2016

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Publication Details

Ali Soofastaei, Saiied Mostafa Aminossadati, Mehmet Siddik Kizil and Peter Knights, Reducing Fuel Consumption of Haul Trucks in Surface Mines Using Artificial Intelligence Models, in Naj Aziz and Bob Kininmonth (eds.), Proceedings of the 16th Coal Operators' Conference, Mining Engineering, University of Wollongong, 10-12 February 2016, 477-489.

REDUCING FUEL CONSUMPTION OF HAUL TRUCKS IN SURFACE MINES USING ARTIFICIAL INTELLIGENCE MODELS

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Abstract: Energy saving has become an important aspect of every business activity as it is important in terms of cost savings and greenhouse gas emission reduction. This study aims to develop a comprehensive artificial intelligence model for reducing energy consumption in the mining industry. Many parameters influence the fuel consumption of surface mining haul trucks. This includes, but not limited to, truck load, truck speed and total haul road resistance. In this study, a fitness function for the haul truck fuel consumption based on these parameters is generated using an Artificial Neural Network (ANN). This function is utilised to generate a multi-objective model based on Genetic Algorithm (GA). This model is used to estimate the optimum values of the haulage parameters to reduce fuel consumption. The developed model is generated and tested using real data collected from four large surface mines. It is found that for all four mines considered in this study, the haul truck fuel consumption can be reduced by optimising truck load, truck speed and total haul road resistance using the developed artificial intelligence model.

INTRODUCTION

Energy efficiency has become more important worldwide due to the rise of the cost of fuel in recent years. The Mining industry consumed 450 PJ of energy in 2013-14 or 11% of the national energy use in Australia (BREE 2014)[2]. Mining operations use energy in a variety of ways, including excavation, material transfer, ventilation, dewatering, crashing and grinding operations (DOE 2012)[3]. Based on completed industrial projects, significant opportunities exist within the mining industry to reduce energy consumption. The potential for energy savings has motivated both the mining industry and governments to conduct research into the reduction of energy consumption (DOE 2002). In addition, a large amount of energy can be saved by improving mining technologies and energy management systems (Kumar Narayan *et al.,* 2010 and Abdelaziz *et al.,* 2011). Energy saving has also a significant positive impact on greenhouse gas emission reduction because the major energy sources used in the mining industry are petroleum products, electricity, coal and natural gas (Asafu and Mahadevan 2003 and Broom 2013).

In surface mines, the most commonly used means of mining and hauling of materials is via a truck and shovel operation (Beatty and Arthur 1989 and Beckman 2012). The trucks used in the haulage operations of surface mines use a great amount of energy (Sahoo *et al.,* 2010 and DOE 2012) and this has encouraged truck manufacturers and major mining corporations to carry out a large number of research projects on the energy efficiency of haul trucks (Chingooshi *et al.,* 2010).

The rate of energy consumption is a function of a number of parameters. The study conducted by Antoung and Hachibli (2007) was concerned with the implementation of power-saving technology to improve the motor efficiency of mining equipment. The focus of their study was on the technical performance of motor components and how they contributed to the reduction of friction and the improvement of the motor efficiency. Beatty and Arthur (1989) investigated the effect of some general parameters, such as cycle time and mine planning, on the energy used by haul trucks. They determined the optimum values of these parameters to minimise fuel consumption in hauling operations. The research presented by Carmichael *et al.,* (2014) was concerned with the effects of haul truck fuel

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consumption on costs and gas emissions in surface mining operations; however, the simulation used in their research did not include the pertinent factors affecting the fuel consumption. Coyle (2007) also researched the effects of load on truck fuel consumption. In this study, Coyle analysed the effect of load density variation based on the blasting procedures on fuel consumption by haul trucks.

The studies reported in the literature are mainly based on the theoretical models used to calculate the fuel consumption of haul trucks. These models are based on the Rimpull-Speed-Grad curve prepared by the truck manufacturer for the performance of trucks (Alarie and Gamache 2002; Beckman 2012; Caterpillar 2013).In this study, the effects of three major parameters; Load (L), Truck Speed (S) and Total Haul Road Resistance (TR), on fuel consumption of haul trucks have been examined. Calculating the impact of these parameters on fuel consumption for a haul truck operating on a real mine site is not an easy task. Therefore, Artificial Neural Network (ANN) and Genetic Algorithm (GA) techniques have been used to develop a model to estimate and reduce fuel consumption. This model has been completed and tested based on comprehensive datasets collected from four large surface mines in The United States and Australia. The developed model can estimate the fuel consumption of haul trucks in surface mines using an ANN and can also find the optimum value of L, S and TR using a GA.

