Chapter

The Application of Artificial Intelligence to Reduce Greenhouse Gas Emissions in the Mining Industry

Ali Soofastaei

Abstract

Mining industry consumes a significant amount of energy and makes greenhouse gas emissions in various operations such as exploration, extraction, transportation and processing. A considerable amount of this energy and gas emissions can be reduced by better managing the operations. The mining method and equipment used mainly determine the type of energy source in any mining operation. In surface mining operations, mobile machines use diesel as a source of energy. These machines are haul trucks excavators, diggers and loaders, according to the production capacity and site layout and they use a considerable amount of fuel in surface mining operation; hence, the mining industry is encouraged to conduct some research projects on the energy efficiency of mobile equipment. Classical analytics methods that commonly used to improve energy efficiency and reduce gas emissions are not sufficient enough. The application of artificial intelligence and deep learning models are growing fast in different industries, and this is a new revolution in the mining industry. In this chapter, the application of artificial intelligence methods to reduce the gas emission in surface mines with some case studies will be explained.

Keywords: artificial intelligence, deep learning, fuel consumption, gas emissions, mining operations, prediction models, optimization methods

1. Introduction

Energy consumption in mining is rising due to lower grade ores, located deeper underground [1]. Mining operations use a different type of energies in a variety of ways, including excavation, material handling and transferring, ventilation and dewatering [2]. Based on completed industrial projects, significant opportunities exist within the mining industry to reduce energy consumption [2]. The potential for energy used reduction has motivated both governments and the mining industry to research the decrease energy consumption [3].

The most usually used means of mining and hauling of materials is via a truck and shovel operation in surface mines [4, 5]. The trucking of overburden constitutes a significant portion of energy consumption [3]. The amount of energy consumption is a function of some parameters. The research presented by Carmichael et al. [6] is concerned with the effects of the density of the load, the geology of the site, road surfaces and gradients on the energy consumption of haul trucks. Cetin [7] examined the relationship between haul truck energy efficiency and loading rates, vehicle efficiency, and driving practices. Beatty and Arthur [4] investigated the effect of some overall factors, such as mine planning and cycle time, on the energy consumed by trucks. They determine the optimum values of these parameters to minimize fuel consumption in hauling operations. The study conducted by Coyle [8] is concerned with the effects of payload on truck fuel consumption. In this study, he shows the impact of load density variation based on the blasting procedures on fuel consumption by haul trucks. Soofastaei et al. completed many different projects in the field of haul truck energy efficiency in surface and underground mines [9–17].

To the authors' best knowledge, the investigations presented in the literature are based mostly on the theoretic methods used to estimate the fuel consumption of mine trucks. These models work based on the curves prepared by the truck manufacturer for the performance of haul mining trucks [5, 18–23].

In this chapter, the effects of the three main effective parameters on fuel consumption of haul trucks have been examined. These parameters are payload (P), truck speed (S) and total resistance (TR). On a real mine site, the correlation between fuel consumption and the parameters mentioned above is complex. Therefore, in this study, two artificial intelligence methods have been used to create a model to estimate and reduce fuel consumption. This model has been completed and tested in a surface coal mine in central Queensland, Australia. The developed model can predict the energy consumption of one type of truck in open-pit and open-cut mines using an artificial neural network (ANN) and can also find the optimum value of P, S and TR using a Genetic Algorithm (GA).

2. Calculation of haul truck fuel consumption

Fuel consumption by mine trucks is a function of some parameters (**Figure 1**). The most important of these parameters can be categorized into seven main groups including fleet management, mine planning, modern technology, haul road, design and manufacture, weather condition and fuel quality [9, 22].

In the present chapter, the effects of the P, S and TR on the fuel consumption of mine trucks were investigated. The total resistance is equivalent to the sum of the grade resistance (GR) and the rolling resistance (RR) [22].

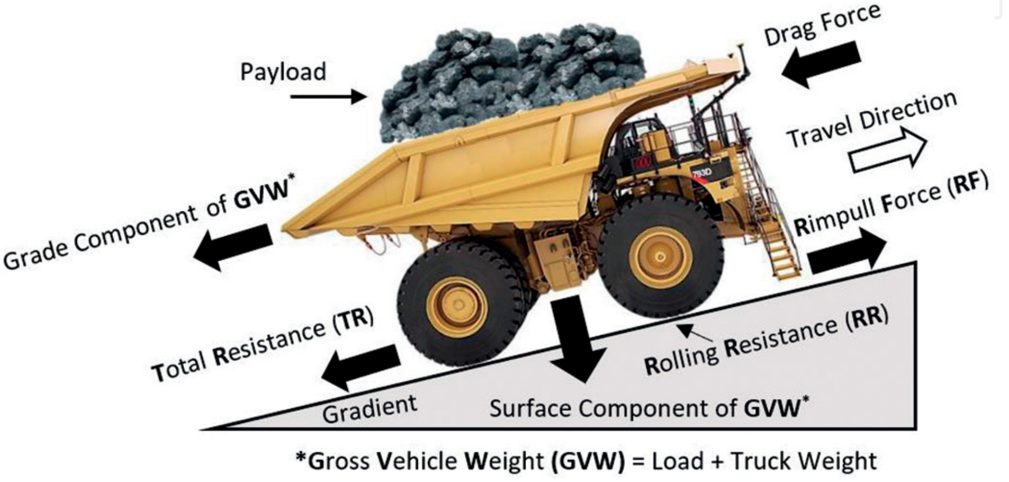

Figure 1.
Haul road and truck key parameters.

