An Innovative Method to Decrease Fuel Consumption of Haul Trucks in Surface Mines

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***Abstract*—This paper develops a comprehensive artificial intelligence model, based on advanced data analytics methods, to improve trucks energy efficiency for surface mines. Payload, truck speed and the haul road total resistance are critical parameters that affect truck energy efficiency. The relationship between the principal parameters and the truck energy consumption is estimated by using an Artificial Neural Network (ANN) model. The ANN is trained,validated and tested using operational data collected from four large surface mines located in the United States of America and Australia. The ANN model efficiently creates a fitness function for the truck energy consumption. This function is applied to develop a digital learning algorithm based on a Genetic Algorithm (GA) and estimates the optimum values of effective haulage parameters to reduce the diesel fuel consumption by haul trucks at surface mines.**

***Index Terms*—Energy Efficiency; Haul Truck; Surface Mine; Simulation; Optimization; Artificial Intelligence; Artificial Neural Network; Genetic Algorithm**

I. Introduction

Energy consumption in mining is rising due to lower grade ores, located deeper underground, requiring greater mining effort to extract, transport and process [1]. Mining operations use energy in a variety of ways: excavation; material transfer; milling and processing; ventilation, dewatering etc. [2]. Based on the experience of completed industrial projects, significant opportunities exist within the industry to reduce energy consumption [2]. The potential to reduce energy use has motivated both governments and the mining industry to research the topic [3].

The most frequently used method of mining and hauling 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 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] examined 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 load density variation, based on the blasting procedures, has on fuel consumption f haul trucks. Soofastaei et al. completed many different projects in the field of haul truck energy efficiency in surface and underground mines [9-16].

To the authors best knowledge, the investigations presented in the literature are based primarily on the theoretical models used to estimate the fuel consumption of mine trucks. These models are based on the curves prepared by the truck manufacturer for the performance of mine haul trucks [5, 17-22].

In the current research, 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 (AI) methods have been used to create a model to estimate and then reduce fuel consumption. The AI model developed has been completed and tested in four case studies. All datasets have been collected from four surface mines in the United States of America and Australia. The model developed can estimate the energy consumption of one model of truck in open-pit and open-cut mines using an Artificial Neural Network (ANN) and can then find the optimum values of P, S and TR that minimize fuel consumption by using a Genetic Algorithm (GA).

II. Calculation of Haul Truck Fuel Consumption

Fuel consumption by mine trucks is a function of several factors. The most important influences can be categorized into seven main groups: fleet management; mine planning; modern technology; haul road; design and manufacture; weather condition and fuel quality [12]. In the current research, 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) [21].

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

The rolling resistance depends on the tire and road surface features is applied to estimate the Rimpull Force (RF), which is the force that resists motion as the truck tire 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 a soft spongy base for road condition [12].

The GR is the gradient of the road and is measured as a percentage and calculated as the ratio between the horizontal and the length rise of the route [12]. For example, a section of the haul road that rises 15 m over 100 m length has a GR of 15%. The GR can be positive or negative depends on a truck traveling up or down a slope.

The truck Fuel Consumption (FC) can be calculated from (2) [23]:

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

Where SFC is the engine Specific Fuel Consumption at full power (0.2130.268 kg/(kw.hr)) and FD is the Fuel Density (0.85 kg/L for diesel), LF is the engine Load Factor and Pois Truck Power The simplified version of (3) is presented by [24]:

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

The engine Load Factor LF is estimated as the percentage of normal load to the maximum payload in an operating cycle [25]. P_o in (4), Truck Power (kW), is determined by:

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

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

A practical index FC_{Index} (L/hr.tonne) used on this research project was devised based on the data availability at the mine sites as well as the literature review. The FC_{Index} can be determined as demonstrated in (5).

$$FC_{Index} = \frac{FC}{P} \tag{5}$$

This index is the target of the fuel consumption prediction phase which can be seen as a regression problem in machine learning field. The formulation of this index has a huge potential and benefits for the optimization phase which will be explained in details on the GA section.

III. Data Collection

In this study, datasets collected by mine engineers at four big surface mines in the United States of America and Australia, over a six months period were analyzed to create all the models presented. Summary information about each mine has been tabulated in Table I.

