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Development of an Advanced Data Analytics Model to Improve the Energy Efficiency of Haul Trucks in Surface Mines

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Abstract

Truck haulage is responsible for a majority of cost in a surface mining operation. Diesel fuel, which is costly and has a significant environmental footprint, is used as a source of energy for haul trucks in surface mines. Reducing diesel fuel consumption would lead to a reduction in haulage cost and greenhouse gas emissions. The determination of fuel consumption is complex and requires multiple parameters including the mine, fleet, truck, fuel, climate and road conditions as input. Data analytics is used to simulate the complex relationships between the input parameters affecting the truck fuel consumption. This technique is also used to optimise the input parameters to minimise the fuel consumption without losing productivity or further capital expenditure for a specific surface mining operation.

The aim of this research thesis is to develop an advanced data analytics model to improve the energy efficiency of haul trucks in surface mines. The most important controllable parameters affecting fuel consumption are first identified, namely payload, truck speed and total resistance. These parameters are selected based on the results of an online survey. A comprehensive analytical framework is developed to determine the opportunities for minimising the truck fuel consumption. The first stage of the analytical framework includes the development of an artificial neural network model to determine the relationship between truck fuel consumption and payload, truck speed and total resistance. This model is trained and tested using real data collected from some large surface mines in USA and Australia. A fitness function for the haul truck fuel consumption is successfully generated. This fitness function is then used in the second stage of the analytical framework to develop a computerised learning algorithm based on a novel multi-objective genetic algorithm. The aim of this algorithm is to estimate the optimum values of the three effective parameters to reduce the diesel fuel consumption.

The following studies are also conducted to enhance the analysis of haul truck fuel consumption. First, a comprehensive investigation of loading variance influence on fuel consumption and gas emissions in mine haulage operation is carried out. Then, a discrete-event model to simulate the effect of payload variance on truck bunching, cycle time and hauled mine materials is developed. The influence of rolling resistance on haul truck fuel consumption in surface mines is investigated.

Five papers have been generated and published or accepted for publication in peer-reviewed journals. Presented thesis is completed according to The University of Queensland format for paper based PhD thesis.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my research higher degree candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

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Publications during candidature

ISI Journal Papers

Published

1. Soofastaei, A., Aminossadati, S.M., Arefi, M.M. and Kizil, M.S., Development of a multi-layer perceptron artificial neural network model to determine haul trucks energy consumption. International Journal of Mining Science and Technology, (2016). 26(2): P. 285-293.

2. Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P., A Discrete-Event Model to Simulate the Effect of Payload Variance on Truck Bunching, Cycle Time and Hauled Mine Materials. International Journal of Mining Technology, (2016).
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3. Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P., A Comprehensive Investigation of Loading Variance Influence on Fuel Consumption and Gas Emissions in Mine Haulage Operation. International Journal of Mining Science and Technology, (2016).

4. Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P., The Influence of Rolling Resistance on Haul Truck Fuel Consumption in Surface Mines. Tribology International Journal, (2016).

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Non-ISI Journal Papers

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2. Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P., Payload variance plays a critical role in the fuel consumption of mining haul trucks. Australian Resources and Investment, (2014). 8(4): P. 64-64.

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3. Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P., Rolling Resistance in Haul Truck Operations. Australian Mining Journal, (2016).

4. Soofastaei, A. and Davis, J., Advanced Data Analytic: A new competitive advantage to increase energy efficiency in surface mines. Australian Resources and Investment, (2016).

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1. Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P., Reducing Fuel Consumption of Haul Trucks in Surface Mines Using Artificial Intelligence Models, in Coal Operators' Conference, Aziz, P.N., Editor. (2016): University of Wollongong, New South Wales, Australia P. 487-500.

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Fuel Consumption, Greenhouse Gas Emissions, Haul Truck, Surface Mine, Artificial Neural Network, Genetic Algorithm, Artificial Intelligence Models, Data Mining

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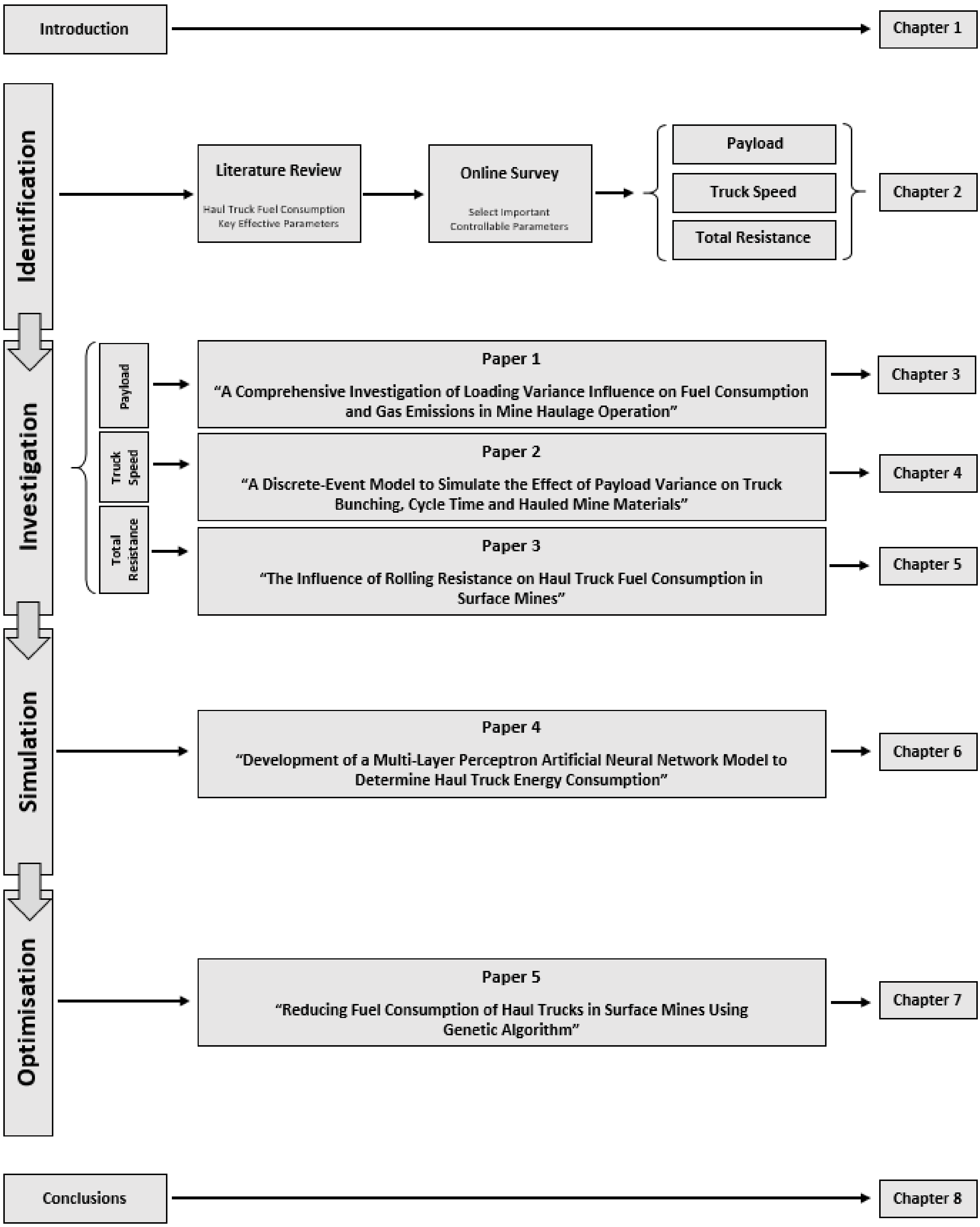

Glossary of Terms

ANN	Artificial neural network
B	Bucket of loader
b	Bias
CCS	Carbon dioxide capture and storage
CC_S	Core case scenario
CO_2-e	CO_2 equivalent
$CO_{2\ Index}$	CO_2 index (kg/ (hr. tonne))
CO_2-e_{Index}	CO_2 equivalent index (kg/ (hr. tonne))
D	Dumping
E	Summation function
EEF	Energy efficiency factor (%)
EF	Emission factor
EIA	Energy information administration
f	Fill factor
F	Transfer function
F_a	Activation function
FC	Truck fuel consumption (L/hr)
FC_{Index}	Fuel consumption index (L/ (hr. tonne))
FD	Fuel density (kg/L)
F_i	Fuel input rate (L/sec)
G	Gradient (%)
g	Gravity (m/s^2)
GHG_S	Greenhouse gases
GR	Grade resistance (%)
GVW	Gross vehicle weight (tonne)
GWP	Global warming potential
GA	Genetic algorithm
H	Hauling
HC_S	High cost scenario
I	Counter of sub segment

i	Input
J	Counter of time or timer (s)
j	Counter of input variables
k	Counter of trucks (k = 0 → N)
k	Counter of neural network node in hidden layer
LA_S	Limited alternatives scenario
LF	Engine load factor (%)
l	Length of segment (m)
L	Total length of haul road; Total length of return road (m)
LF	Engine load factor (%)
L_O	Loading
M	Number of cycles
m	Number of neural network nodes in hidden layer
M_A	Manoeuvring
M_I	Maintenance interval (Day)
MSE	Mean square error
Max	Maximum
N	Number of trucks
n	Decision variable for checking velocity of truck
n_o	Normalised
$NGHG_S$	Non-greenhouse gases
NIO_S	No International offsets scenario
O	Output
Out	Final output
P	Payload (tonne)
p	Maximum loader passes to fill the truck tray
Po_f	Fuel input power (kW)
Por	Rimpull power (kW)
PW	Truck engine power (kW)
QL	Queuing for loading
QD	Queuing for dumping

q	Number of input variables
r	Truck wheel radius (m), Number of cycle in each shift
R	Rimpull (tonne)
RF	Rimpull force (kN)
RR	Rolling resistance (%)
R_e	Returning
RFF	Rolling friction force (N)
RMSE	Root mean square error
R^2	Correlation coefficient
S, V	Truck speed, Truck velocity (km/hr)
S_{max}, V_{max}	Maximum truck speed, Maximum truck velocity (km/hr)
SFC	Engine specific fuel consumption (kg/kW.hr)
T	Traveling
t	Time (sec)
T_r	Torque (N.m)
TR	Total resistance (%)
T_{rq}	Torque (N.m)
TP	Tyre pressure (kPa)
U	Decision variable for first segment of haul road
V_b	Bucket rated capacity (m^3)
VIMS	Vehicle information management system
W_{ikj}	Number of trucks at queue in front of truck (k) at time (j) in sub segment (i)
w	Weight of the variables
X	Value of parameter to calculate standard deviation
x	Input variable
y	Target (real) output
Z	Number of available data for each parameter to calculate standard deviation
z	Estimated output
μ	Mean
ρ	Density (tonne/m^3)
σ	Standard deviation

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CHAPTER 1

1. Introduction

1.1 Background

Based on the latest statistics, annually about 607 Pita Joule (PJ) energy is consumed in Australian mining industry of which 11% are saveable[1]. This amount of saving has motivated both miners and the government to conduct a number of research studies on how to reduce the energy consumption in this industry.

Reducing energy consumption has been important since the early stages of utilisation of machines in the mining operations. The importance of energy consumption reduction has gradually increased since the rise in the cost of fuel in the 1970s. Up until now, different countries such as USA, Canada and China have carried out a number of research and industrial projects to reduce energy consumption in various mining operations [2-4].

Approximately 34% of the total energy used in Australian mines is related to diesel consumption [1]. Trucks use a great amount of energy in the Australian surface mines in haulage operation system. This has caused truck manufacture companies and major mining corporations to carry out a number of researches with the aim of reducing the amount of energy used by these large machines. However, a significant progress has not yet been achieved in this field of research due to the complexity of the parameters involved. Haul truck fuel consumption is a function of various parameters, the most significant of which have been identified and categorised into some main groups such as fleet management, mine planning, modern technologies, haul road, design and manufacture, weather condition and fuel quality. Each group has a couple of parameters. In the present study, the effects of payload, truck speed and haul road total resistance on the energy consumption of the haul trucks are examined.