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

The rolling resistance depends on the tyre and road surface features and is applied to estimate the Rimpull force (RF), which is the force that resists motion as the truck tyre rolls on the haul road. The typical range of values for RR is between 1.5 and 4.0%. However, RR can be more than 10% in the mud-with soft spongy base for road condition [9].

The GR is the gradient of the road and is measured as a percentage and considered as the ratio between the horizontal and the length rise of the route [9, 24]. For example, a section of the haul road that rises at 15 m over 100 m has a GR of 15%. The GR can be positive or negative depends on a truck traveling up or down the ramp. The relationship between the above-mentioned parameters is illustrated by truck manufacture technical Rimpull-Speed-Grade ability Curve (**Figure 2**).

The truck fuel consumption (FC) can be calculated from Eq. (2) [24]:

$$FC = (SFC \times LF \times P_o)/FD \tag{2}$$

where SFC is the engine Specific Fuel burnt at full power (0.213–0.268 kg/(kW h)) and FD is the fuel density (0.85 kg/L of diesel). Eq. (3) illustrates the simplified version of Eq. (2) [25].

$$FC = 0.3\ (LF \times P_o) \tag{3}$$

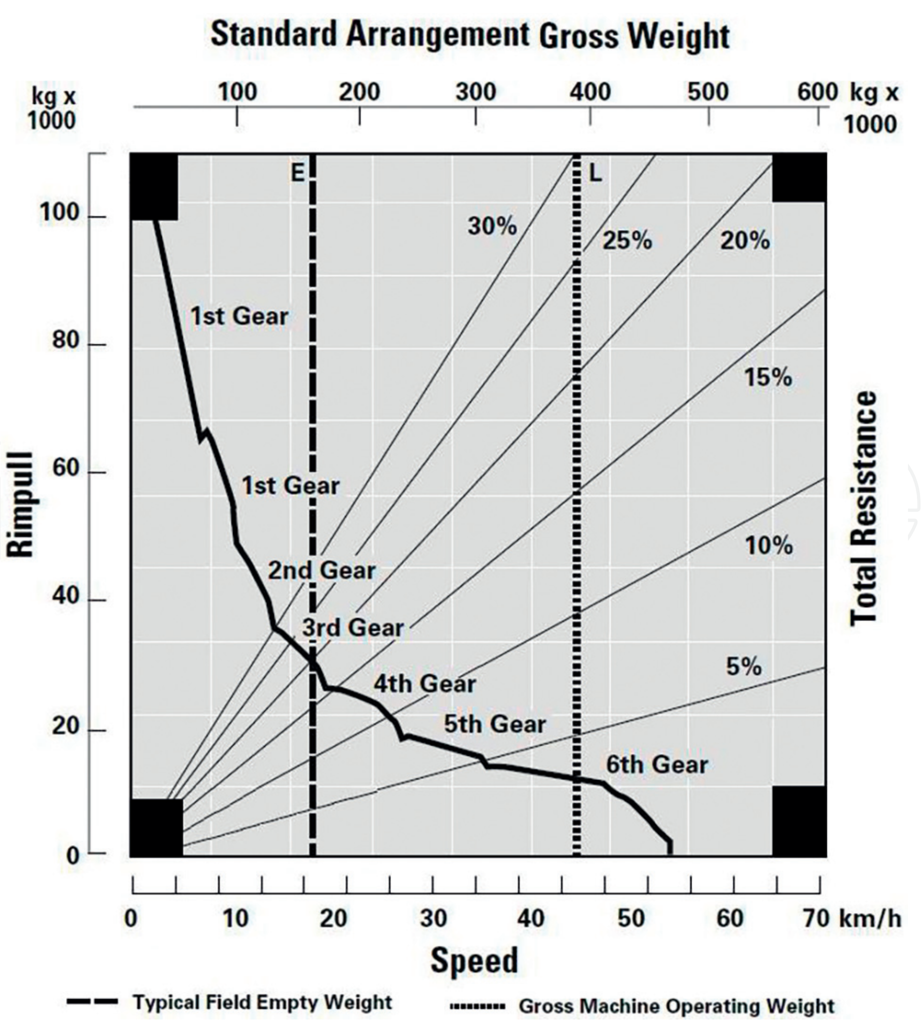

Figure 2.
Rimpull-Speed-Grade ability Curve for Haul Mine Truck (CAT 793D).

Operating conditions	LF (%)	Road condition
Low	20–30	Constant operation at a reasonable Gross Vehicle Weight less than suggested. There is not over payload
Average	30–40	Constant operation at a regular Gross Vehicle Weight suggested, minimum over payload
High	40–50	Continuous operation at or above the maximum suggested Gross Vehicle Weight

Table 1.
Typical values of load factors (LF) [22].

where LF is the engine load factor and is estimated as the percentage of normal load to the maximum payload in an operating cycle [26]. The typical values of LF are presented in **Table 1** [22]. P_o in Eq. (3) is the truck power (kW) and it is determined by:

$$P_o = (RF \times S)/3.6 \quad (4)$$

where the RF is calculated by the product of Rimpull (R) and the gravitational acceleration (g) and S is truck speed.