TABLE I: Mine sites studied (General Information)

No	Type	Product	Location	Fleet size
1	Open Cut	Coking Coal	Queensland, Australia	184 Truck
2	Open Pit	Iron Ore	Western Australia	67 Truck
3	Open Pit	Copper	Arizona, USA	124 Truck
4	Open Pit	Copper	Arizona, USA	79 Truck

The mine site datasets include date, payload (tonne), truck speed (S) (km/hr), cycle time (hh:mm:ss), cycle distance (km), RR (%), GR (%), TR (%) and FC (L/hr) for a fleet of CAT rigid body trucks. The data measured was collected using a Vehicle Information Management System (VIMS). VIMS is an electronic package consisting of a main processor and a network of sensors installed on all new Caterpillar equipment, designed to capture a wide range of data in order to manage the performance of a given machine. In fact, todays CAT equipment generates huge volumes of data to enable miners to monitor machine health and condition, track equipment hours and usage, to optimize work flows and production cycles, maximize equipment uptime and ultimately, to reduce mine operating costs per tonne [26].

The correlation between truck fuel burnt and nominated factors in this study (P, S and TR) is complex and nonlinear requiring a robust machine learning model to determine. The next section of this paper contains the details of the artificial neural network model that was created to determine how the truck fuel consumption changes with variations in the nominated factors.

IV. Estimation of Haul Truck Fuel Consumption

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

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

where E can be determined by :

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

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.

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:

$$Out = (\sum_{k=1}^{m} w_{ok} f(E_k)) + b_0 \tag{8}$$

Mean Square Error (MSE) and Coefficient of Determination (R2) were calculated for different amounts of nodes in the hidden layer to find the optimal number of nodes in the hidden layer. The minimum MSE and the maximum R2 (best performance) were observed for 12, 9, 15, 10 nodes in the hidden layer for Mine1,2,3, and 4 respectively.

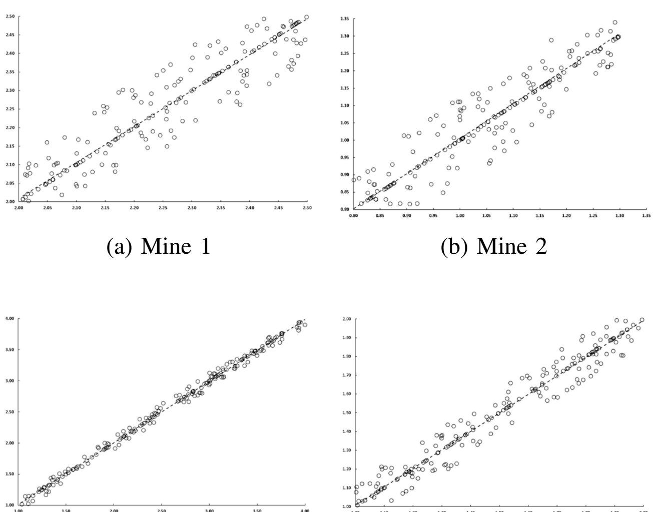
A. ANN Learning and Testing

For training and validating the developed ANN model, it was used a hold out approach with 80% for training and 20% for validation, from real datasets collected for the four mine sites studied. It was also used an *EarlyStopping* and *ModelCheckPoint* techniques to avoid overfitting.

The *EarlyStopping* technique implemented checks for every loss improvement in the validation set in comparison with the last iteration. In case it doesn't improve it starts counting until a threshold called *patience* is reached when the training process is interrupted. The value of patience was set to 10. Also the *ModelCheckPoint* implemented saves the weights matrix at every improvement of the validation loss to further analysis or possible transfer learning.

After achieving stable results on the validation set, the models were tested with independent samples.

The test results show acceptable agreement between the actual and estimated values of fuel consumption for all the mine sites investigated. The test results of the synthesized networks are shown in Figures 1a,1b,1c and 1d where the horizontal and vertical axes indicate the estimated fuel consumption rate (FC_{Index}(Liters/hour.tonne) values and the actual fuel consumption rate values respectively.



(a) Mine 1 (b) Mine 2

(c) Mine 3 (d) Mine 4

Fig. 1: Comparison of actual values with the estimated value of haul truck fuel consumption rate FC_{Index} by the developed ANN model

Figures 2,3,4,5 illustrate the correlation between P, S, TR and FC_{Index} created by the developed ANN models for a normal range of payloads for a different type of truck for the four mines sites studied.

The graphs presented show that there is a nonlinear correlation between FC_{Index} and 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 models developed also show that the amount FC_{Index} changes with variation in truck speed and payload. However, there is no clear correlation between all effective factors and energy consumption.