THEORETICAL CALCULATION OF HAUL TRUCK FUEL CONSUMPTION

Haul truck fuel consumption is a function of a variety of parameters. Figure 1 shows a schematic diagram of a typical haul truck and the key factors affecting the performance of the truck.

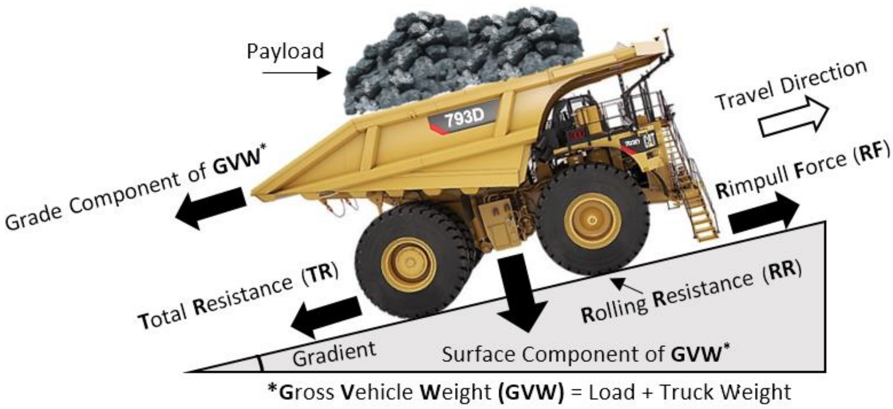

Figure 1: A schematic diagram of a typical haul truck and effective key factors on truck performance

This study examined the effects of the L, S and TR on the fuel consumption of haul trucks. The TR is equal to the sum of the Rolling Resistance (RR) and the Grade Resistance (GR) (Burt *et al.,* 2012).

$$TR = RR + GR \quad (1)$$

The RR depends on tyre and haul road surface characteristics and is used to calculate the Rimpull Force (RF), which is the force that resists motion as the truck tyre rolls on the haul road. The GR is the slope of the haul road, and is measured as a percentage and calculated as the ratio between the rise of the road and the horizontal length (EEO 2012)[1].

The truck Fuel Consumption (FC) can be calculated from Equation 2 (Filas 2002):

[1] *Energy Efficiency Opportunities (EEO), Australia*

$$FC = \frac{SFC}{FD}(LF.P) \tag{2}$$

Where SFC is the engine Specific Fuel Consumption at full power (0.213–0.268 kg/kw.hr) and FD is the Fuel Density (0.85 kg/L for diesel). The simplified version of Equation 2 is presented by Runge (1998):

$$FC = 0.3(LF.P) \tag{3}$$

Where LF is the engine Load Factor and is defined as the ratio of average load to the maximum load in an operating cycle (Kecojevic and Komljenovic 2010). The typical values of LF are presented in Table 1 (Caterpillar 2013).

Table 1: Typical Values of Load Factors (LF)

Operating Conditions	LF (%)	Condition
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

P is the truck power (kW) and it is determined by:

$$P = \frac{1}{3.6}(RF.S) \tag{4}$$

Where the RF is calculated by the product of Rimpull (R) and the gravitational acceleration (g) and S is Truck Speed.

ESTIMATION OF HAUL TRUCK FUEL CONSUMPTION

Artificial Neural Network Model

Artificial Neural Networks (ANNs) are a popular artificial intelligence model to simulate the effect of multiple variables on one major parameter by a fitness function. 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 (Picton 1994). ANNs are a 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. 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 (LeCun *et al.,* 1998) and do not require the mathematical description of the phenomena involved in the process. This method can be used to determine fuel consumption by taking into consideration a number of variables that influence the fuel consumption of haul trucks. ANNs have been used in many engineering disciplines such as materials (Sha and Edwards 2007; Reihanian *et al.,* 2011; Hammood 2012; Pourasiabi *et al.,* 2012 and Xiang *et al.,* 2014), biochemical engineering (Talib *et al.,* 2009), medicine (McCulloch and Pitts 1943) and mechanical engineering (Ekici and Aksoy 2009; Rodriguez *et al.,* 2013 and Beigmoradi *et al.,* 2014).

In this study, an ANN was developed to create a Fuel Consumption Index (FC_{Index}) as a function of L, S and TR. This index shows how many litres of diesel fuel are consumed to haul one tonne of mined material in one hour.