3. Greenhouse gas emissions

Diesel engines emit both Greenhouse Gases (GHG_S) and Non-Greenhouse Gases ($NGHG_S$) [27] into the environment. Total greenhouse gas emissions are calculated according to the Global Warming Potential (GWP) and expressed in CO_2 equivalent or CO_2-e [28, 29]. The following equation can be used to determine the haul truck diesel engine GHG_S emissions [28, 30].

$$GHG_{Emissions} = (CO_2\text{-e}) = FC \times EF \quad (5)$$

where FC is the quantity of fuel consumed (kL) and EF is the emission factor. EF for haul truck diesel engines is 2.7 t CO_2-e/kL.

4. Estimation of haul truck fuel consumption

The correlation between truck fuel burnt and nominated factors in this study (P, S and TR) is complicated and requires an artificial intelligence method to determine. The following subsection contains the details of an artificial neural network model that was settled to determine how the truck fuel consumption varies with the variation of these parameters.

4.1 Artificial neural network

Artificial neural networks (ANNs) are a standard synthetic intelligence method to simulate the effect of multiple variables on one primary factor by a fitness function. This model can be used to determine fuel consumption by taking into consideration some parameters which affect the fuel consumption of mine trucks. ANNs have been used in various engineering disciplines such as material [31–33], biochemical engineering [34], and mechanical engineering [35–37]. ANNs are required answers for multifaceted challenges as they can interpret the compound relationships between the multiple issues involved in a problem. One of the main benefits of ANN application is that they can simulate both nonlinear and linear correlation between factors, applying the data providing to learn the network. ANN, also known as parallel distributed processing, are the representation of models that the brain uses for learning [37]. They are a series of mathematical techniques which imitate some of the known characteristics of standard nerve arrangements and draw on the analogies of adaptive accepted learning. The critical section of an ANN paradigm could be the unusual arrangement of the information processing classification. An appropriate neuronal modeling is thus comprised of weighted connectors. ANNs are utilized in numerous computer applications to solve multifaceted problems.

In this chapter, an ANN was settled to make a Fuel Consumption Index (FC_{Index}) as a function of P, S and TR. This defined parameter shows how many liters of diesel is burnt to move one ton of mined material in one hour.

4.2 Developed model

The configuration of the created ANN algorithm for function estimate is a feed-forward, multi-layer perceptron NN with three input variables and one output (**Figure 3**). The activation functions in the hidden layer (f) are the continuous, differentiable nonlinear tangents sigmoid presented in Eq. (6).

$$f = \tan\text{sig}(E) = \frac{2}{1 + \exp(-2E)} - 1 \tag{6}$$

where E can be determined by Eq. (7).

$$E_k = \sum_{j=1}^{q} (w_{ijk} x_j + b_{ik}) \qquad k = 1, 2, \ldots, m \tag{7}$$

Where x is the normalized 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.

Eq. (7) can be used as the activation function between the hidden and output layers (in this equation, F is the transfer function).

$$F_k = f(E_k) \tag{8}$$

The production layer calculates the weighted sum of the signals provided by the hidden layer and the associated coefficients. The network output can be assumed by Eq. (9).

$$Out = \left(\sum_{k=1}^{m} w_{ok} F_k\right) + b_o \tag{9}$$

4.3 Developed network application

The developed ANN algorithm can use to estimate the truck fuel consumption as a function of P, S, and TR, based on the following steps:

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

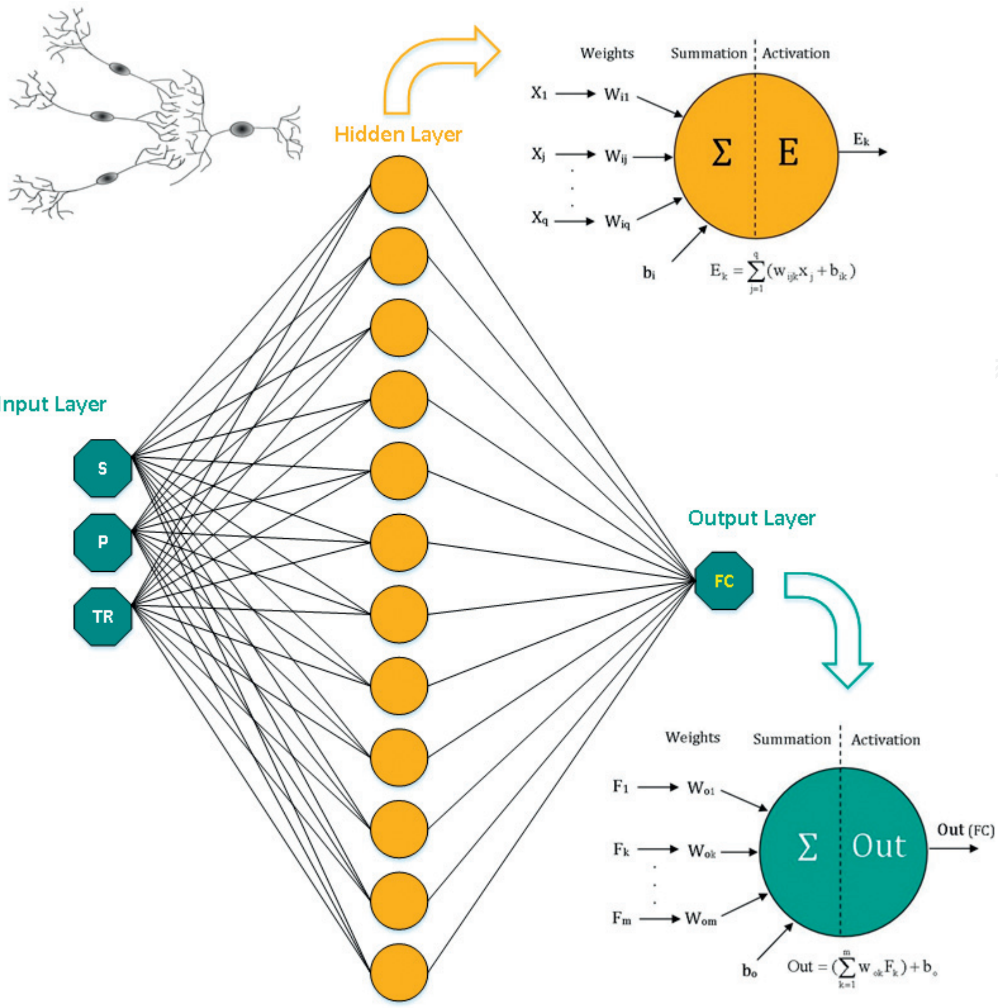

Figure 3.
The schematic structure of the designed ANN (sample).

$$x_n = \left(\frac{x - x_{min}}{x_{max} - x_{min}} \times 2\right) - 1 \tag{10}$$

Step 2: Calculating the E parameter for each hidden node

$$E_k = \sum_{j=1}^{q}(w_{i,j,k}x_j + b_{i,k}) \qquad k = 1,2,\dots,15 \tag{11}$$

Step 3: Calculating the F parameters

$$F_k = \frac{2}{1 + \exp(-2E_k)} - 1 \qquad k = 1,2,\dots,15 \tag{12}$$

Step 4: Calculating Normalized Fuel Consumption Index ($FC_{Index(n)}$)

$$FC_{Index(n)} = \left(\sum_{k=1}^{15} w_{o,k}F_k\right) + b_o \tag{13}$$

Step 5: Denormalizing $FC_{Index(n)}$

$$FC_{Index} = 13.61 + \frac{(FC_n + 1)(237.92 - FC_n)}{2} \tag{14}$$

4.4 Applied model (case study)

Testing and validating phase of the developed model has been completed based on a few datasets collected by mine engineers in big surface mines in the center of Queensland Australia. Overall information about this mine has been tabulated in **Table 2**.

To train the developed ANN model, few pairing data were randomly selected from mine site collected real datasets (**Table 3**). To test the network accuracy and validate the model, independent samples were used. The results show acceptable agreement between the actual and estimated values of fuel consumption in all investigated mine site. The test results of the synthesized networks are shown in **Figure 4** where the horizontal, and vertical axes indicate the estimated fuel consumption values the actual fuel consumption values and by the model, respectively.

4.5 Developed model results

Figure 5 illustrates the correlation between P, S, TR and FC_{Index} created by the developed ANN model for a normal range of payloads for a specific type of trucks in the studied mine sit. The presented graphs show that there is a nonlinear correlation between FC_{Index} and Gross Vehicle Weight (GVW). GVW is the empty truck weight plus payload. The rate of energy consumption increases intensely with increasing total resistance. However, this energy consumption rate does not change suddenly with changing truck speed. The developed model also shows that the amount of FC_{Index} changes by variation of truck speed and payload. However, there is no clear correlation between all effective factors and energy consumption. As a result, completing another artificial intelligence model is needed to find the optimum value of the selected elements to minimize the mine truck fuel consumption.

The generated greenhouse gas emotions by haul trucks in surface mines can be estimated by predicted FC_{Index} by developed ANN model. **Table 4** shows the estimated $(CO_2\text{-e})_{Index}$ for CAT 793D in studied mine site in Australia. The presented indicator shows that how much CO_2-e will be made to move one ton of mine material in one hour.

The achieved results illustrate that there is a logical relationship between generated greenhouse gas emissions and truck operation parameters. Increasing the truck speed and total resistance will increase the gas emissions. The minimum amount of gas will be produced when the truck is moving with recommended payload by the manufacturer. Having overloaded trucks in the fleet can increase gas emissions dramatically.

Product	Location	Reserves	Fleet size	Truck type
Coking coal	Queensland, Australia	877 Mt	184 truck	CAT 793D

Table 2.
Studied mine sites (general information).

Used pairing data for training	Used pairing data for validation
1,500,000	2,000,000

Table 3.
Used data sets for model training and validation.

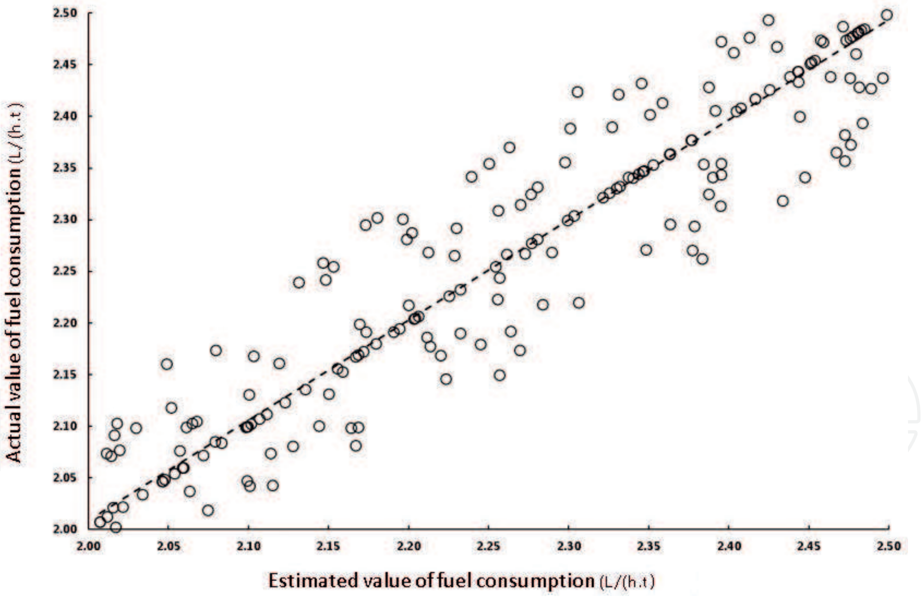

Figure 4.
Comparison of actual values with the estimated value of haul truck fuel consumption by developed ANN model.