One of the innovative parts of this research is the use of artificial neural network and genetic algorithm in the analysis of energy consumption. Currently, these methods are used as an evolutionary algorithm in different applications such as civil, mechanic, aerospace and electrical industries. The results of applications of these methods are being published annually in literature. However, a review of literature indicates that artificial neural network and genetic algorithm have not previously been used to minimise fuel consumption by haul trucks in surface mines. Hence, this project utilises these methods, which have been successfully used in other applications, with the aim of determining the optimum values of pertinent parameters on energy consumption with trucks in surface mines.

1.2 Statement of the problem

Truck haulage is responsible for a majority of cost in a surface mining operation. Diesel fuel, which is costly and has a significant environmental footprint, is used as a source of energy for haul trucks in surface mines. Reducing diesel fuel consumption would lead to a reduction in haulage cost and greenhouse gas emissions. The determination of fuel consumption is complex and requires multiple parameters including the mine, fleet, truck, fuel, climate and road conditions as input.

1.3 Research question

How data analytics can be applied to reduce the fuel consumption of the current fleet without capital expenditure?

1.4 Aims and objectives

The aim of this research is to develop an advanced data analytics model for analysing the complex interactions that influence the energy efficiency of haul trucks in surface mining. To accomplish this aim, the following objectives have been established:

- Identify key parameters driving energy efficiency;
- Select the most important controllable parameters;
- Develop regression models to quantify the impact of the selected parameters;
- Create predictive model to simulate the combined interaction of the parameters;
- Develop an optimisation model to maximise resultant energy efficiency gains; and
- Validate the resultant models.

1.5 Significance to the mining industry

This thesis identifies a real issue of concern in surface mine operations. The presented thesis develops a data analytics model for haul truck fuel consumption that can be applied in other applications.

1.6 Scope

This project is limited to investigate about fuel consumption by Rigid-Body off-road haul trucks in surface coal and copper mines. Three important and controllable effective parameters on fuel consumption by haul trucks are studied. The focus of this project is on Artificial Neural Network for predictive simulation and Genetic Algorithm for optimisation.

Energy consumption in underground mines, uncontrollable effective parameters on haul truck fuel consumption, truck design improvement, truck maintenance, fuel quality, alternative fuels, tyre management and driver skills are not investigated in this study.

The focus of this study is on just three controllable parameters (payload, truck speed and total resistance) on fuel consumption by haul trucks in surface mines. The presented model can be developed for other parameters in the future. This thesis shows how data analytics models can be used to increase energy efficiency in mining industry by completing an example for just three parameters.

1.7 Methodology

All completed phases in this project are illustrated in Table 1-1.

Table 1-1: All phases of project and methods

Phase		**Method**
Identify key parameters driving energy efficiency	→	Literature Review
Select the most important controllable parameters	→	Survey
Quantify the impact of the selected parameters	→	Data Analysing (Non- linear Regressions)
Simulate the combined interaction of the parameters	→	Artificial Neural Network (ANN)
Maximise resultant energy efficiency gains	→	Genetic Algorithm (GA)
Validate the resultant models	→	Analysing Mine Site Real Data Sets

CHAPTER 2

2. Review of Haul Truck Energy Efficiency Opportunities and Data Analytics Models

2.1 Energy efficiency opportunities

2.1.1 Introduction

Mining plays a vital role in our national security, national economy and in the life of every individual. Each year, million tonnes of materials should be mined for each person to maintain his or her standard of living [5-7]. The mining industry is a very important part of the global economy and provides essential raw materials such as coal, metals, minerals, sand and gravel to the factories and building industries, utilities and other businesses [8, 9]. In other words, mining is and will remain a vital part of the global economy for many years.

Mining activity in Australia is relatively diverse and involves extracting minerals, oil, gas and coal from the ground, either through open cut mining on the earth's surface or using underground mining methods. Generally, Australia is one of the major producers of mineral material.

Australia has one of the largest energy-intensive industrial sectors relative to population and energy demand is growing year by year. Because of some factors like low energy prices and lower rates of capital investment in the manufacturing sector, Australia's industrial sector had not improved its energy intensity as much as that of other countries [9, 10]. The international energy agency estimates that by 2030, Australia energy need will be 60% higher than today. There are around 1-2 million companies in Australia and estimated that 70% of business energy use is consumed by 250 large corporations [11-14].

2.1.2 Energy consumption

2.1.2.1 Australian industry sectors

Based on the researches done by the Australian government, Transport, Metal Manufacturing, Oil and Gas, and Mining were the industry sectors with the highest energy use in 2013–14 [15]. A quarter of annual energy in Australia is consumed for transportation. This amount of energy consumption is about 1516 PJ/Year. Almost 16% of energy use, or 971 PJ/Year, was attributed to the manufacturer of metal products such as aluminium, steel, nickel, lead, and iron, zinc, copper, silver, and gold. The second largest energy-using industry sector was Oil and Gas, which is consuming 789 PJ/Year, or 13% of participants' energy use. Activities in this sector include the conversion of gas into liquefied petroleum gas (LPG). The other sectors with the largest energy use in 2013–14 are illustrated in Figure 2-1.

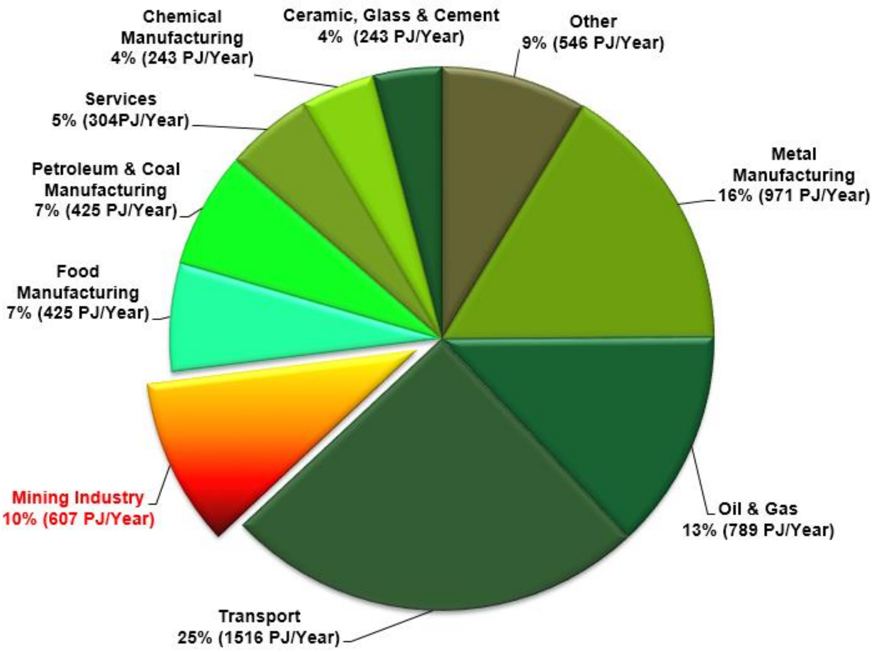

Figure 2-1: Top energy users by industry sector 2013–14 (Total 6069 PJ) [15-18]

Energy use by the remaining industry sectors has been aggregated under the category 'Others' in Figure 2-1 includes corporations in the construction and other manufacturing sectors.

Since the scope of this project is limited to mining industry, it is necessary to investigate the energy consumption in this industry more precisely.

2.1.2.2 Australian mines

The energy consumption intensity in mines depends on the type of mineral being extracted, as well as the type of production processes and the extraction technologies used by the mining businesses.

The three largest energy-using mining industries and the proportionate share of energy use are tabulated in Table 2-1.

Table 2-1: Energy use by mining sub-division [19, 20]

Mining Sub-division	Energy Use (PJ/Year)	Energy Use (%)
Coal Mining	48	20
Oil and Gas Extraction	72	31
Metal Ore Mining	83	36
Others	30	13
Sum	**607**	**100**

The type of fuel used at a mine site will depend on the mine type (surface or underground) and on the processes, which are employed. The energy sources in mining operations are diesel fuel, electricity, natural gas, coal, and gasoline, with participation in total energy consumption of 34%, 32%, 22%, 10%, and 2%, respectively (see Figure 2-2).

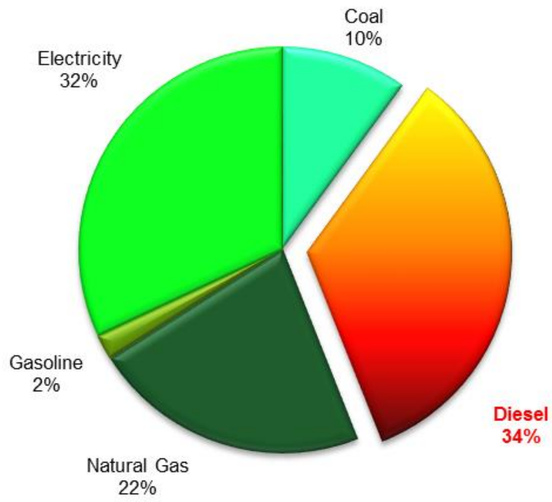

Figure 2-2: Fuel consumed in the mining industry [19, 21, 22]

The current energy use by equipment category in the mining industry is illustrated in Figure 2-3. The largest energy consuming equipment types are grinding (40%) and materials handling by diesel equipment (17%).

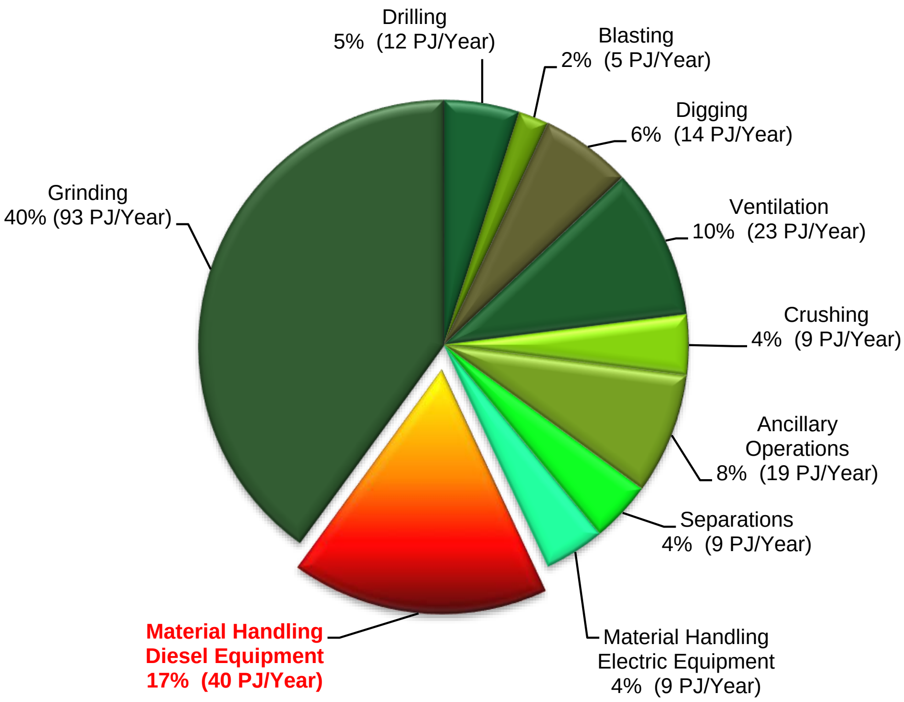

Figure 2-3: Contribution of energy use by equipment across the mining industry [19, 21, 22]

2.1.3 Energy saving opportunities

2.1.3.1 Australian industry sectors

Potential energy savings in Australia reported in 2013–14 were divided into the industry sectors shown in Figure 2-4. Corporations in the oil and gas and metals manufacturing sectors identified the largest energy savings, with 44 PJ (26% of energy assessed) of savings for oil and gas and 35 PJ (21% of energy assessed) of savings for metals manufacturing. As observed in other years, the industries with the highest energy use were typically the industries that identified the highest energy savings.