DEVELOPED MODEL

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 Equations 5, 6, 7). Figure 2 shows a simple structure of developed model in this study (it should be noted that the hidden layer nodes may use any differentiable activation function to generate their output).

$$E_k = \sum_{j=1}^{q}(w_{i,j,k}x_j + b_{i,k}) \qquad k = 1, 2, ..., m \tag{5}$$

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.

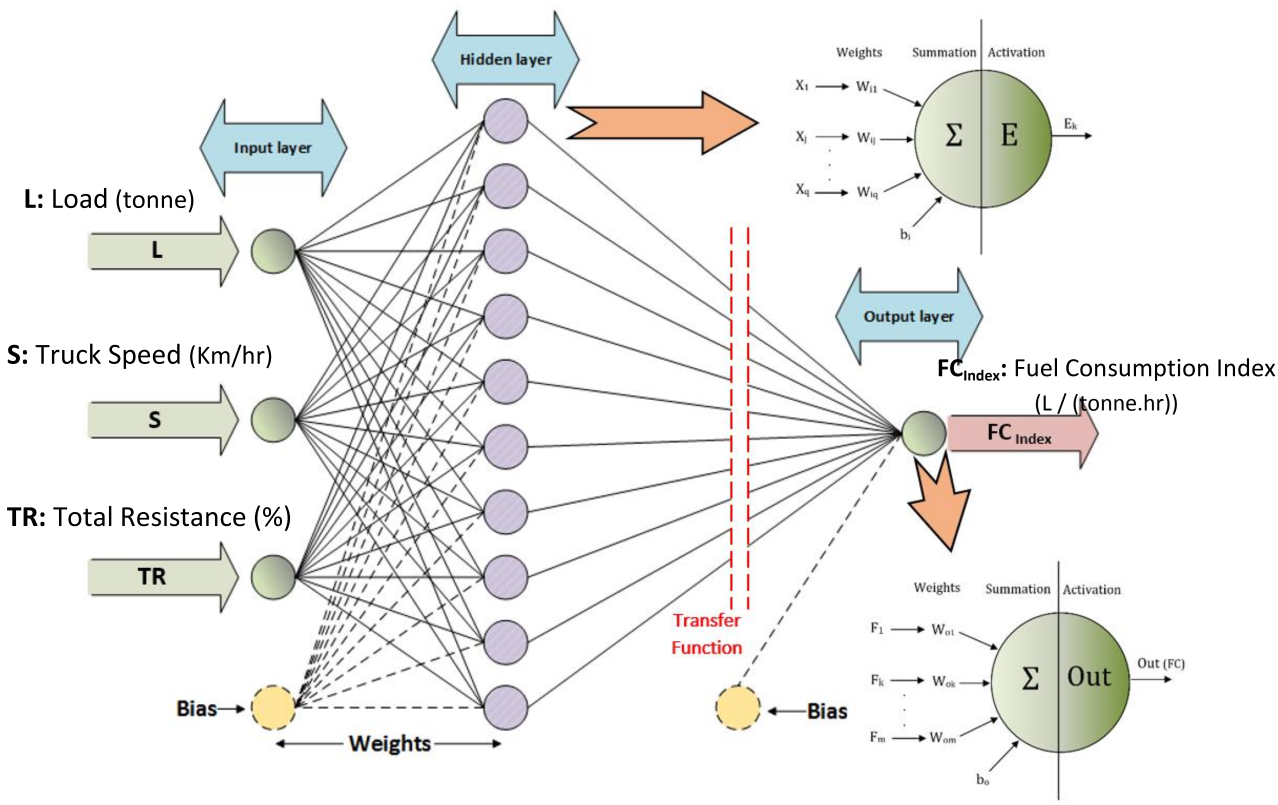

Figure 2: A simple structure of ANN developed model

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 $b_{i,k}$. Equation 6 can be used as the activation function between the hidden and the output layers (in this equation, f is the transfer function).

$$F_k = f(E_k) \tag{6}$$

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 Equation 7.

$$\text{Out} = (\sum_{k=1}^{m} w_{o,k} F_k) + b_o \tag{7}$$

This paper presents a study in which different types of algorithms were examined in order to determine the best back-propagation generating algorithm. In comparison to other back-propagation algorithms, the Levenberg–Marquardt (LM) back-propagation generating algorithm has the minimum Mean Square Error (MSE), Root Mean Square Error (RMSE) and Correlation Coefficient (R^2) (See Equations 8, 9 and 10).