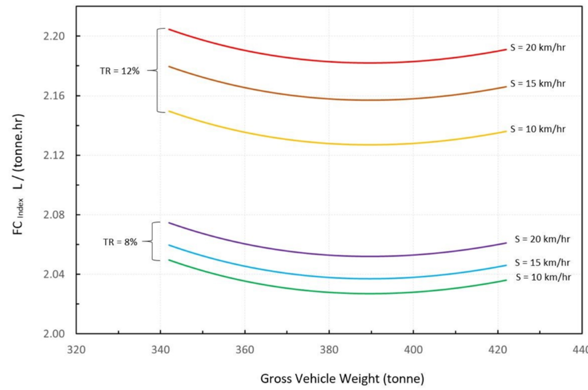


Fig. 2: Mine: 1 truck: CAT 793D

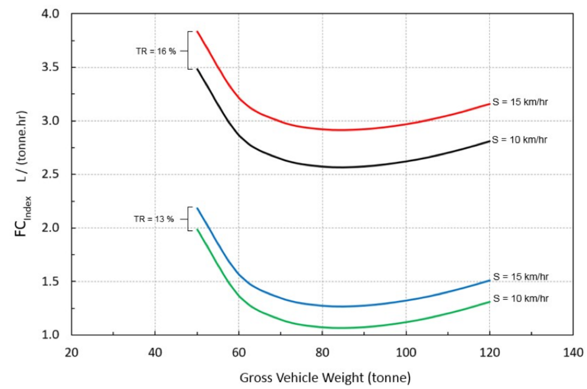


Fig. 3: Mine: 2 truck: CAT 785D

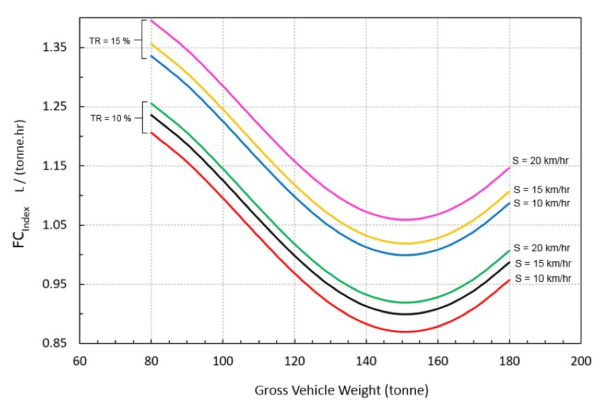


Fig. 4: Mine: 3 truck: CAT 777D

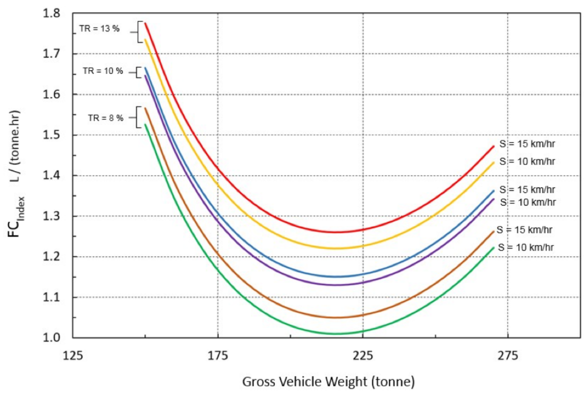


Fig. 5: Mine: 4 truck: CAT 775G

Even though predicting the amount of fuel consumed for haul trucks is really useful, it is highly desired for mining companies to know how reduce the fuel consumption or in other words what would be the practical actions needed to minimize the fuel burnt. As a result, completing another artificial intelligence model is required to find the optimum value of the selected factors to minimize the mine truck fuel consumption.

V. Optimization of Effective Parameters on Haul Truck Fuel Consumption

In this project, GA models were developed to improve three critical parameters that influence the energy consumption of haul trucks in the mine sites studied. The genetic algorithm was selected as a mono-objective optimization strategy mainly because of its capability to handle diverse operational situations and its parallelization power in the searching process. All GA processes in the model developed are illustrated in Figure 6.