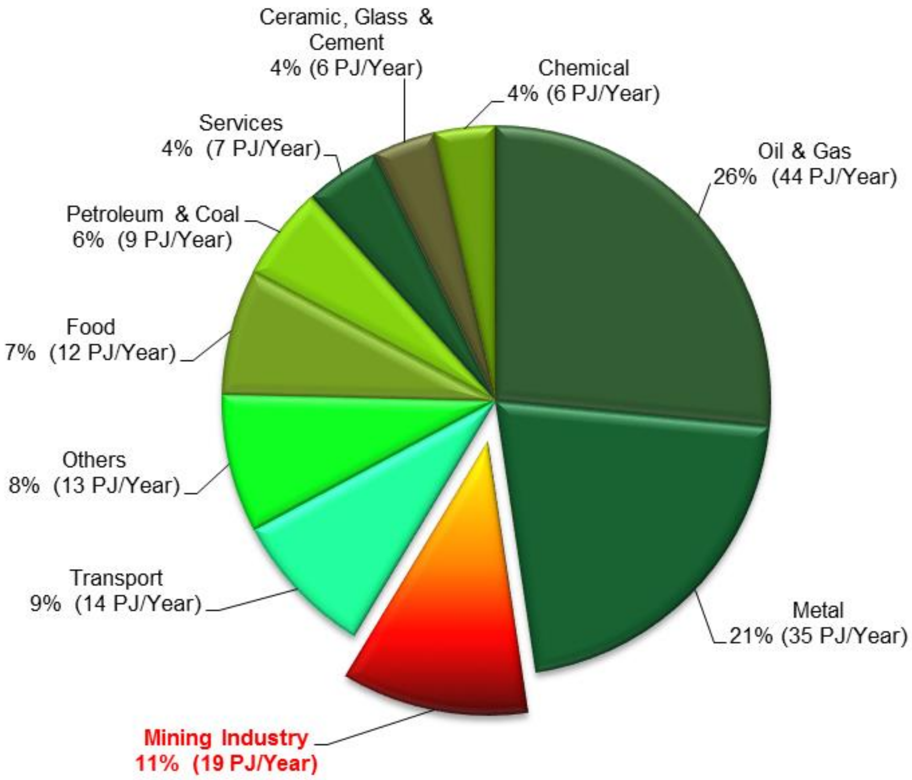

Figure 2-4: The energy saving by industry sectors (2013-14) [19, 23, 24]

2.1.3.2 Australian mines

The mining businesses identified 19 PJ/Year of energy savings as a result of their assessment process. Businesses involved in oil and gas extraction dominated the identification of energy savings, with their opportunities accounting for 12 PJ or just over two-thirds of total energy savings for the entire mining division. The level of energy savings identified by the miners is shown in Figure 2-5.

The metal ore miners identified the second largest share of energy savings at 4 PJ or 21% of savings. About 2 PJ of energy savings were found in projects reported by the coal mining industry, or 8% of total savings in mining. The remaining 'others' category accounted for almost 4% of the industry's identified savings.

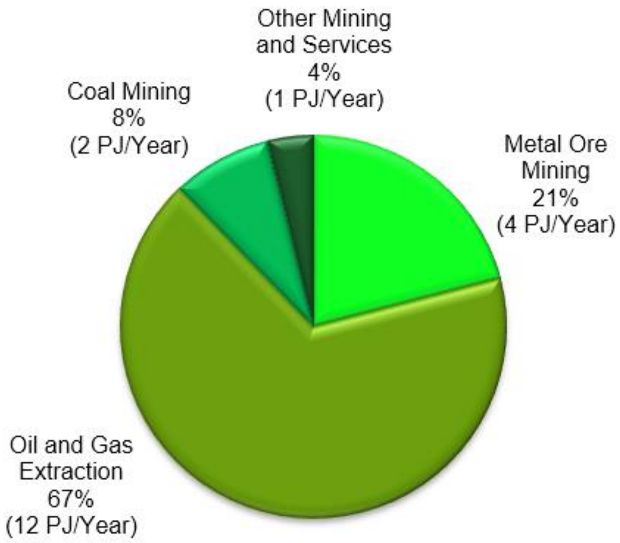

Figure 2-5: Energy savings per year identified by mining sub-division [15, 21, 22]

In order to do more precise researches on the field of energy consumption in Australian surface mines, it is necessary to provide detailed data on different productions of these mines and analyse them as well. So that the importance of doing research on coal mine in Australia will be identified.

2.1.4 Energy efficiency in mining

Historically, energy optimisation projects have been one of the highest priorities especially in the mining industry. Great progress has been made in the rational use of energy during the last three decades [3, 25]. Since 1973, industry in general has been reducing its consumption of energy in order to offset considerable increases in energy cost. Early studies carried out during the 1980s showed a trend of widespread usage of electricity for trolley-assisted trucks, in-pit crushers, and belt conveyor systems to reduce the diesel consumption [26, 27].

During the 1990s, there has been remarkable growth in computing and communication technology, which has transformed the mining industry from what, was once an intensive labour and very dangerous occupation to a highly technological industry [27]. These advances in technology development were the keys to the mining industry's sustainability and profitability but this increases the dependency of mining industries on energy.

Today, in order to reach the goals of cleaner and more energy-efficient processes at the same time, the industry continuously reduces the costs of production [28]. Initiative for energy reduction in mining processes is accepted throughout the world. The South African Department of Minerals has set a goal to reduce current energy consumption by 15% by 2018 [29]. Recently, a similar approach was established for Canadian open-cut mines. The Mining Association of Canada provides complete benchmarking for energy consumption in mining operations based on measurements collected from seven Canadian mines [30].

In an effort to make more efficient use of America's domestic energy and mineral resources, the US Department of Energy (DOE) defined research and development projects which are related to energy efficiency in mining [3]. As a result, several studies have been published. The studies revealed the benchmarks, ideas for energy saving and methods for calculating the energy consumption. This research is improving production, environmental effects, health and safety [3]. In June 2007, the DOE published a second document that has provided energy bandwidth in the mining industry. The document showed statistics for energy consumed in the mining industry and total energy saving opportunities that exist in the industry if the current processes are improved by implementing more energy-efficient practice and by using advanced technologies. As opposed to the previous DOE study, this report emphasises on the average energy consumption of similar equipment types to estimate the potential for energy savings. The equipment is divided into categories based on their processes (e.g., digging, blasting, material handling, crushing, etc.) within different mining industries (coal, metal, and non-metal) [3]. In this document, the information for energy requirements is calculated by the SHERPA software. However, the document shows a methodology to indicate energy saving opportunities and based on the results the greatest reduction for the mining processes can be represented in the coal and metal mining industries.

Recently, the mining industry has started implementing advanced Information Technology (IT) technologies (e.g., truck dispatching system, GPS system, etc.) which are usually multi-software and multi-vendor [31]. The general goal of these systems is to improve processes and reduce the operating costs. However, these systems are not designed to manage energy consumption of all production units at a mine site, yet they recognise information systems as a key for productivity improvements in mines [32].

With increasing energy consumption in Australia especially in mining industry, in July 2006, the Australian government started a program to do researches and encourage the industries to use energy optimally [21]. This program was named "Energy Efficiency Opportunities" (EEO). The aim of EEO program is to encourage Australia's large energy-using businesses to identify and implement projects that will save energy, reduce greenhouse gas emissions and lower their business costs [15]. Introduced in July 2006, participation in the program is mandatory for companies, which are using more than 0.5

PJ of energy per year. Currently 226 companies have registered for the program, with 199 of these having registered within the first trigger year of 2005–06. The program’s first five-year cycle was run from 2006 to 2011[15].

The EEO program was set up with the aim to improve the energy efficiency of the country’s largest energy users who account for a major share of national energy use together. Their performance is critical to achieve Australia’s energy and climate change goals [33].

After this literature review, mining processes should be identified and three topics of energy, cost and greenhouse gas emission linked directly to each other will be investigated

2.1.5 Energy cost analysis for surface mining

Cost analysis is one of the most important parts of energy management in the mines. The results of all gathered data and analysed energy costs for different processes in Australian surface mines are illustrated in Table 2-2.

Table 2-2: The energy costs for surface mining processes [34, 35]

Mining process	Low Energy Cost*	High Energy Cost*	Mean Energy Cost*	Percentage
Drilling	0.13	29	14.56	3.38 %
Blasting	56	275	165.50	39.85 %
Material Loading	15	98	56.50	13.53 %
Hauling	65	158	111.50	26.81 %
Mine Dewatering	0	86	43.00	10.39 %
Mine Support Equipment	6	44	25.00	6.04 %

* ($ / Kilotons of material removed)

As is shown in Table 2-2, blasting and hauling have the maximum amount of energy cost respectively and this can emphasise the importance of reducing energy consumption in haulage operation systems in surface mines.

2.1.6 Financial benefits of identified energy saving opportunities

The mining industry reported that they could potentially achieve net financial benefits of $257.3 million per year as a result of energy savings projects that they identified through their energy efficiency assessments, as shown in Table 2-3. This was the highest level of financial savings of any industry sector, representing 35% of the $735.8 million in financial benefits estimated by 199 corporations in Australia for a one-year period (2013-14).

Table 2-3: Net financial benefits from energy savings opportunities [36]

Mining sub-division	Energy savings (PJ)	Financial savings ($ million/year)	Financial savings ($/GJ)
Coal mining	1.37	56.2	41.08
Oil and gas extraction	11.17	NP	NP
Metal ore mining	3.60	77.2	21.46
Other mining and services	0.66	NP	NP
Total mining	16.80	257.3	15.32

NP = Data not published to maintain confidentiality of commercially sensitive information

The net financial benefits of the energy efficiency opportunities identified by the miners were also expressed on a per unit (Gigajoule) basis in Table 2-3.

The dollar-per-gigajoule figures can vary across an industry because of factors such as differences in energy pricing. Other factors are fuel types production technologies, other business costs and benefits attributed to energy saving projects.

On average, the mining businesses together identified financial savings of $15.32 per GJ if they were to implement their energy efficiency projects.

The coal miners reported the highest financial benefits of $41.08 per GJ saved, while the metal ore miners identified savings of almost half that amount of $21.46 per GJ saved.

2.1.7 Truck energy consumption

The understanding of the energy efficiency of a haul truck should not be limited to the analysis of vehicle--specific parameters. Mining companies can often find greater benefits by expanding the analysis to include many other factors that affect the amount of energy used across an entire fleet [37, 38]. This project is focused on identifying and optimising these parameters.

Trucks in surface mines are used to haul ore and overburden from the pit to a stockpile, dumpsite or to the next stage of a mining process. Their use is planned in combination with other machinery, such as loaders, diggers and excavators, according to the site layout and production capacity [39-42]. Trucks are expensive to purchase, maintain and use a major amount of diesel in Australian surface mines [39].

Many parameters such as site production rate, age and maintenance of the vehicles, payload, speed, cycle time, mine layout, mine plan, idle time, tire wear, rolling resistance, dumpsite design, engine operating parameters and transmission shift patterns can affect the energy efficiency of the fleet in surface mining. This knowledge can be merged into mine plan costing and design procedures to improve energy efficiency [43-49].

Trucks as the haulage operation system in surface mines can be classified as shown in Figure 2-6.