In addition, network generating with the LM algorithm can run smoothly with the minimum Expanded Memory Specification (EMS) and a fast generating process. MSE, RMSE and R^2 are the statistical criteria utilised to evaluate the accuracy of the results according to following equations (Ohdar and Pasha 2003 and Poshal and Ganesan 2008):

$$\text{MSE} = \frac{1}{p}\sum_{r=1}^{p}(y_r - z_r)^2 \tag{8}$$

$$\text{RMSE} = (\frac{1}{p}\sum_{r=1}^{p}(y_r - z_r)^2)^{\frac{1}{2}} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{r=1}^{p}(y_r - z_r)^2}{\sum_{r=1}^{p}(y_r - \bar{y})^2} \tag{10}$$

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 (Demuth and Beale 1993 and Krose *et al.,* 1993). In this study, 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.

NETWORK RESULTS

Figures 3, 4, 5 and 6 illustrate the correlation between P, S, TR and FC_{Index} created by the developed ANN model for a normal range of loads for four types of popular trucks used in four big surface mines in The United States and Australia. The presented graphs show that there is a nonlinear relationship between FC_{Index} and P. The rate of fuel consumption increases dramatically with increasing TR. However, this rate does not change sharply with changing truck speed, S.

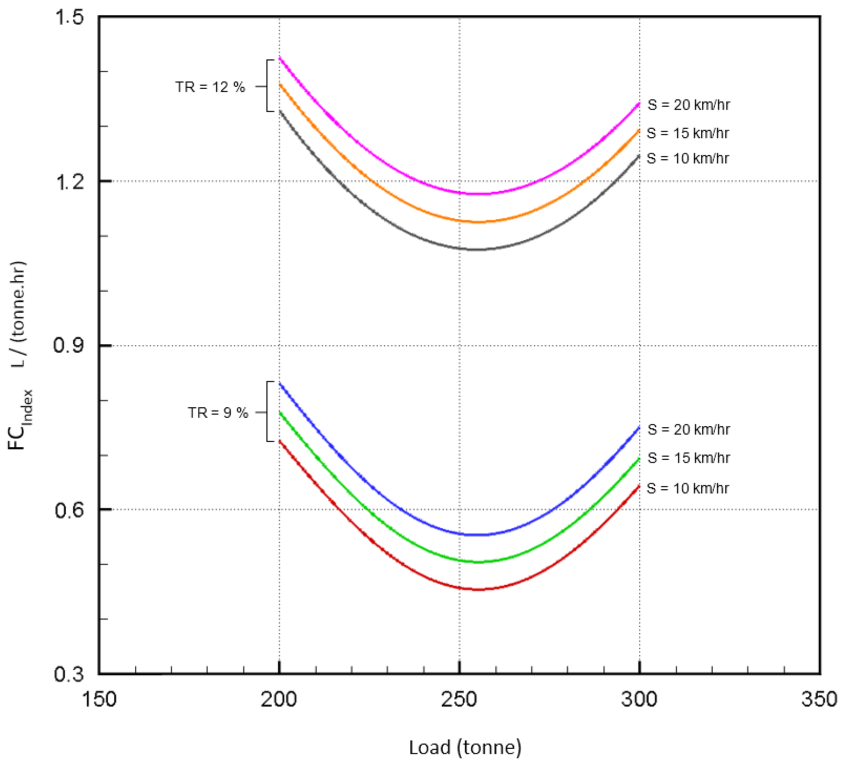

Figure 3: Correlation between L, S, TR and FC_{Index} based on the developed ANN model for CAT 793D. All data have been collected from a surface coal mine located in the Central Queensland, Australia (Mine 1)