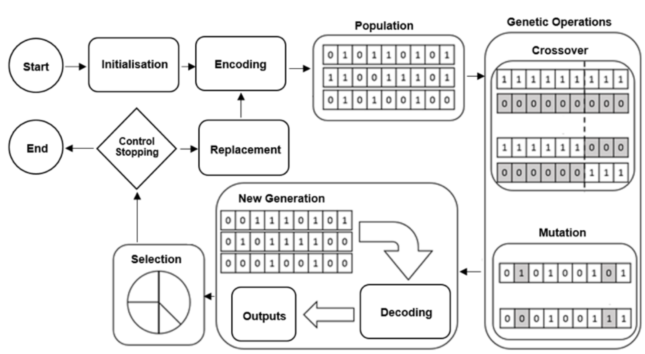


Fig. 6: Genetic algorithm processes (Developed Model)

The capabilities of GA go hand in hand with the primary goal for this optimization process, which is providing a set of P, S and TR values for the final user that will yield a minimum FC_{Index}. This ability to limit the optimization search space in a range of values is significant in real applications; for example, truck drivers cant reach an exact speed or even an average speed during a whole cycle period due to safety recommendations and/or road conditions. Also, using GA has the benefit of choosing one or more solutions from the final population after the optimization process is over. Those are the reasons why gradient-based optimization algorithms werent evaluated - such as making the same, trained ANN aspire to create inputs that minimize the FC_{Index}.

The formulation proposed for the FC_{Index} directly benefits the prediction (ANN) phase as well as the optimization process (GA). It can be noticed in (5) that one of the features (P) used to predict the regression target FC_{Index} is also used to calculate the fuel consumption rate FC_{Index}. This strategy creates a strong relationship between the target FC_{Index} and the features making enhancing the ANN prediction capabilities.

Moreover, as mentioned before the optimization goal is to minimize the FC_{Index} which unit is (Liters/hours.Tonne). It is evident that to achieve this goal the FC (Liters/hours) has to decrease while the P (Tonne) has to increase. At first this might sound simple, but the result of this formulation transformed a multi-objective optimization problem (Minimizing Fuel and Maximizing Productivity) in a mono-objective problem (Minimizing FC_{Index}) resulting in a straight forward solution and more efficient in terms of computational cost.

Another vital factor in successfully using the GA as the optimization process for this project is assessing the characteristics of the population. All the individuals must be checked throughout generations to ensure they are in the same distribution (i.e. maximum and minimum values) in which the ANN was trained. This is for 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 prediction results or the fitness values are reliable only within the constraints of this distribution. Second, the values of each individual attribute must reflect the reality of mine site and truck operational limitations in order to subsequently provide feasible, practical solutions.

In the model developed, payload, truck speed and total resistance are the parameters considered to form a individual, with the primary function of optimization being mine truck fuel consumption FC_{Index}. In this model, the fitness function was created by the ANN algorithm which evaluates each individual throughout the generations assigning a FC_{Index} to a combination of P, S and TR.

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

In these developed model, the key factors applied as stopping criteria was the MSE of overall population related to a predefined optimum value for FC_{Index}. The initial population size was different for different mine sites, and a uniform creation function was defined to generate a new population. Technical details of the developed models for the four mine sites studied are presented in Table III.

TABLE II: GA Procedures

Procedure	Details
Initialization	Produce original population of candidate solutions
Encoding	Digitalizes 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 III: Technical details of GA developed model

Parameters	Mine1	Mine2	Mine3	Mine4
Population type	Double vector	Double vector	Double vector	Double vector
Population size	20	50	30	20
Creation function	Uniform	Uniform	Uniform	Uniform
Scaling function	Rank	Rank	Rank	Rank
Selection function	Stochastic uniform	Stochastic uniform	Stochastic uniform	Stochastic uniform
Elite count for reproduction	2	3	2	2
Crossover fraction	0.8	0.7	0.8	0.9
Mutation function	Uniform	Uniform	Uniform	Uniform
Rate of mutation	0.01	0.02	0.01	0.03
Crossover function	Scattered	Scattered	Scattered	Scattered
Migration direction	Forward	Forward	Forward	Forward
Migration Fraction	0.2	0.1	0.3	0.2
Migration Interval	20	20	20	20
Constraint Parameters (Initial Penalty)	10	10	10	10
Constraint Parameters (Penalty Factor)	100	100	100	100
Stopping criteria	MSE	MSE	MSE	MSE

Finally, the optimized parameters (P, S and TR) are presented by the algorithm. These improved factors can be used to minimize the haul truck fuel consumption. All procedures in the developed models were based on datasets collected from four large surface mines in the United States of America and Australia. However, the methods and models created can be utilized for other surface mines by substituting their data for the original.