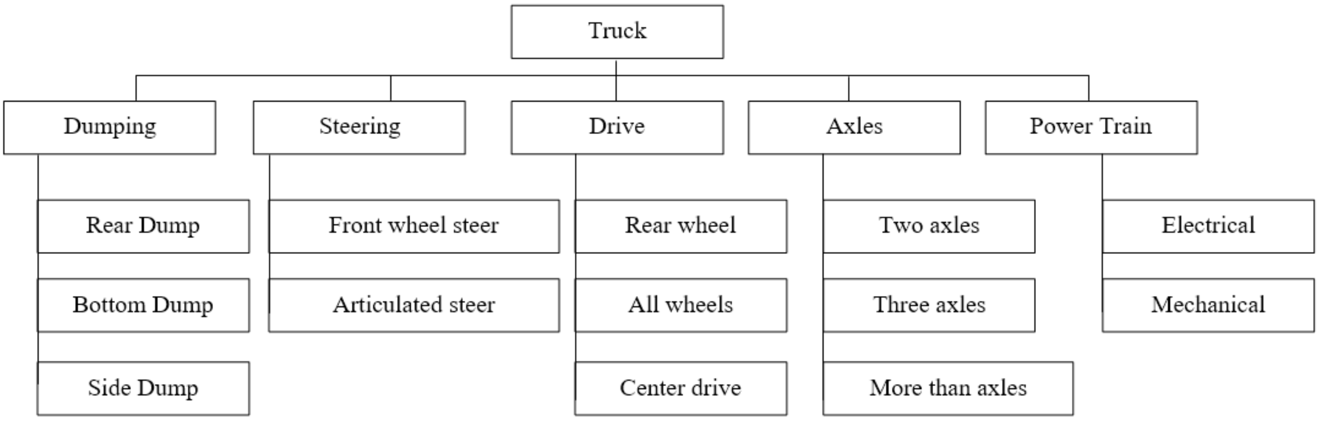

Figure 2-6: Truck types

2.1.7.1 Truck Specifications

This section discusses truck specifications that can be important in analysing energy consumption by truck systems. Some important specifications are: Payload; Dimensions; Performance; Rimpull Curve; Braking Curve; Drive system type; Power; and Tyres.

Payload, net vehicle weight and gross vehicle weight: The amount of useful material carried by trucks is measured either as Bank Cubic Meters (BCM) or as tonnes. It is the weight of the load that is important in terms of the vehicles performance. Manufacturers either define the capacity of their trucks in terms of nominal payload (tonnes) or as a maximum Gross Vehicle Weight (GVW). The GVW system is very sensible as it accounts for the changes in Net Vehicle Weight (NVW).

$$\text{Payload} = \text{GVW} - \text{NVW} \tag{2-1}$$

Equation 2-1 shows that, payload is the difference between GVW and NVW. The NVW for the same trucks at different mines can be quite large. This is because different options selected by each operation include tyres, wear packages, air conditioning, size of fuel tank and body size.

Dimensions: Dimensions of the truck play a main role on the amount of energy consumption. Dimensions of the truck include body size, height, length and width. Truck manufacturers are a good source of data to find the relationship between the energy consumption by truck and the dimensions of it [50].

Power: Power is a major parameter to calculate fuel consumption by trucks, therefore, it is necessary to be analysed precisely. Power is usually quoted as either gross power or flywheel power. Gross power is the maximum power that can be produced by the engine. Flywheel power is less than the gross power used by ancillary equipment on the truck. This equipment includes fan, air cleaner, alternator, water pump, fuel pump, oil pump and muffler. Flywheel power is typically 90 to 95 percent of maximum power.

Performance: Another effective parameter on truck fuel consumption is their performance, which can be achieved by technical chart. Manufacturers' performance chart provides the maximum speed of a truck under given total resistance and truck weight. It also gives information on rim pull available.

Rimpull: Rimpull is the force available at the tyre that is required to move the vehicle forward. This force is limited by traction. The difference between the rim pull required overcoming total resistance and the available rim pull determines vehicle acceleration. This item is very important to calculate the diesel consumption by truck in surface mines.

Braking / Retarding: The braking / retarding systems are different between the types and models of trucks and different braking system have different characteristics. Due to the model and type of a truck selected in this, project braking/retarding curves are available and using them to find the relationship between energy consumption and braking system is easy.

Tyres: Tyres are one of the most important elements of truck cost and energy consumption by truck. There are two basic tyre types: Bias and Radial. In general, radial tyres are becoming more popular in open cut mines. Potential advantages include good flotation, good trip, long tyre life, low fuel consumption and smooth ride.

2.1.8 Effective parameters on truck energy consumption

2.1.8.1 Mine operation parameters

There are a number of parameters that can influence on the amount of energy used by trucks in the mines some of which are tabulated in Table 2-4.

2.1.8.2 Truck travel time

The four ways of calculation travel time that most important parameter of truck productivity include: time study; Rimpull curves; empirical; and computer simulation.

Table 2-4: Effective parameters on haul truck energy consumption

Parameter	Detail
Truck model and type	Each type and model of truck has especial characteristics and these can be effective on energy consumption by truck.
Material	Material which is hauled.
Bucket density	Density of the material being loaded.
Swell factor	Swell factor is the volume increase after material has been disturbed.
Bucket load	Estimated bucket load that the loading unit can carry in BCM.
Calculated passes to fill	Estimate of how many bucket loads (passes) are required to fill the truck to its nominal capacity.
Calculated truck payload	Estimated average payload that the truck will carry after considering all the above factors.
Load factor	Percentage of truck fill compared to its nominal or rated payload.
Time per pass	Time taken for a loading unit to complete one pass.
Load time	Time taken to load the truck.
Spot time	Time during which the loading unit has the bucket in place to dump, but is waiting for the truck to move in to position. Spot time will depend on the truck drivers' ability and the system of loading. Double-side loading should almost eliminate spot time.
Dump time	Time taken for the truck to manoeuvre and dump its load either at a crusher or dump.
Fixed time	Sum of load, spot and dump time. It is called 'fixed' because it is essentially invariable for a truck and loading unit combination.
Travel time	Time taken to haul and return the load.
Wait time	
Cycle time	Round trip time for the truck, it is the sum of fixed, travel and waits times.
Efficiency	Measure of how much productive time is achieved in one hour of operating time. The sort of activities that the efficiency factor includes is: Clean-up by the loading unit or dozer, Crusher and dump slow-downs, Fuelling, Inspections, Loading unit movement, Operator experience, Under trucking, Unusual delays due to weather.
Queue factor	Accounts for time lost due to queuing. It is another measure of wait time.
Productivity	Tonnes of production hauled in an operating hour (t/h) Productivity = Efficiency / (Cycle time × Truck payload × Queuing factor)
Mechanical availability	Depending on machine type, age and maintenance philosophy
Utilisation	Operating time divided by available time
Production	Hourly Productivity × Operating Hours

2.1.8.3 Haul Profile

The basic information for estimating travel time is called haul profile. Haul profile has four sections include:

Distance: Distance is the one-way distance per section in metres

Rolling Resistance (RR): The RR of the road is measured as a percentage of the vehicle weight. RR is a measure of the force required to overcome the retarding effect between the tyres and road. It includes the resistance caused by tyre penetration of the ground and tyre flexing.

Grade: Grade is the slope of the section, measured as a percentage. Slop is the ratio between the rise of the road and the horizontal length.

Speed Limitations: Speed limitations can have different values because of following reasons: operational constraints; operator capability; and safety.

2.1.9 Identify the main parameters to make a comprehensive simulation and optimisation model

Different parameters have influence on truck energy consumption. Because of the limitations of the project, it is not possible to model all the parameters. Therefore, the most important parameters enter the model. Based on the latest governmental reports the mining energy saving opportunities can be grouped in staff operation; maintenance procedures; management systems; energy measurement; energy management parameters; and new technologies [51, 52].

Figure 2-7 shows the level of energy savings, and the proportion of total identified savings, according to the types of energy efficiency opportunities being identified and implemented by the mining companies in the period of 2013-14. Projects that focused on energy management parameters provided the largest amount of energy savings, or 4.61 PJ, accounting for 55% of all savings opportunities identified by the mining entities.

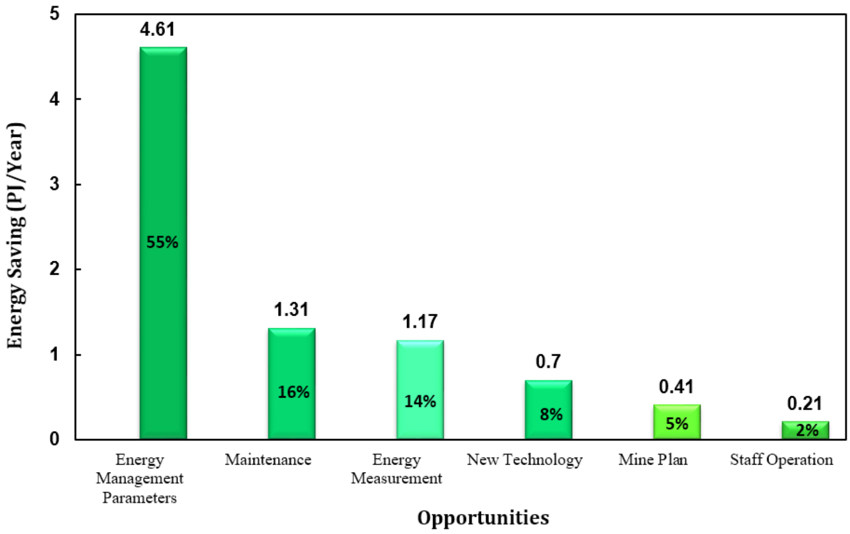

Figure 2-7: Energy saving opportunities in mining industry [51, 52]

The miners' energy savings were evenly distributed among the next three largest categories of savings opportunities: maintenance, which had savings of 1.31 PJ, energy measurement (1.17 PJ) and new technologies (0.7 PJ). Projects that involved management systems and staff operation, recorded the lowest energy savings, accounting for 0.41 PJ and 0.21 PJ of energy savings respectively.

In this project an online survey has been completed to identify three main effective parameters for investigate about reducing haul truck fuel consumption. In this survey, 60 industry personnel have been contacted with an 81% response rate. The results of the survey have shown that payload. Truck speed and haul road total resistance are the most important effective parameters on haul truck fuel consumption.

After identifying the main parameters, it is necessary to select practical methods to create the model. These methods are Artificial Neural Network (ANN) and Genetic Algorithm (GA).

2.1.10 Greenhouse gas emissions

Energy efficiency has the potential to markedly reduce demand for energy and help to lower greenhouse gas emissions, at a relatively low cost to industry and the broader economy. An awareness of opportunities to maximise energy efficiency makes commercial as well as environmental sense. The Australian Bureau of Agricultural and Resource Economics (ABARE) has estimated that energy efficiency measures can play a leading role in reducing greenhouse emissions. By increasing the energy efficiency in Australian mining industry, we not only can save billions of dollars annually but also it is possible to avoid significant emissions of greenhouse gases and other air pollutants. Corporations participating in the EEO program have already identified opportunities to save more than six million tonnes of greenhouse gas emissions per year. This is equivalent to 1.1% of Australia's total greenhouse gas emissions [15].

The greenhouse gas emissions produced by the mining entities were calculated based on their use of different types of fuels, such as electricity, natural gas and diesel. The energy savings reported by the mining entities equated to a potential reduction in greenhouse gas emissions of 1,407-kilo tonnes of Carbon Dioxide-equivalent (kt CO_2-e), as seen in Table 2-5.

Around 823 kt CO_2-e were attributable to direct emissions and 584 kt CO_2-e to indirect emissions. The energy savings of oil and gas entities produced the largest emissions reductions of any mining sub-division, accounting for 42.8% of reductions, or 601.9 kt CO_2-e.

The metal ore miners identified energy savings that would produce the second largest reductions in emissions, of 37.2% or 524 kt CO_2-e.

Table 2-5: Reductions in greenhouse gas emissions by mining sub-division [53-58]

Mining sub-Division	Reductions in energy-related emissions (Kilo tonnes CO_2-e)			Share of emissions reductions (%)
	Direct	Indirect	Total	
Coal mining	52.7	178.0	230.6	16.4
Oil and gas extraction	601.9	---	601.9	42.8
Metal ore mining	125.7	398.2	524.0	37.2
Other mining and support services	43.1	7.5	50.6	3.6
Total mining	823.4	583.7	1,470.0	100

Up to now, different parameters, which influence on energy management in Australian surface mines, have been discussed. Since the scope of this research project is to make a model to reduce fuel consumption for trucks, it is necessary to focus specifically on the characteristics of trucks and effective parameters on their energy consumption.