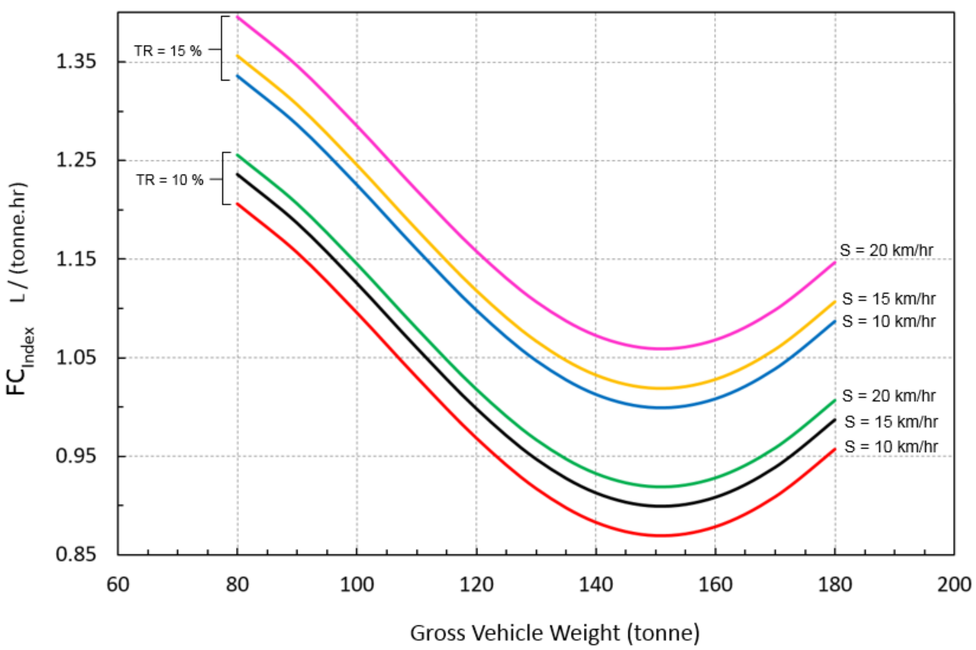

Figure 4: Correlation between GVW, S, TR and FC_{Index} based on the developed ANN model for CAT 777D. All data have been collected from a surface copper mine located in Arizona, USA (Mine 2)

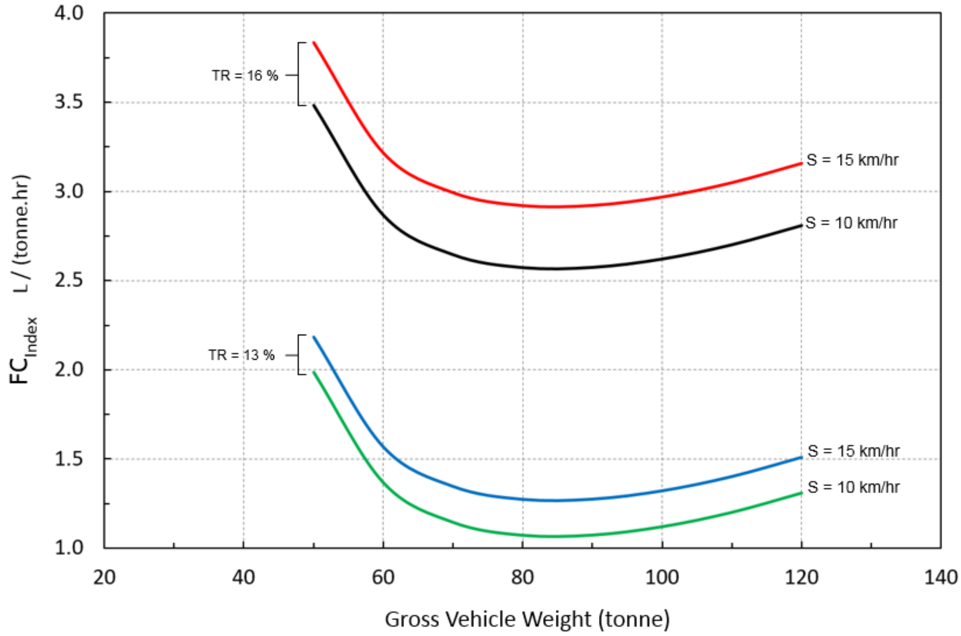

Figure 5: Correlation between GVW, S, TR and FC_{Index} based on the developed ANN model for CAT 775G. All data have been collected from a surface copper mine located in Arizona, USA (Mine 3)