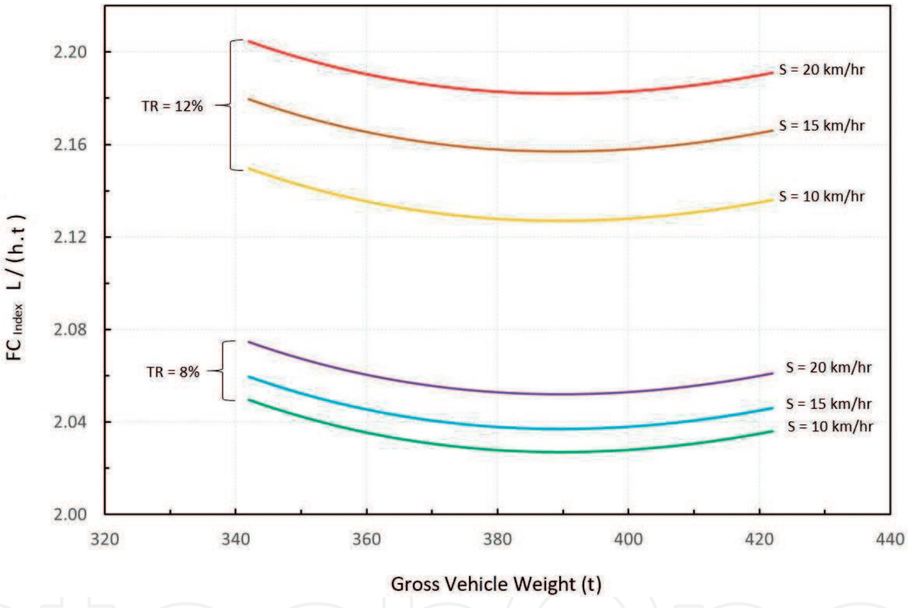

Figure 5.
Correlation between P, S, TR and FC_{Index} estimated by ANN (CAT 793D).

	$(CO_2\text{-}e)_{Index}$ kg/(h t)					
GVW (t)	**Total resistance = 12%**			**Total resistance = 8%**		
	S = 20 km/h	**S = 15 km/h**	**S = 10 km/h**	**S = 20 km/h**	**S = 15 km/h**	**S = 10 km/h**
340	0.599	0.589	0.581	0.559	0.556	0.554
360	0.591	0.586	0.578	0.556	0.554	0.549
380	0.589	0.583	0.575	0.554	0.551	0.548
400	0.589	0.583	0.575	0.554	0.551	0.548
420	0.591	0.586	0.578	0.556	0.554	0.551

Table 4.
Estimated greenhouse gas emissions by ANN (CAT 793D).

5. Optimization of effective parameters on haul truck fuel consumption

5.1 Optimization

Optimization as a part of computational science is an actual way to discover the best quantifiable solution for problems. To solve the technical issues, it is essential to consider two components. The first one is the research area and the second one is an objective function. In the research area, all the potentials of the solution are considered, and the objective function is a mathematical function that connections each point in the answer area to an actual value, appropriate to assess all the members of the research area. Solving the multifaceted computational problems has been a persistent challenge in mining engineering. Traditional optimization models are characterized by the stiffness of its mathematical models that they are challenging to represent in real dynamic and complex situations. Presenting the optimization techniques based on Artificial Intelligence, as the heuristic search-based ones have reduced the problem of stiffness. Heuristic rules can be well-defined as applied rules, resulting from the experience and observation of behavior tendencies of the system in the analysis. They are suitable to solve all types of technical problems in engineering. Using equivalences with nature, some heuristic models were suggested during the 50s by trying to simulate biological phenomena in engineering. These models, named Natural Optimization Methods. One of the best benefits of applying the mentioned models is their random characteristic. By emerging the computers during the 80s, the use of these models for optimization of functions and processes became achievable, when traditional models were not successful in this field. During the 90s some novel heuristic models developed by the previously completed algorithms, as simulated annealing, swarm algorithms, ant colony optimization and genetic algorithms.