2.2 Data analytics models

2.2.1 Artificial neural network

Artificial Neural Networks (ANNs) are a popular artificial intelligence method to simulate the effect of multiple variables on one major parameter by a fitness function. 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 ANNs is that they can simulate both linear and nonlinear relationships between parameters, using the information provided to train the network. ANNs, also known as parallel distributed processing, are the representation of methods that the brain uses for learning. ANNs are computing systems made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs. 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 parameters and do not require the mathematical description of the phenomena involved in the process.

ANNs have been used in many engineering disciplines such as materials [50, 59-64], biochemical engineering[65], medicine [66] and mechanical engineering [67-71].

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. 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.

There are a group of models that imitate a few of the known characteristics of natural nerve systems and draw 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. ANNs are utilised in various computer applications to solve complex problems.

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. ANNs 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. Figure 2-8 shows a simple structure of ANNs.

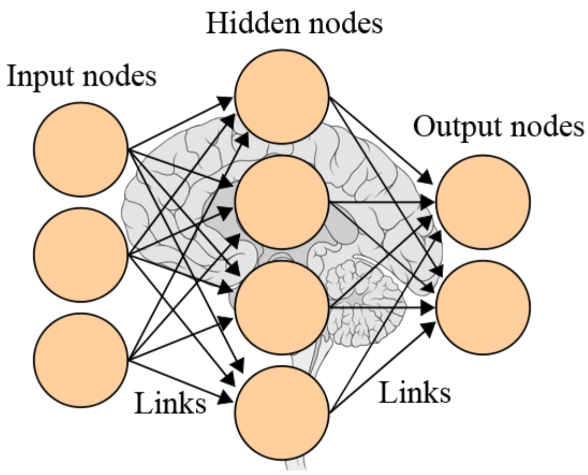

Figure 2-8: A simple structure of ANNs [50]

There are some grounds for ANNs application such as: ANNs are fault tolerant and straightforward models that do not require information for identifying the related parameters; ANNs do not need the mathematical description of the phenomena involved in the process; and ANNs are utilised in various computer application to solve complex problem.

2.2.2 Genetic algorithm

Genetic Algorithm (GA) provides a method for solving optimisation problems by imitating the evolutionary process based on the mechanics of Darwin's natural selection [72]. GAs are the search methods based on principles of natural selection and genetics [72]. GAs can be categorised as Meta heuristics with global perspective. GA has been applied to a diverse range of scientific, engineering and economic problems [73-78].

Recently, GAs have received considerable attention regarding their potential as an optimisation technique for complex problems and have been successfully applied in the area of industrial engineering [79-86]. GAs are implemented as a computer simulation to find better solutions. They encode the decision variables of a search problem into finite-length strings of alphabets of certain cardinality. The strings, which are candidate solutions to the search problem, are referred to as chromosomes. The alphabets are referred to as genes and the values of genes are called alleles. In contrast to traditional optimisation techniques, GAs work with coding of parameters, rather than the parameters themselves. To evolve good solutions and implement natural selection, it is essential to measure for distinguishing good solutions from bad solutions. The measure could be an objective function that is a mathematical model or a computer simulation, or it can be a subjective function where humans choose better solutions over worse ones. In essence, the fitness measure must determine a candidate solution's relative fitness, which will subsequently be used by the GA to guide the evolution of good solutions. Another important concept of GAs is the notion of population [87-90]. Unlike traditional search methods, genetic algorithms rely on a population of candidate solutions. The population size, which is usually a user-specified parameter, is one of the important parameters affecting the scalability and performance of genetic algorithms. Once the problem is encoded in a chromosomal manner and a fitness measure for discriminating good solutions from bad ones has been chosen, the evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

2.2.2.1 Genetic Algorithm vocabulary

Since genetic algorithms are rooted in both natural genetics and computer science, the terminologies used in genetic algorithm literature are mixture of the natural and the artificial science[91-93]. The correspondence of genetic algorithm terms and optimisation terms are summarised in Table 2-6.

Table 2-6: Explanation of genetic algorithm terms

Genetic Algorithms	Explanation
Chromosome (String, Individual)	Solution (Coding)
Genes (Bits)	Part of solution
Locus	Position of gene
Alleles	Values of gene
Phenotype	Decoded solution
Genotype	Encoded solution

2.2.2.2 Genetic Algorithm terminology

Some basic terminologies for genetic algorithm are illustrated in following:

Fitness Function: The fitness function is function you want to optimise. For standard optimisation algorithms, this is known as the objective function.

Individuals: An individual is any point to which you can apply the fitness function. The value of the fitness function for an individual is its score. An individual is sometimes referred to as a genome and the vector entries of an individual as genes.

Populations and Generations: A population is an array of individuals. At each iteration, the genetic algorithm performs a series of computations on the current population to produce a new population. Each successive population is called a new generation.

Diversity: Diversity refers to the average distance between individuals in a population. A population has high diversity if the average distance is large; otherwise, it has low diversity.

Fitness Value: The fitness value of an individual is the value of fitness function for that individual.

Parents and Children: To create the next generation, the genetic algorithm selects certain individuals in the current population, called parents, and uses them to create individuals in the next generation, called children. Typically, the algorithm is more likely to select parents that have better fitness values.

2.2.2.3 Genetic Algorithms' steps

The following steps can be applied to use GA in the industrial projects.

Initialization: The initial population of candidate solutions is usually generated randomly across the search space. However, domain-specific knowledge or other information can be easily incorporated.

Evaluation: Once the population is initialized or an offspring population is created, the fitness values of the candidate solutions are evaluated.

Selection: Selection allocates more copies of those solutions with higher fitness values and thus imposes the survival-of-the-fittest mechanism on the candidate solutions. The main idea of selection is to choose better solutions out of worse ones, and many selection procedures have been proposed to accomplish this idea, including roulette-wheel selection, stochastic universal selection, ranking selection and tournament selection, some of which are described in the next section.

Recombination: Recombination combines parts of two or more parental solutions to create new, possibly better solutions (i.e. offspring). There are many ways of accomplishing this (some of which are discussed in the next section), and competent performance depends on a properly designed recombination mechanism. The offspring under recombination will not be identical to any particular parent and will instead combine parental traits in a novel manner.

Mutation: While recombination operates on two or more parental chromosomes, mutation locally but randomly modifies a solution. Again, there are many variations of mutations, but it usually involves one or more changes being made to an individual's trait or traits. In other words, mutation performs a random walk in the vicinity of a candidate solution.

Replacement: The offspring population created by selection, recombination, and mutation replaces the original parental population. The algorithm usually selects individuals that have better fitness values as parents. The GA creates three types of children for the next generation:

- Elite children are the individuals in the current generation with the best fitness values. These individuals automatically survive to the next generation.
- Crossover children are created by combining the vectors of a pair of parents.
- Mutation children are created by introducing random changes, or mutations, to a single parent.

The three types of children are illustrated in Figure 2-9.

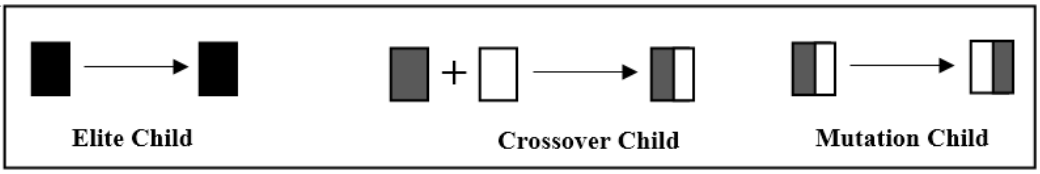

Figure 2-9: Three types of children for the next generation

2.2.2.4 Stopping conditions for the Algorithm

All conditions to stop a GA algorithm are illustrated in Table 2-7 [72].

Table 2-7: Stopping conditions for the algorithm

Stopping Condition	Explanation
Generations	The algorithm stops when the number of generations reaches the value of Generations.
Time limit	The algorithm stops after running for an amount of time in seconds equal to Time limit.
Fitness limit	The algorithm stops when the value of the fitness function for the best point in the current population is less than or equal to Fitness limit.
Stall generations	The algorithm stops if there is no improvement in the objective function for a sequence of consecutive generations of length Stall generations.
Stall time limit	The algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to stall time limit.

The algorithm stops as soon as any one of five conditions mentioned in Table 2-7 is met. The searching procedure of GA is shown in Figure 2-10.

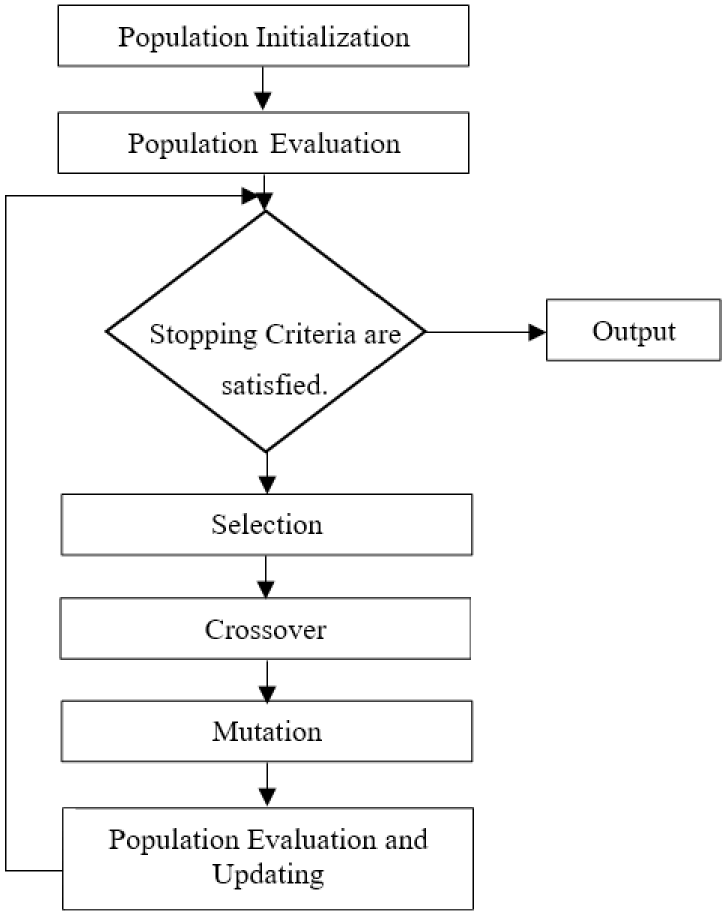

Figure 2-10: The flow diagram of a GA optimisation model

2.2.2.5 Differences of Genetic Algorithm

The GAs differ from conventional optimisation and searching procedure in several fundamental ways as follows:

- GAs work with a coding of solution set, not the solutions themselves;
- GAs search a population of solutions, not a single solution;
- GAs use payoff information (Fitness Function), not derivative or other auxiliary knowledge;
- GAs use probabilistic transition rules, not deterministic rules.

2.2.2.6 Major advantages of Genetic Algorithm

The GAs have received considerable attention regarding their potential as a novel optimisation technique. There are four major advantages when applying genetic algorithms to optimisation problems.

- GAs do not have much mathematical requirements about the optimisation problems. Due to their evolutionary nature, GAs will search for solutions without regarding the specific inner workings of the problem.
- GAs can handle any kind of objective functions and any kind of constraints (i.e., linear or nonlinear) defined on discrete, continuous or mixed search spaces.
- The periodicity of evolution operators makes GAs very effective at performing global search (in probability).
- The GAs provide us a great flexibility to hybridize with domain dependent heuristics to make an efficient implementation for a specific problem.

2.3 Summary

In summary, it found that a main part of energy use in Australia is consumed in mining industry and there are a lot of energy efficiency opportunities in mine material haulage systems. A main part of these opportunities were identified in surface mines by reducing haul trucks fuel consumption.