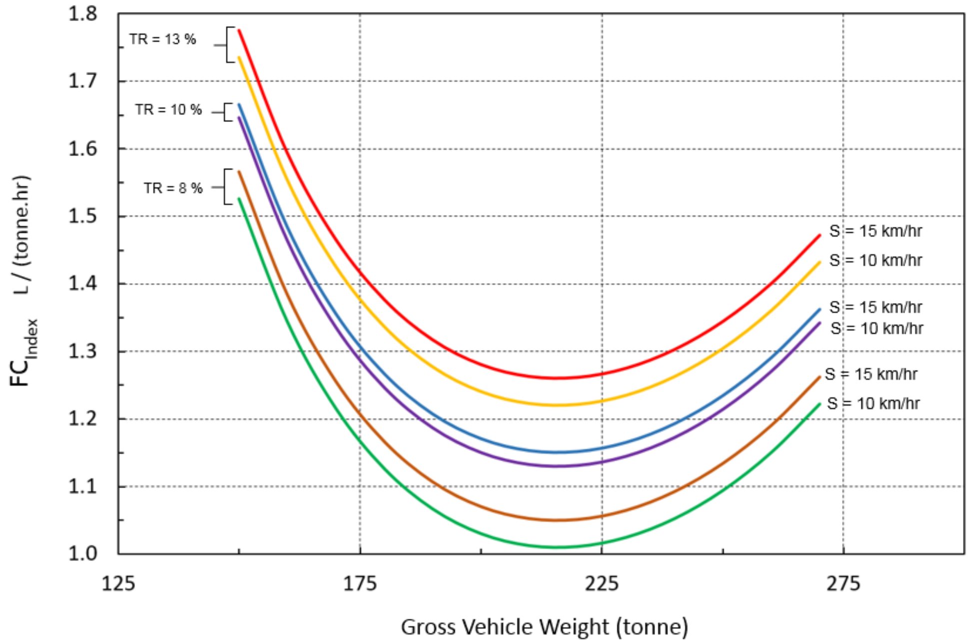

Figure 6: Correlation between GVW, S, TR and FC_{Index} based on the developed ANN model for CAT 793D. All data have been collected from a surface coal mine located in Arizona, USA (Mine 4)

ANN GENERATING AND VALIDATION

In order to generate the proposed ANN model, 1,000,000 data were randomly selected from the collected real datasets from four mine sites individually. In order to test the network accuracy and validate the model, 1,000,000 independent samples were used again. The results show good agreement between the actual and estimated values of fuel consumption. Figures 7 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 for four studied mines.

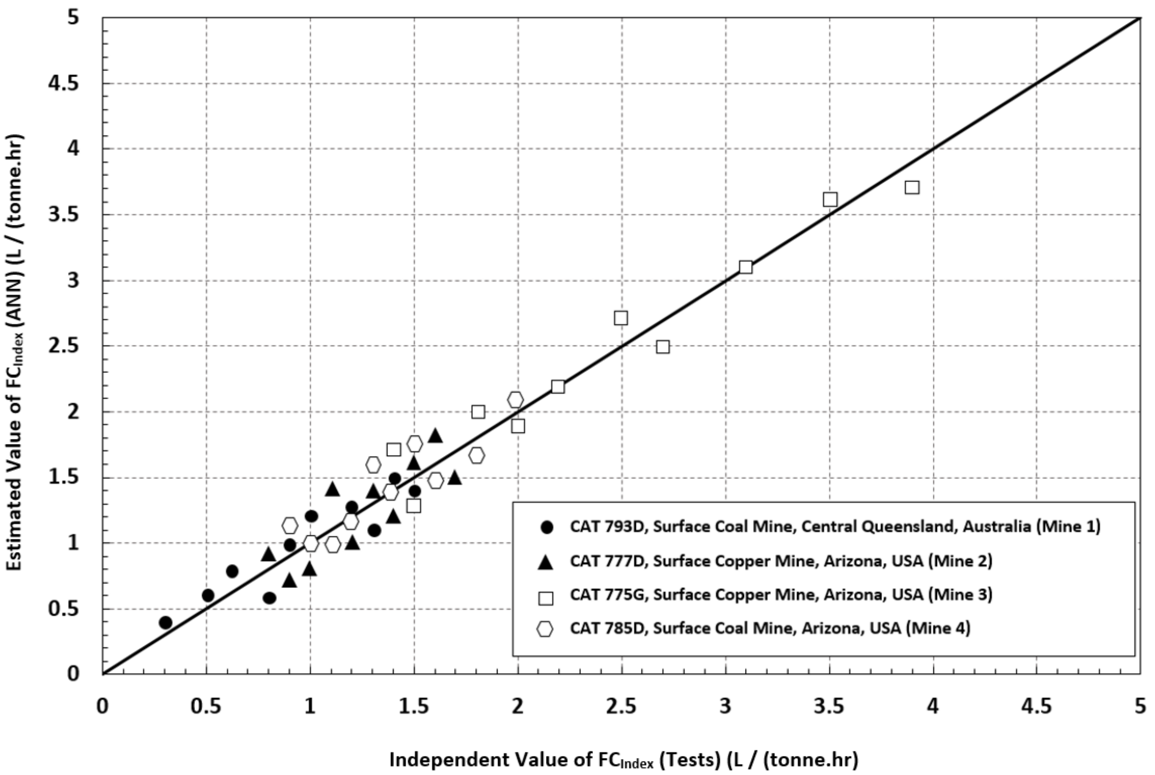

Figure 7: Sample values for the estimated (using the ANN) and the independent (tested) Fuel Consumption Index.