5.2 Genetic algorithms

Genetic algorithms (GAs) were proposed by Holland (1975) as an abstraction of biological evolution, drawing on ideas from natural evolution and genetics for the design and implementation of robust adaptive systems [38]. The new generation of GAs is moderately recent optimization models. They do not use any data of derivate. So, they have good chances of escape from a local minimum. Their application in related engineering problems brings to global optimal, or, at least, to solutions more acceptable than those obtained by other traditional mathematical models. They apply a straight analogy of the evolution phenomena in nature. The individuals are randomly nominated from the research area. The fitness of the answers, which is the result of the parameter that is to be optimized, is determined consequently by the fitness function. The individual that creates the best fitness within the population has the maximum chance to go into the next generation, with the opportunity to replicate by crossover, with another individual, creating decedents with both characteristics. If a GA is adequately developed, the population (a group of possible solutions) will converge to an optimal answer for the defined problem. The procedures that have more involvement in the evolution are the crossover, based on the assortment, reproduction and the mutation. Genetic algorithms have been used in a diverse range of engineering, scientific, and economic problems [36, 38–41] due to their potential as optimization methods for multifaceted functions. There are four significant benefits when using GAs for optimization problems. Firstly, genetic algorithms do not have numerous mathematical requirements regarding optimization problems. Secondly, genetic algorithms can handle some types of objective functions and restrictions defined in discrete, continuous or mixed research areas. Thirdly, the periodicity of evolution operators makes genetic algorithms very useful for performing global searches. Lastly, genetic algorithms provide us with significant flexibility to hybridize with domain-dependent heuristics to allow an efficient implementation of a problem. Besides of genetic operators, it is also essential to analyze the influence of some variables in the behavior and the performance of the GA, to find them according to the problem requirements and the available properties. The impact of each factor in the algorithm performance depends on the class of issues that are being treated. Therefore, the determination of an optimized group of values to these factors will depend on a significant number of experiments and tests. There are many primary parameters in the GA method. Details of these critical parameters are tabulated in **Table 5**.

The primary GA parameters are the size of the population that affects the total performance and the efficiency of the GA, the mutation rate that avoids that a given position remains standing in value, or that the search becomes fundamentally random.

5.3 Developed GA model

In this chapter, the GA model is introduced to improve three effective critical parameters on the energy consumption of haul trucks in studied mine site. The genetic algorithm was selected as an optimization strategy mainly due to its capacity of providing diverse solutions and its parallelization power in the searching process. Those characteristics go hand in hand with the primary goal for this optimization process, which is offering a set of P, S and TR values for the final user that would yield a minimum FC_{Index}. This range of values it is significant in real applications, for instance, the truck drivers cannot reach an exact point of speed or even an average during a whole cycle period. This fact is the reason why gradient-based optimization algorithms were not evaluated, such as making the same ANN trained dream of inputs that minimize the FC_{Index}.

A vital point for using the GA as the optimization process is controlling the feasibility of population. All the individuals must be checked throughout generations if they are in the same distribution (i.e. maximum and minimum values) in which the ANN was trained for mainly two reasons. First, the ANN only mapped the relationship among P, S, TR and FC_{Index} based on the data provided during the training phase and the predictions results or the fitness values are reliable only in this distribution. Second, the values of each attribute must reflect the reality of mine sites and trucks operation limitations to provide feasible solutions.

GA parameter	Details
Fitness function	The primary function of the optimization
Individuals	An individual is any parameter to apply to the fitness function
Populations and generations	A population is an array of individuals. At each iteration, the GA performs a series of computations on the current population to produce a new generation
Fitness value	The fitness value of the individual is the value of the fitness function for each
Children and parents	To make the next generation, the genetic algorithm chooses certain individuals in the existing population, called parents, and uses them to develop individuals in the next generation, called children

Table 5.
Genetic algorithm parameters.

In the developed model payload, truck speed and total resistance are the individuals and the primary function of optimization is mine truck fuel consumption. In this model, the fitness function was created by the ANN algorithm. All GA processes in the developed model are illustrated in **Figure 6**.

In this model, seven main processes were defined. These procedures are initialization, encoding, crossover, mutation, decoding, selection, and replacement. The details of the procedures mentioned above are presented in **Table 6**.

In this developed model, the key factors applied to control the algorithms were R^2 and MSE. Technical details of the developed models for the studied mine site are presented in **Table 7**.

In this study, the developed ANN and GA models were completed by writing computer code in Python. Payload, truck speed and total resistance are input parameters of the algorithm in the first step. The completed model creates the fitness function based on the completed ANN model. This function is a relationship between mine truck fuel consumption and inputs. In the second step, the developed function goes to the genetic algorithm (optimization) phase of the computer code as an input. The finalized codes start all GA procedures under stopping criteria well-defined by the model (MSE and R^2).

Finally, the optimized parameters (P, S and TR) will be presented by the algorithm. These improved factors can be used to minimize the haul truck fuel