There are a lot of effective parameters on energy use by trucks and some of them are not controllable. Payload, truck speed and total resistance as three main effective and consolable parameters on fuel consumption by haul trucks were selected. Literature review shows that there is not any comprehensive advanced data analytics model to find the relationship between more than one parameter and fuel consumption and there is not also any multi-function optimisation model to improve effective parameters on haul truck fuel consumption.

This research thesis aims to develop an advanced data analytics model to improve energy efficiency for haul trucks in surface mines. This model consists of Artificial Intelligence methods for developing a fitness function for haul truck fuel consumption, and optimising the important controllable parameters that result in minimum fuel consumption. In order to enhance the analysis, the effects of payload variance and rolling resistance on fuel consumption and gas emissions are investigated as well.

Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P.,
A Comprehensive Investigation of Loading Variance Influence on Fuel Consumption and Gas Emissions in Mine Haulage Operation.
International Journal of Mining Science and Technology, (2016).

Abstract

The data collected from haul truck payload management systems at various surface mines show that the payload variance is significant and must be considered in analysing the mine productivity, diesel energy consumption, greenhouse gas emissions and associated costs. The aim of this study is to determine the energy and cost saving opportunities for truck haulage operations associated with the payload variance in surface mines. The results indicate that there is a non-linear relationship between the payload variance and the fuel consumption, greenhouse gas emissions and associated costs. A correlation model, which is independent of haul road conditions, has been developed between the payload variance and the cost saving using the data from an Australian surface coal mine. The results of analysis for this particular mine show that a significant saving of fuel and greenhouse gas emissions costs is possible if the Standard Deviation of payload is reduced from the maximum to minimum value. [94]

Keywords: Energy Consumption; Haul Truck; Surface Mine; Greenhouse Gas Emissions; Cost

CHAPTER 3

3. A Comprehensive Investigation of Loading Variance Influence on Fuel Consumption and Gas Emissions in Mine Haulage Operation

3.1 Introduction

Mining industry consumes a large amount of energy in various operations such as exploration, extraction, transportation and processing [2, 95]. A considerable amount of this energy can be saved by better managing the operations [3, 25, 49, 96]. The mining method and equipment used mainly determine the type of energy source in any mining operation [97]. In surface mining operations, haul trucks use diesel as the source of energy [39, 98, 99]. Haul trucks are generally used in combination with other equipment such as excavators, diggers and loaders, according to the production capacity and site layout [95]. Haul trucks use a great amount of fuel in surface mining operation; hence, mining industry is encouraged to conduct a number of research projects on the energy efficiency of haul trucks [100, 101].

There are many kinds of parameters that affect the rate of fuel consumption for haul trucks such as payload, truck velocity, haul road condition, road design, traffic layout, fuel quality, weather condition and, driver skill [102-105]. A review of the literature indicates that the understanding of energy efficiency of a haul truck is not limited to the analysis of vehicle-specific parameters; and mining companies can often find greater energy saving opportunities by expanding the analysis to include other effective parameters such as payload distribution and payload variance [105-108].

Loading process in truck and shovel operations is a stochastic process [107, 109]. An analysis of the haul truck payload data obtained from a number of mine sites around the world shows that the payload distribution can be estimated by a normal distribution function with a satisfactory error; and the variance associated with haul truck payloads is typically large[106-108, 110]. The payload variance depends on a number of parameters such as the particle size distribution, the swell factors, the material density, truck-shovel matching, number of shovel passes and the bucket fill factor [106, 108, 109, 111]. Many attempts have been made to reduce the payload variance by using the latest developed technologies such as truck on-board payload measurement system, direct connection between this system and the shovel control system and on-line fleet monitoring system [106, 107, 112].

The payload variance not only affects the production rate and fuel consumption, but it is also an important parameter in the analysis of gas emissions and cost. Many research studies have already been conducted on the measurement of the haul truck gas emissions in the mining industry[48, 113-116]. In addition, several numbers of economic models have been presented to predict the cost of diesel and gas emissions [117].

In this paper, the effects of payload variance on fuel consumption for a mostly used haul truck in Australia surface coal mines (CAT 793D) are investigated. A model is presented to estimate the effect of payload variance on the gas emissions and the total cost associated with fuel consumption and gas emissions. The corresponding energy saving opportunities to the reduction of payload variance are also investigated.

3.2 Theoretical analysis

3.2.1 Haul truck payload variance

Loading performance depends on different parameters such as bench geology, blast design, muckpile fragmentation, operators' efficiency, weather conditions, utilisation for trucks and shovels, mine planning and mine equipment selection [106, 107]. In addition, for loading a truck in an effective manner, the shovel operator must also strive to load the truck with an optimal payload. The optimal payload can be defined in different ways, but it is always designed so that the haul truck will carry the greatest amount of material with lowest payload variance [103]. The payload variance can be illustrated by carrying different amount of ore or overburden by same trucks in each cycle. The range of payload variance can be defined based on the capacity and power of truck. The payload variance in a surface mine fleet can influence productivity greatly due to truck bunching phenomena in large surface mines [106]. The increasing of payload variance decreases the accuracy of maintenance program. This is because the rate of equipment wear and tear is not predictable when the mine fleet faces with a large payload variance [118]. Minimising the variation of particle size distribution, swell factors, material density and fill factor can decrease the payload variance but it must be noted that some of the mentioned parameters are not controllable. Hence, the pertinent methods to minimise the payload variance are real-time truck and shovel payload measurement, better fragmentation through optimised blasting and improvement of truck-shovel matching.

3.2.3 Haul truck fuel consumption

The fuel consumption for haul trucks is determined based on the following parameters (see Figure 3-1):

- The Gross Vehicle Weight (GVW), which is the sum of the weight of an empty truck and the payload;
- The Haul Truck Velocity (V);
- The Total Resistance (TR), which is equal to the sum of Rolling Resistance (RR) and The Grade Resistance (GR) when the truck is moving against the grade of the haul road; and
- The Rimpull Force (RF), which is the force available between the tyre and the ground to propel the truck [119].

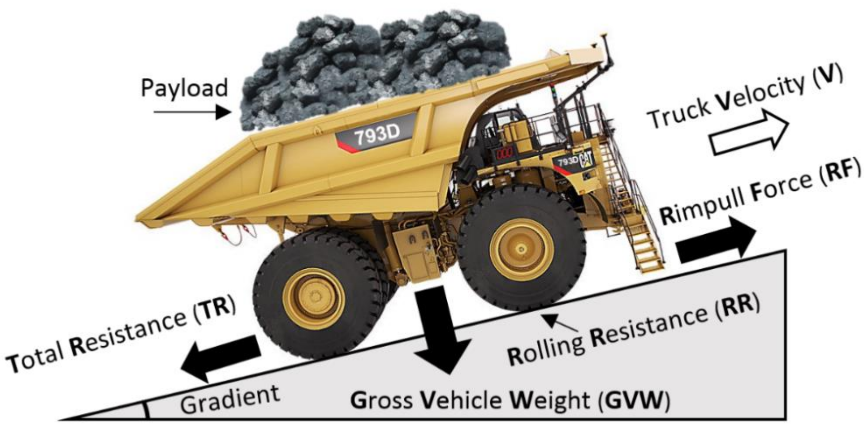

Figure 3-1: Haul road and truck key parameters

Caterpillar trucks are the most popular vehicles amongst all different brands of trucks used in Australian mining industry [119]. Based on the power and capacity of haul truck and mine productivity, CAT 793D was selected for the analysis presented in this study. The specification of selected truck is presented in Table 3-1.

Table 3-1: Cat 793D haul truck specifications [120]

Specification	Value
Engine	
Engine model	CAT 3516B HD
Gross power	1801 kW
Net power	1743 kW
Weights - Approximate	
Gross weight	384 tonnes
Nominal payload	240 tonnes
Body Capacity	
Struck	96 m^3
Heaped	129 m^3
Tyre	
Torque converter	102.0 L
Standard tires	40.00R57

Figure 3-2 presents the Rimpull-Speed-Grade ability curve extracted from the manufacturer's catalogue for CAT 793D [120]. [1]

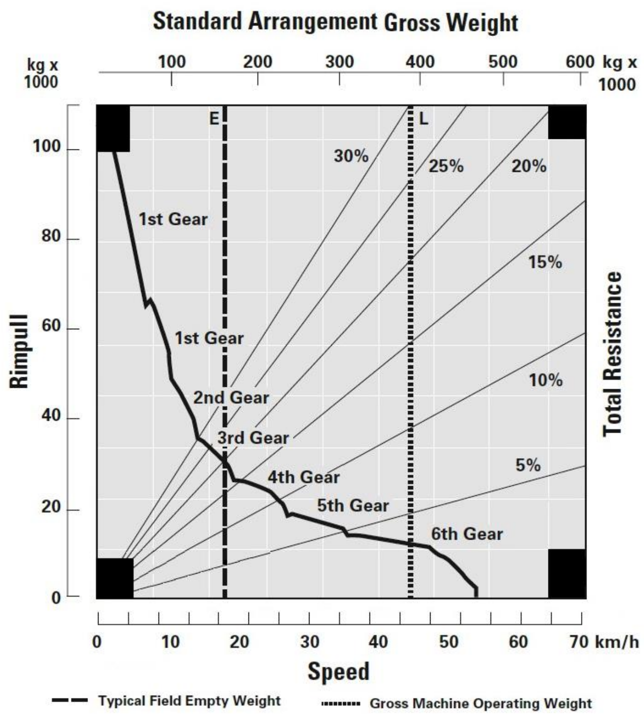

Figure 3-2: Rimpull-Speed-Grade Ability Curve for Truck CAT 793D [120]

[1] All developed models in the thesis have been completed based on the latest CAT handbook (2015). Payload is one of the main identified effective parameters on fuel consumption by haul trucks. Therefore, just Rimpull Curve has been used and studding about returning trucks from up to down in surface mines is not in the scope of project. It means that we don't need Retarding Performance investigation in this thesis.

Figure 3-3 illustrates the relationship between the haulage operation parameters and truck fuel consumption.

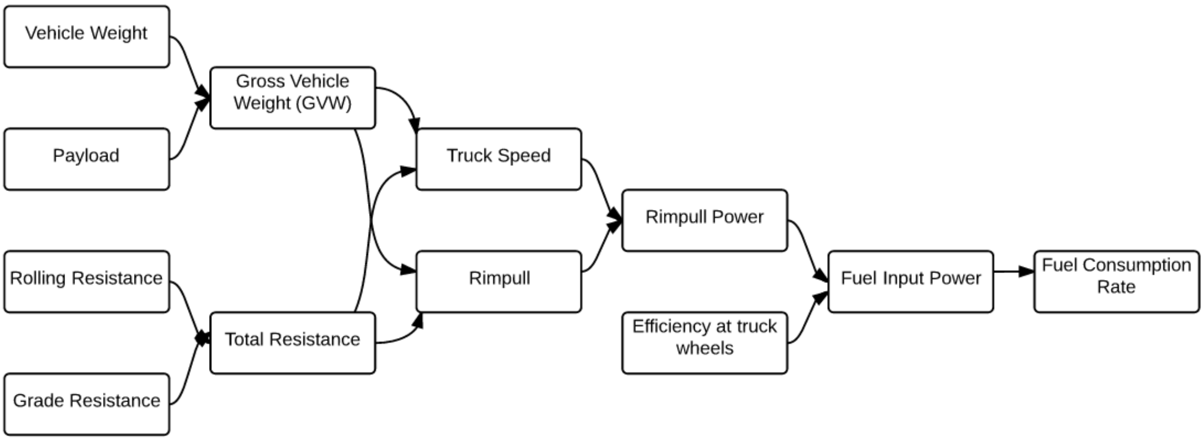

Figure 3-3: Variable relationships required for truck fuel consumption estimation

The rate of haul truck fuel consumption can be calculated by the following equation [114, 118].

$$FC = 0.3\,(LF.\,P) \tag{3-1}$$

where LF is the ratio of average payload to the maximum load in an operating cycle. the percentage of LF in different condition is presented in Table 3-2 [114] and P is the truck power (kW).