OPTIMISATION OF EFFECTIVE PARAMETERS ON HAUL TRUCK FUEL CONSUMPTION

Genetic Algorithm

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 (Amy *et al.,* 2012). The new generation of GAs are comparatively recent optimisation methods. They do not use any information of derivate, therefore, they have a good chance of escape from local minimum. Their application in practical engineering problems generally leads to optimal global solutions, or, at least, to solutions more satisfactory than those ones obtained by other traditional mathematical methods. They use a direct analogy of the evolution phenomena in nature. The individuals are randomly selected from the search area. The fitness of the solutions, which is the result of the variable that is to be optimised, is determined subsequently from the fitness function. The individual that generates the best fitness within the population has the highest chance to return in the next generation, with the opportunity to reproduce by crossover, with another individual, producing decedents with both characteristics. If a genetic algorithm is developed correctly, the population (group of possible solutions) will converge to an optimal solution for the proposed problem. The processes that have more contribution to the evolution are the crossover, based in the selection and reproduction and the mutation (see Table 2 and Figure 8).

Table 2: Genetic Algorithm processes (Goldberg 1989)

Process	Details
Initialisation	Generate initial population of candidate solutions
Encoding	Digitalise initial population value
Crossover	Combine parts of two or more parental solutions to create new
Mutation	Divergence operation. It is intended to occasionally break one or more members of a population out of a local minimum space and potentially discover a better answer.
Decoding	Change the digitalized format of new generation to the original one
Selection	Select better solutions (individuals) out of worse ones
Replacement	Replace the individuals with better fitness values as parents

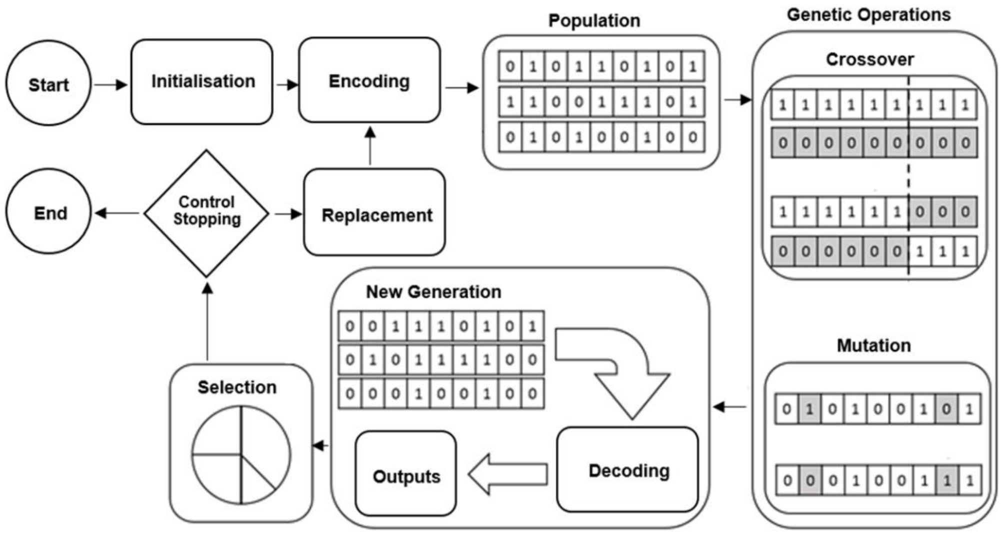

Figure 8: A simple structure of Genetic Algorithm model

GAs have been applied to a diverse range of scientific, engineering and economic problems (Velez 2005; Opher and Ostfeld 2011; Reihanian *et al.,* 2011; Amy *et al.,* 2012 and Beigmoradi *et al.,* 2014) due to their potential as optimisation techniques for complex functions. There are four major advantages when applying GAs to optimisation problems. Firstly, GAs do not have many mathematical requirements in regard to optimisation problems. Secondly, GAs can handle many types of objective functions and constraints (i.e., linear or nonlinear) defined in discrete, continuous or mixed search spaces. Thirdly, the periodicity of evolution operators makes GAs very effective at performing global searches (in probability). Lastly, The GAs provide a great flexibility to hybridize with domain dependent heuristics to allow an efficient implementation for a specific problem. It is also important to analyse the influence of some parameters in the behaviour and in the performance of the genetic algorithm, to establish them according to the problem necessities and the available resources. The influence of each parameter in the algorithm performance depends on the class of problems that is being treated. Thus, the determination of an optimised group of values to these parameters will depend on a great number of experiments and tests.

There are a few main parameters in the GA method. Details of these five key parameters are tabulated in Table 3.