A. *Optimization results*

The first step in applying the developed optimization model is defining the range (minimum and maximum values) of all the variables (individuals). The variable ranges estimated are based on the collected datasets in the established model. The parameters used to evaluate the quality of the candidate solutions was the MSE of overall individuals related to a optimum value predefined. In this mine (Mine 1 as an example), the optimum value for FC_{Index} was around 0.04 which was achieved after the 47th generation as presented in figure 7

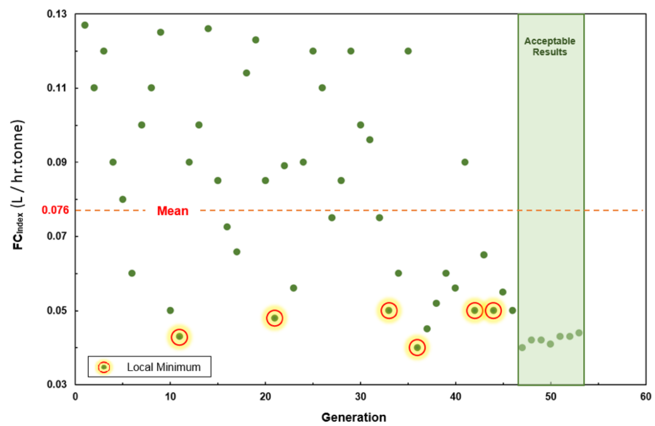


Fig. 7: Fuel Consumption (Fitness Value) in all generations (Sample for Mine1)

From this generation forward, the MSE values of overall population were roughly constant, but the algorithm continued all procedures until the 53rd. That is because it was also defined a confidence interval of generations for convergence of the candidate solutions to ensure that reliable results were obtained. The value of the fitness function (FC_{Index}) in all generations is illustrated in Figure 7. The simulated value of mine truck fuel consumption varies between 0.03 and 0.13 (L/(hr.tonne)). The mean of the estimated results is 0.076 (L/(hr.tonne)), and more than 45% of results are located above the average line. The model presented could find some local minimized fuel consumption, but the acceptable results are generated after the 47th generation. Figure 7 also shows that the FC_{Index} is about 0.04 (L/(hr. tonne)), which lies in the acceptable area. It means that by improving the payload, truck speed and total resistance in the mine site studied, the minimum FC_{Index} for the CAT 793D haul truck was found to be about 0.04 (L/(hr. tonne)).

The optimum range of variables to minimize fuel consumption for the specified haul trucks in mine sites studied are tabulated in Table IV, where GVW stands for Gross Vehicle Weight.

VI. Summary

The purpose of the studies presented was to develop a genetic algorithm model to improve mine truck fuel consumption, based on the correlations between payload, truck speed and haul road total resistance, created by analysis using real datasets collected from surface mining operations in four open-pit and open-cut mine sites located in the United States of America and Australia. The correlations were complicated and required artificial intelligence methods to create a consistent, reliable algorithm to tackle this challenge. In the first part of the project, an ANN algorithm was established to find a

TABLE IV: Optimization model recommendations

Mine	Truck	Variables	Normal		Optimized	
			Min	Max	Min	Max
1	CAT 793D	GVW(tonne)	150	380	330	370
		TR(%)	8	20	8	9
		S(Km/hr)	5	25	10	15
2	CAT 777D	GVW(tonne)	65	150	145	155
		TR(%)	9	25	9	11
		S(Km/hr)	10	45	10	12
3	CAT 775G	GVW(tonne)	45	95	75	90
		TR (%)	13	20	13	14
		S(Km/hr)	5	55	9	13
4	CAT 785D	GVW(tonne)	125	215	200	215
		TR(%)	8	15	8	9
		S(Km/hr)	5	45	10	15

relationship between the parameters investigated. The results illustrated that fuel consumption has a nonlinear correlation with the parameters studied. The ANN was subsequently taught and then validated using the real mine sites datasets that had been gathered. The results demonstrated that there was good agreement between the estimated and actual values of haul truck fuel consumption. In the last phase of the project, 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 driving energy consumption is possible. The algorithm established was able to find the local minimums for the fitness functions. The GA model developed demonstrated satisfactory capabilities to minimize the rate of fuel burnt in surface mines. The haul truck parameters that affect fuel consumption were investigated, within the data range available, and were optimized, and the best values of payload, truck speed and haul road total resistance that would minimize FC_{Index} were identified.

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