Table 3-2: Load Factors (LF) for different conditions [114]

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

For the best performance of the truck operation, P is determined by [37]:

$$P = \frac{1}{3.6}\,(RF\,.\,V_{max}) \tag{3-2}$$

where the RF is the force available between the tyre and the ground to propel the truck and the unit of this parameter is (N). It is related to the Torque (T, (N.m)) that the truck is capable of exerting at the point of contact between its tyres and the road and the truck wheel radius (r, (m)).

$$RF = \frac{T}{r} \tag{3-3}$$

In this paper, the fuel consumption by haul trucks has been simulated based on the above mentioned formulas.

3.2.3 Greenhouse gas emissions

Diesel engines emit both Greenhouse Gases (GHGs) and Non-Greenhouse Gases (NGHGs) into the environment [117]. Total greenhouse gas emissions are calculated according to the Global Warming Potential (GWP) and expressed in CO_2 equivalent or CO_2-e [113, 114]. The following equation can be used to determine the haul truck diesel engine GHGs emissions [113, 121].

$$\mathrm{GHG}_{\mathrm{Emissions}} = (\mathrm{CO}_2 - \mathrm{e}) = \mathrm{FC} \times \mathrm{EF} \tag{3-4}$$

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 $\mathrm{CO}_2 - \mathrm{e/kL}$ [122-124].

3.2.4 Cost of greenhouse gas estimation and fuel consumption

3.2.4.1 Cost of greenhouse gas emissions

There are many empirical models for the cost estimation of greenhouse gas emissions, based on the US potential CO_2 legislation [116]. For this research project, the US Energy Information Administration (EIA) model, which is known as a conservative model, is selected. This model assumes different allowance prices per year or in other words a CO_2 penalty under various scenarios: Core Case scenario (CCs), High Cost scenario (HCs), No International Offsets scenario (NIOs), Limited Alternatives scenario (LAs) and NIOs / LAs [113].

Table 3-3 presents a prediction of cost GHGs emissions for difference years (from 2015 to 2050) based on the mentioned scenarios [116].

Table 3-3: Different kinds of scenarios to estimate the cost of greenhouse gas ($/tonne CO_2-e)

Scenarios	2015	2020	2030	2040	2050
Core Case scenario (CCs)	20.91	29.88	61.01	124.57	254.37
High Cost scenario (HCs)	26.60	38.01	77.61	158.48	323.60
No International Offsets scenario (NIOs)	31.03	41.53	84.81	173.17	353.60
Limited Alternatives scenario (LAs)	48.83	44.34	90.54	184.87	377.50
No Intl. Offsets / Lim. Alt scenario (LAs / NIOs)	53.53	76.50	156.20	318.95	395.28

In this study, the latest scenario which is a combination of (NIOs) and (LAs) scenarios has been used to calculate the GHGs cost. This scenario states that the key low emissions technologies, nuclear, Carbon dioxide Capture and Storage (CCS) and renewables will be developed in a timeframe consistent with emissions reduction requirements without encountering major obstacles where the use of international offsets is severely limited by cost or regulation.

3.2.4.2 Cost of fuel consumption

The cost of fuel depends on many economic and international policy parameters. There are several numbers of models which can be used to estimate the future diesel price [125]. The EIA model can be used in this area as well. A graph showing the forecast of diesel price estimated from this mode is shown in Figure 3-4.

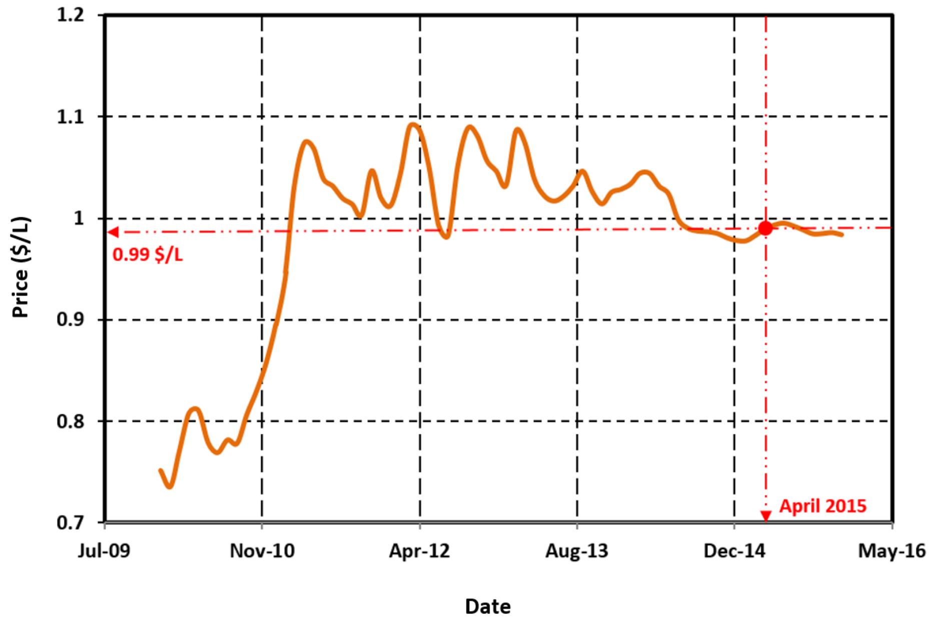

Figure 3-4: Forecast of diesel price [125]

3.3 Results and discussions

3.3.1 Haul truck payload variance

The payload variance is indicated by its standard deviation (σ). Standard deviation measures the amount of variation from the average. A low standard deviation indicates that the data points tend to be very close to the mean; a high standard deviation indicates that the data points are spread out over a large range of values. Figure 3-5 illustrates the different kinds of normal payload distribution (the best estimation function for payload distribution [107]) based on the difference σ for CAT 793D.

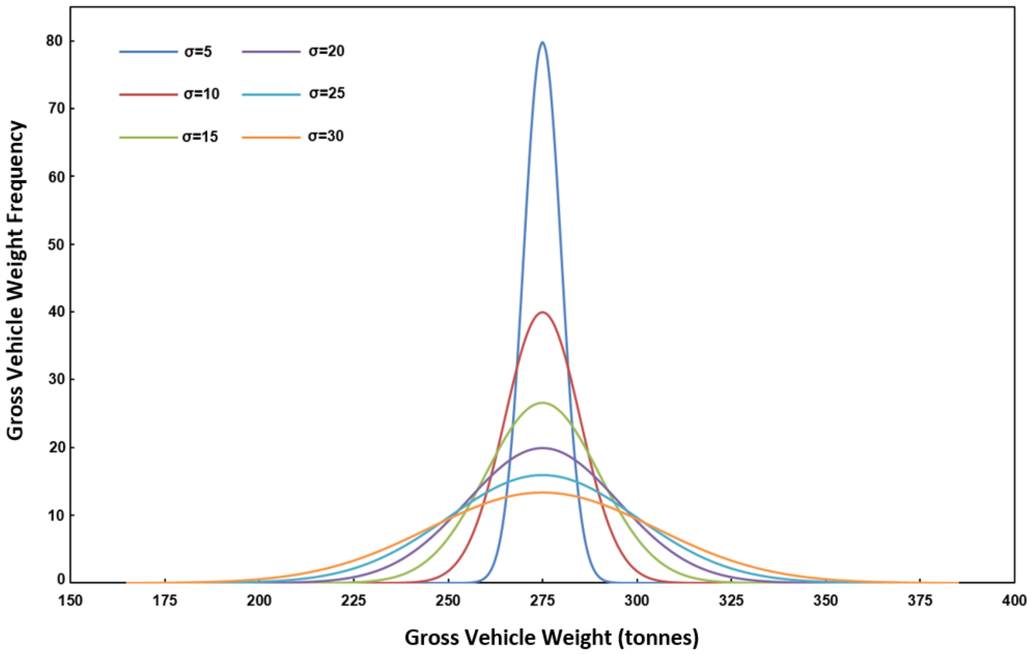

Figure 3-5: Normal payload distribution for difference standard deviations (σ) (CAT 793D)

This illustration shows that by reduction of σ, the range of GVW variation is reduced as well. Based on the CAT 793D technical specifications the range of GVW variation is between 165 tonnes (empty truck) and 385 tonnes (maximum payload). Hence, the maximum σ for this truck can be defined as 30; that is because, for higher σ, the minimum GVW is less than the weight of empty truck and the maximum GVW is more than the maximum capacity of truck.

3.3.2 Haul truck fuel consumption

3.3.2.1 Rimpull analysis

The Rimpull-Speed-Grade ability curve for CAT 793D truck (see Figure 3-2) is used to determine the Rimpull (R) and the Maximum Truck Velocity (V_{max}) of the truck based on the values of GVW (in the range of 165 to 385 tonnes) and TR (in the range of 1 to 30%). In this study DataThief® 5.6 and Curve Expert Professional V.2.1 were used to find an equation for R as a function of TR and GVW.

$$R = 0.183\, GVW\, (0.006 + 0.053\, TR)$$

(3-5)

3.3.2.2 Maximum truck velocity

The data for maximum truck velocity curve are collected by DataThief® software and the best correlation between R and V_{max} has been defined by applying a non-linear regression method (Curve Expert Professional Software V.2.1). The following equation presents this correlation.

$$V_{max} = a - b \times \exp(-c \times R^{d}) \quad (3\text{-}6)$$

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

3.3.2.3 Fuel consumption

Figure 3-6, illustrates the variation of V_{max} and FC with GVW for six values of TR. The results generally show that for all values of total resistance, the V_{max} decreases and the FC increases as the GVW increases. It must be noted that the rate of fuel consumption is calculated based on the best performance of the truck recommended by the manufacturer, which are for the maximum truck velocity and the corresponding Rimpull.

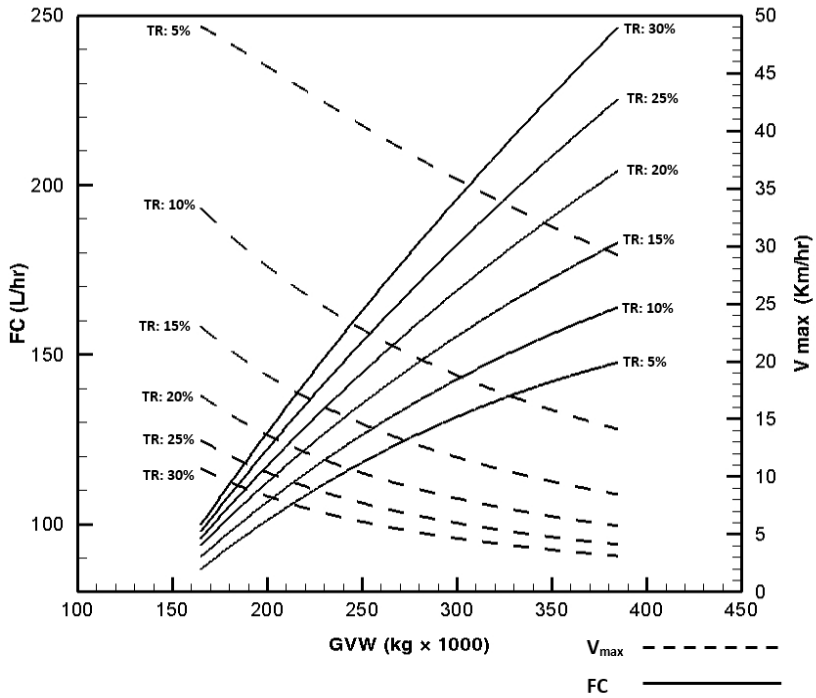

Figure 3-6: Variation of V_{max} and FC with GVW for different TR

3.4 Effects of payload variance on fuel consumption

The effect of payload variance on haul truck fuel consumption in different haul road conditions is illustrated in Figure 3-7.