Table 3: Genetic Algorithm parameters (Velez 2005)

GA Parameter	Details
Fitness Function	The main function for optimisation
Individuals	An individual is any parameter to apply into the fitness function. The value of the fitness function for an individual is its score.
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 population. Each successive population is called a new generation.
Fitness Value	The fitness value of an individual is the value of the fitness function for that individual.
Parents and Children	To create the next generation, the GA selects certain individuals in the current population, called parents, and uses them to create individuals in the next generation, called children.

The principal genetic parameters are the size of the population that affects the global performance and the efficiency of the genetic algorithm, the mutation rate that avoids that a given position remains stationary in a value, or that the search becomes essentially random.

MODEL RESULTS

In this study, a GA model was developed to improve the key effective parameters on the energy consumption of haul trucks. In this model L, S and TR are the individuals and the main function for optimisation of the fitness function is fuel consumption. In this model a fitness function was created by the ANN Model. In this developed model, the main parameters used to control the algorithm were R^2 and MSE. The population size for the first generation was 20 and a uniform creation function was defined to generate a new population. The completed ANN and GA model were developed by writing computer codes in MATLAB software. L, S and TR are inputs of the code in the first step. The completed code creates the fitness function based on the developed ANN model. This function is a correlation between haul truck fuel consumption, L, S and TR. After the first step, the completed function goes to the GA phase of the computer code as an input. The developed code starts all GA processes under stopping criteria defined by the model (MSE and R^2). Finally, the improved L, S and TR will be presented by the code. These optimised parameters can be used to minimise the fuel consumption of haul trucks. All processes in the developed model work based on the present dataset collected from four large surface mines, but the completed method can be developed for other surface mines by replacing the data. The results of using developed model for real mentioned mines are tabulated in tables 4 to 7.

Table 4: The range of normal values and optimised range of variables by GA model to minimise fuel consumption by haul trucks. (Caterpillar 793D in Mine 1)

Variables	Normal Values		Optimised Values	
	Minimum	Maximum	Minimum	Maximum
Gross Vehicle Weight (tonne)	150	380	330	370
Total Resistance (%)	8	20	8	9
Truck Speed (Km/hr)	5	25	10	15

Table 5: The range of normal values and optimised range of variables by GA model to minimise fuel consumption by haul trucks. (Caterpillar 777D in Mine 2)

Variables	Normal Values		Optimised Values	
	Minimum	Maximum	Minimum	Maximum
Gross Vehicle Weight (tonne)	65	150	145	155
Total Resistance (%)	9	25	9	11
Truck Speed (Km/hr)	10	45	10	12

Table 6: The range of normal values and optimised range of variables by GA model to minimise fuel consumption by haul trucks. (Caterpillar 775G in Mine 3)

Variables	Normal Values		Optimised Values	
	Minimum	Maximum	Minimum	Maximum
Gross Vehicle Weight (tonne)	45	85	75	90
Total Resistance (%)	13	20	13	14
Truck Speed (Km/hr)	5	55	9	13

Table 7: The range of normal values and optimised range of variables by GA model to minimise fuel consumption by haul trucks. (Caterpillar 785D in Mine 4)

Variables	Normal Values		Optimised Values	
	Minimum	Maximum	Minimum	Maximum
Gross Vehicle Weight (tonne)	125	215	200	225
Total Resistance (%)	8	15	8	9
Truck Speed (Km/hr)	5	45	10	15

CONCLUSIONS

The aim of this study was to develop a model based on the ANN and GA methods to improve haul truck fuel consumption. The relationship between L, S, TR and FC in an actual mine site is complex. In the first part of the study, an ANN method was developed to find a correlation between the key parameters and FC. The results showed that FC has a nonlinear relationship with the investigated parameters. The ANN was generated and tested using the collected real mine site datasets and the results showed that there was good agreement between the actual and estimated values of FC. In the last part of the study, to improve the energy efficiency in haulage operations, a GA method was developed. The results showed that by using this method, optimisation of the effective parameters on energy consumption was possible. The developed method was used to estimate the local minimums for the fitness function. The presented genetic algorithm method highlighted the acceptable results to minimise the rate of fuel consumption. The range of all studied effective parameters on fuel consumption of haul trucks was optimised, and the best values of P, S and TR to minimise FC_{Index} were highlighted. The developed model was applied to analyse data for four big coal and metal surface mines (Open-Cut and Open-Pit) in the United States and Australia.

ACKNOWLEDGEMENTS

The authors would like to acknowledge The University of Queensland for financial support for this study.

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