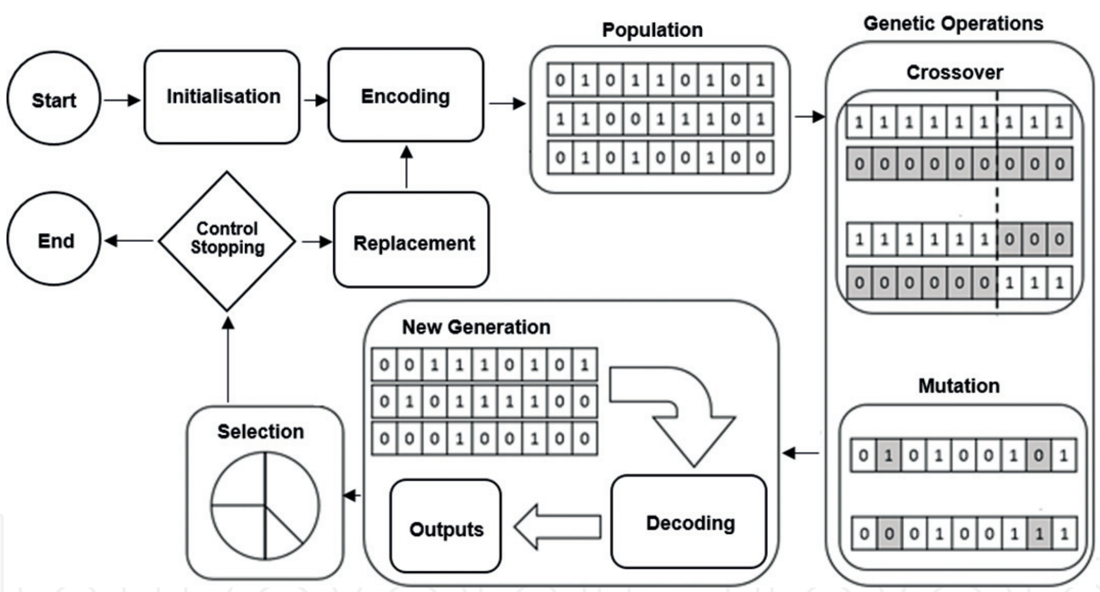

Figure 6.
Genetic algorithm processes (developed model).

Procedure	Details
Initialization	Produce original population of candidate solutions
Encoding	Digitalize original population value
Crossover	Combine parts of two or more parental answers to make a new one
Mutation	Deviation process. It is intended to infrequently break one or more participants of a population out of minimum local space and potentially discover a better answer.
Decoding	Change the digitalized format of a new generation to the original one
Replacement	Replace the individuals with better fitness values as parents

Table 6.
Genetic algorithm procedures.

Parameters	Details
Population type	Double vector
Population size	20
Creation function	Uniform
Scaling function	Rank
Selection function	Stochastic uniform
Elite count for reproduction	2
Crossover fraction	0.8
Mutation function	Uniform
Rate of mutation	0.01
Crossover function	Scattered
Migration direction	Forward
Migration fraction	0.2
Migration interval	20
Constraint parameters (initial penalty)	10
Constraint parameters (penalty factor)	100
Stopping criteria	MSE and R^2

Table 7.
Technical details of genetic algorithm developed model.

consumption. All procedures in the developed models work based on the existing dataset collected from a big surface mine in Australia, but the completed methods can be prepared for other surface mines by replacing the data.

5.4 Results

The first step of applying the developed optimization model is defining the range (minimum and maximum values) of all variables (individuals). This variable range is estimated based on the collected datasets in the established model. The parameters used to control the generated models are R^2 and MSE. **Figure 7** demonstrates the variation of these parameters in generations in studied mine site.

In the studied mine site, the value of R^2 was about 0.98, and the value MSE was 0, of after the 47th generation. These values were not changed until the genetic algorithm was stopped in the 53rd generation. Correspondingly, the values of control factors were constant after the 47th generation, but the algorithm continued all procedures until the 53rd. That is because a confidence interval was defined for the algorithm to catch dependable results. The value of the fitness function (FC_{Index}) in all generations has been illustrated in **Figure 8**. The simulated value of mine truck fuel consumption is different between 0.03 and 0.13 (L/(h t)). The mean of the estimated results is 0.076 (L/(h t)), and more than 45% of results are located above the average line. The presented model could find some local minimized fuel consumption, but the acceptable results can be found after the 47th generation. **Figure 8** also shows that the FC_{Index} is about 0.04 (L/(h t)), which lies in the acceptable area. It means that by improving the payload, truck speed and total resistance in the studied mine site, the minimum FCIndex for the CAT 793D is about 0.04 (L/(h t)).

The optimum range of variables to minimize fuel consumption by the selected haul truck in these case studies (all mine sites) are tabulated in **Table 8**.

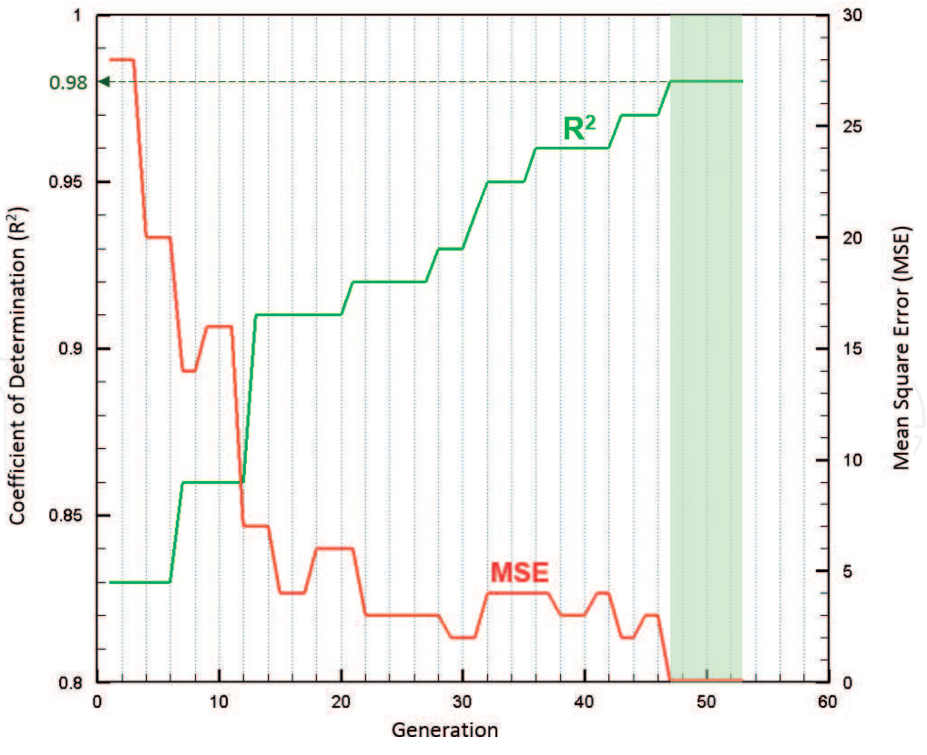

Figure 7.
The coefficient of determination and mean square error for all generations.

