC (ANN) (L/h)	Independent value of FC (tests) (L/h)	Absolute error (%)
13.79	13.71	0.58
15.79	15.74	0.32
17.13	17.09	0.20
19.34	19.33	0.06
58.78	58.71	0.12
60.87	60.79	0.13
63.52	63.47	0.08
74.63	74.59	0.06
97.78	97.75	0.03
99.38	99.31	0.07

4.4. Network test

In order to test the network accuracy and validate the model, 2030 independent samples were used. The test results of the synthesised network are shown in Fig. 15 where the vertical and horizontal axes show the estimated fuel consumption values by the model and the actual fuel consumption values, respectively.

The results show good agreement between the actual and estimated values of fuel consumption. Table 9 also presents sample values for the estimated (using the ANN) and the independent (tested) fuel consumption in order to highlight the insignificance of the values of the absolute errors in the analysis.

5. Sensitivity analysis

To identify the critical parameters and their degree of significance in relation to the outputs of the model, a sensitivity analysis

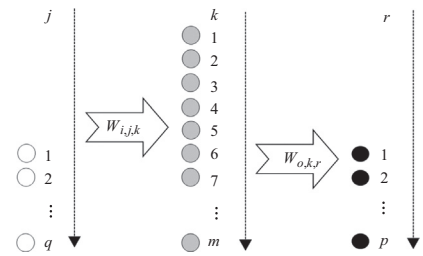

Fig. 16. Weight method structure for sensitivity analysis.

Table 10
Relative important of input variables (%).

Input variable	Importance
Maximum truck velocity (V_{max})	60
Total resistance (TR)	26
Gross machine weight (GVW)	14
Total	100

was carried out. There are many methods to assess the relative importance of the input variables in the ANN, such as 'PaD', 'Profile', 'Stepwise' and 'Weight' [38–44]. In this paper, the 'Weight' method, based on the neural net weight matrix and the Garson equation [42] was utilised. Garson proposed an equation based on the partitioning of connection weights, as illustrated in Eq. (21):

$$Q_{j,r} = \frac{\sum_{k=1}^{m}\left(\left(w_{i,j,k}/\sum_{j=1}^{q} w_{i,j,k}\right) w_{o,k,r}\right)}{\sum_{j=1}^{q}\left(\sum_{k=1}^{m}\left(\left(w_{i,j,k}/\sum_{j=1}^{q} w_{i,j,k}\right) w_{o,k,r}\right)\right)} \tag{21}$$

where $\sum_{j=1}^{q} w_{i,j,k}$ denotes the sum of the connection weights between the input nodes (q) and the hidden node (k) (Fig. 16). $Q_{j,r}$ represents the relative importance of the input variable (x_i) on the output (y_r), in relation to the rest of the input variables, in such a way that the sum of this index must give a value of 100% for all of the input variables [43].

Table 10 presents the relative importance of the input variables calculated by Eq. (21) and it is clearly shown that all three variables have a noticeable effect on the haul truck fuel consumption. The V_{max}, with a relative importance of 60%, appeared to be the most influential parameter in this study.

6. Conclusions

The aim of this study was to develop an ANN model to determine haul truck fuel consumption based on the relationship between GVW, V and TR. For an actual dataset obtained from surface mining operations, this relationship was complex and required an artificial intelligence method to create a reliable model to analyse the problem. In the first part of the study, to determine the best performance of the haul truck, the fuel consumption was calculated based on the collected data for GVW from a real mine site and the corresponding Rimpull and V_{max} for various values of TR. The results showed that fuel consumption increased as the TR and the GVW were increased. In the second part of the study, an ANN model was developed, which was found to perform best with the configuration of three input variables, 15 hidden nodes and one output. This model was then trained based on the truck's best performance characteristics, using real values for GVW collected from a surface mining operation and the associated fuel consumption values. The network was tested using the remaining values of the collected dataset and the results showed that there was good agreement between the actual and estimated values of fuel consumption. The sensitivity analysis showed that all three

input variables have a noticeable effect on the haul truck fuel consumption and that the V_{max} proved to be the most influential parameter, with the relative importance of 60%. The developed model can be used to estimate the fuel consumption for any dataset obtained from real surface mine truck operations.

Acknowledgments

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