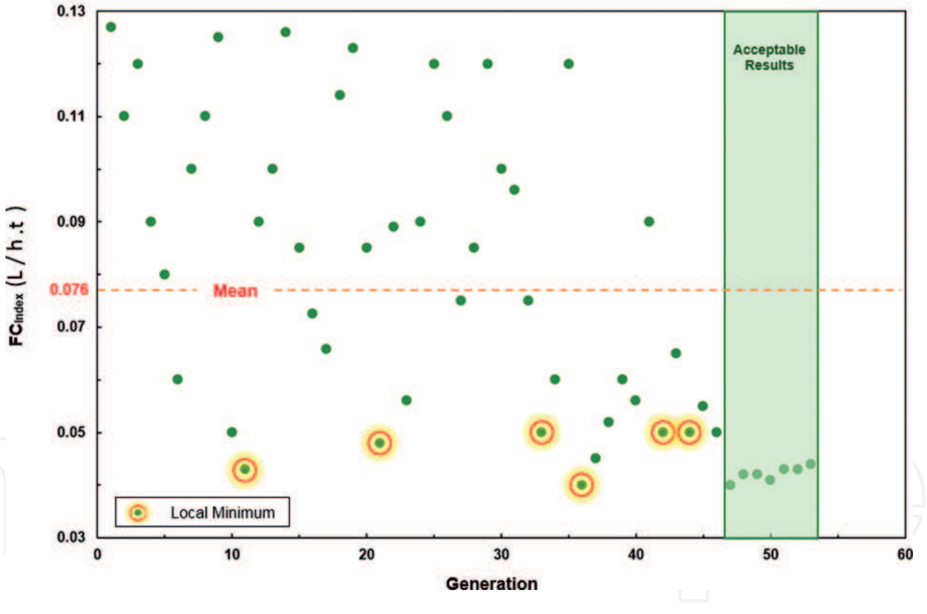

Figure 8.
Fuel consumption (fitness value) in all generations (studied mine site).

Truck	Variables	Normal		Optimized	
		Min	Max	Min	Max
CAT 793D	Gross Vehicle Weight (t)	150	380	330	370
	Total resistance (%)	8	20	8	9
	Truck speed (km/h)	5	25	10	15

Table 8.
Optimization model recommendations to maximize energy efficiency gains.

As a final result of using suggested optimization model in studied mine site, mine managers approved that they had 9% fuel consumption reduction and related Greenhouse gas emissions by using the developed application in mine for 6 months. Five per cent productivity improvement was also announced by the operation team in the application testing period.

6. Conclusion

The purpose of these presented methods and algorithms was to improve mine truck fuel consumption and reduce greenhouse gas emissions based on the correlations between payload, truck speed and haul road total resistance by investigating on real datasets. These correlations were complicated and required artificial intelligence methods to create a consistent algorithm to tackle this challenge. In the first section of this chapter, an ANN algorithm was explained to find a relationship between investigated parameters. The results illustrated that fuel consumption has a nonlinear correlation with the studied parameters. The ANN was learned and validated using the gathered real mine sites datasets as an example. The achievements presented that there was good agreement between the estimated and actual values of haul truck fuel consumption. In the second section of this chapter, to minimize the fuel consumption in haulage operations, a genetic algorithm was developed. The results showed that by applying this method, optimization of the effective factors on energy consumption is possible. The established algorithm could find the local minimums for the fitness function. The offered GA model highlighted the satisfactory results to minimize the rate of fuel burnt in surface mines. The range of all investigated effective parameters on haul trucks fuel consumption was optimized, and the best values of payload, truck speed and haul road total resistance to minimize FC_{Index} were highlighted. There are some possibilities to improve the presented models in this chapter by increasing the number of input parameters. Selected parameters are controllable in real mine sites. However, changing the total resistance and control the payload variance are a little difficult by using current technologies. There are other manageable parameters such as idle time, queuing time etc. that can potentially replace with modeled parameters in the presented algorithms in this chapter.

Nomenclature

ANN	artificial neural network
b	bias
E	summation function
f	activation function
F	transfer function
FC	truck fuel consumption (L/h)
FD	fuel density (kg/L)
GA	genetic algorithm
GR	grade resistance (%)
GVW	Gross Vehicle Weight (t)
LF	engine load factor (%)
m	number of neural network nodes in the hidden layer
MSE	mean square error
Out	final output
p	number of neural network outputs

P	truck payload (t)
P_o	truck power (kW)
q	number of input variables
r	truck wheel radius (m)
R	Rimpull (t)
RF	Rimpull force (KN)
RMSE	root mean square error
RR	rolling resistance (%)
R^2	correlation coefficient
S	truck speed (km/h)
SFC	engine specific fuel consumption (kg/kW h)
T	torque (kN m)
TP	truck power (kW)
TR	haul road total resistance (%)
VIMS	vehicle information management system
w	the weight of the variables
x	input variable
y	target (real) output
z	estimated output

Subscripts

i	input
j	the counter of input variables
k	the counter of a neural network node in the hidden layer
max	maximum
n	normalized
o	output
r	the counter of network outputs

Author details

Ali Soofastaei
The University of Queensland, Brisbane, Australia

*Address all correspondence to: ali@soofastaei.net

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