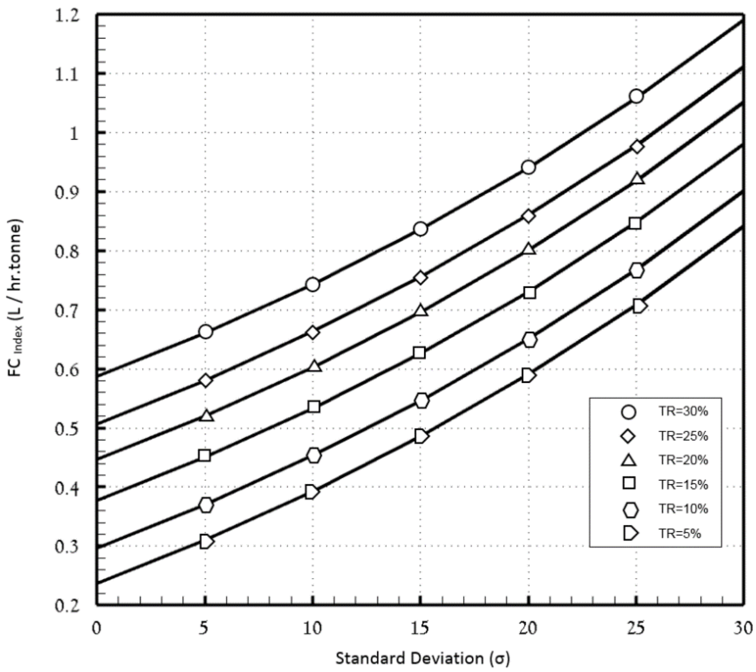

Figure 3-7: The variation of FC_{Index} with standard deviation (σ) (CAT 793D)

In this figure, TR has been changed from 5% to 30% and σ is varied between 0 and 30. It is noted that, to have a better understanding, a Fuel Consumption Index (FC_{Index}) has been defined. This index presents the quantity of fuel used by a haul truck to move one tonne of mine material (Ore or Overburden) in an hour. Figure 3-7 demonstrates that, there is a non-linear relationship between σ and FC_{Index} for all haul road total resistance. Moreover, the FC_{Index} rises with increasing TR.

3.5 Effects of payload variance on greenhouse gas emissions

The variation of CO_2-e with standard deviation for CAT 793D is presented by $CO_2\text{-}e_{Index}$ in Table 3-4. The $CO_2\text{-}e_{Index}$ presents the amount of greenhouse gas emissions generated by truck to haul one tonne ore or overburden in an hour.

Table 3-4: The variance of CO_2-e $_{Index}$ (kg/hr. tonne) with payload Standard Deviation (σ)

σ	TR=5%	TR=10%	TR=15%	TR=20%	TR=25%	TR=30%
0	0.64	0.80	1.02	1.21	1.37	1.58
5	0.84	1.00	1.22	1.40	1.57	1.78
10	1.06	1.22	1.44	1.63	1.79	2.01
15	1.31	1.47	1.69	1.88	2.04	2.26
20	1.59	1.76	1.97	2.16	2.32	2.54
25	1.91	2.07	2.29	2.48	2.64	2.86
30	2.27	2.43	2.65	2.84	3.00	3.22

Based on the tabulated results, it is obvious that there is a non-linear relationship between CO_2-e$_{Index}$ and the standard deviation for each haul road total resistance. The minimum greenhouse gas is emitted for the minimum total resistance (TR=5%) when the standard deviation has been zero (σ=0) and the maximum pollution is generated for the maximum total resistance and standard deviation (TR=30% and σ=30).

3.6 Effects of payload variance on cost

3.6.1 Cost of greenhouse gas emissions

All scenarios that can be used to predict the cost of greenhouse gas emissions estimate that this cost is in the range of \$20.91 to \$53.53 in 2015 (Table 3-3). In this project, the maximum cost of CO_2-e emissions (\$53.53 per tonne) was considered.

3.6.2 Cost of fuel consumption

Figure 3-3 illustrates that there is a vast difference in the price of diesel between 2010 and 2015 but it is estimated that the price of this type of fuel will be approximately \$1 per litter in 2015 for industrial use. Hence, in this project the price of fuel for haul trucks in surface mines is assumed \$0.99 per litter in 2015.

3.6.3 Total cost

The calculated FC_{Index}, the cost of fuel consumed by haul truck for each σ (Fuel $Cost_{Index}$), the greenhouse gas emitted by haul truck to move one tonne of mine material in an hour (CO_2-e$_{Index}$), the cost of greenhouse gas emissions (CO_2-e $Cost_{Index}$) and Total $Cost_{Index}$ for CAT 793D with TR=15% in 2015 are tabulated in Table 3-5.

Table 3-5: Calculated indexes for CAT 793D with TR=15% in 2015 (Sample)

σ	**FC $_{Index}$** L/(hr. tonne)	**Fuel Cost $_{Index}$** \$/(hr. tonne)	**CO_2-e $_{Index}$** kg/(hr. tonne)	**CO_2-e Cost $_{Index}$** \$/(hr. tonne)	**Total Cost $_{Index}$** \$/(hr. tonne)
0	0.38	0.37	1.02	0.05	0.42
5	0.45	0.44	1.22	0.07	0.51
10	0.53	0.52	1.44	0.08	0.60
15	0.63	0.61	1.69	0.09	0.70
20	0.73	0.72	1.97	0.11	0.83
25	0.85	0.83	2.29	0.12	0.95
30	0.98	0.96	2.65	0.14	1.10

In this haul road condition, there is a direct relationship between increasing the payload variance and Total Cost$_{Index}$. The Total Cost $_{Index}$ presents the total cost of fuel consumed and CO_2-e emitted to haul one tonne mine material by truck in an hour. In this case, the Total Cost$_{Index}$ can be vary between \$0.42 and \$1.10 per (hr. tonne) for different values of standard deviation (σ = 0 to 30).

3.6.4 Saving opportunities

The variation of total cost of fuel consumption and greenhouse gas emissions can be used for saving opportunities. Using a truck on-board payload measurement system, developing a direct connection between the truck payload measurement system and the shovel, improvement of truck-shovel matching or developing an on-line fleet monitoring can be used to reduce the payload variance. Figure 3-8 illustrates the correlation between the standard deviation reduction (Δσ) and the Saving $_{Index}$. The Saving $_{Index}$ presents the amount of saving cost with reducing diesel consumption and greenhouse gas emissions for hauling one tonne mine material (Ore or Overburden) in one hour. This graph is independent of haul road condition (RR and GR) and presents the quantity of saving for different kinds of standard deviation reduction.

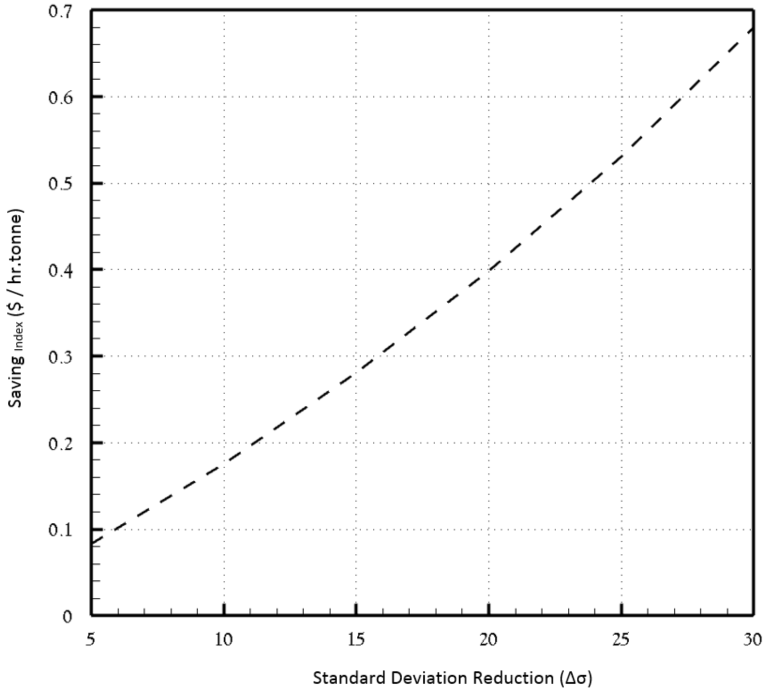

Figure 3-8: Correlation between standard deviation reduction (Δσ) and Saving $_{\text{Index}}$

Finding the best correlation between the standard deviation reductions (Δσ), and the Saving $_{\text{Index}}$ can be very important in calculation of the effect of payload variance on production cost. Hence, the following equation has been developed to estimate the Saving $_{\text{Index}}$ for different road conditions and values of the standard deviation reductions.

$$\text{Saving}_{\text{Index}} = 0.01(\Delta\sigma)^{1.25} \quad (3\text{-}7)$$

Equation 3-7 presents the correlation between Saving $_{\text{Index}}$ and standard deviation reductions.

3.7 Case study

The effect of payload variance on haul truck fuel consumption and GHGs emissions is an important matter in real mine sites. In this project, a large surface mine in Australia has been investigated to determine the effect of payload variance on energy used, GHGs emitted by haul trucks and the cost of them to find saving opportunities.

Figure 3-9 shows a schematic diagram of the surface parameters used to model haul truck fleet requirements. The mine parameters used for this case study are presented in Table 3-6.

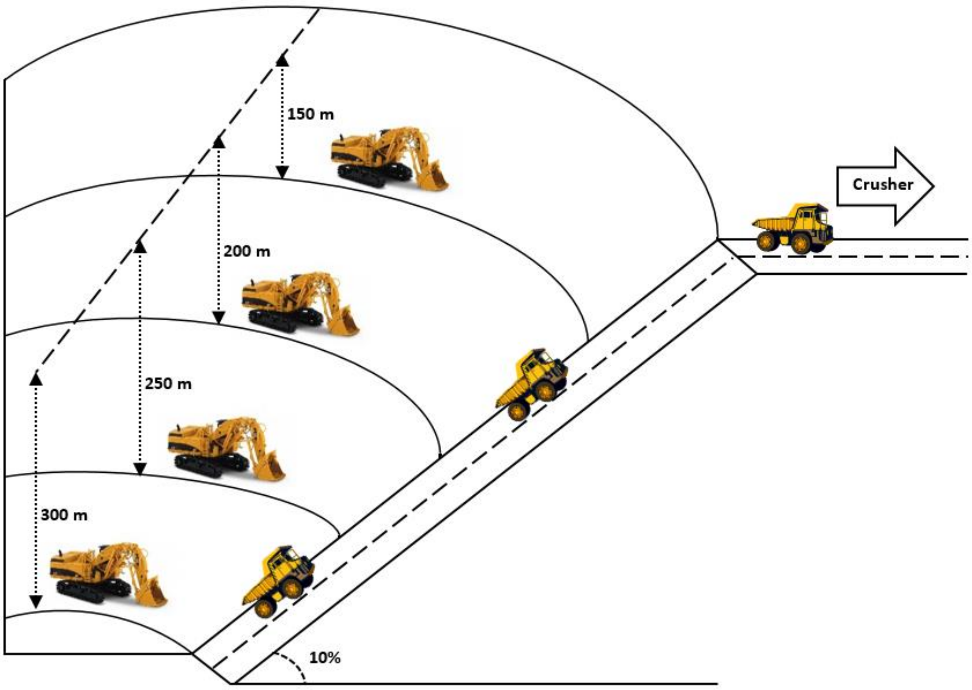

Figure 3-9: Schematic of open pit used to model fleet requirements

Table 3-6: The mine parameters of case study

Parameter	Value	Unit	Description
Operating Hours per Year	4799	Op Hr/Year	
Pit depth	300	m	
Total ore and wast	2500	M t	Haulage Requirement
Haulage routs	4		150, 200, 250 and 300m
Ramps	2		
Length of the longest	3	Km	
Horizontal haulage distance	60	m	In-Pit
	120	m	Ex-Pit
Width of haul road	35	m	
Truck down ramp speed	30	km	Limited due to safety
Grade Resistance (GR)	10	%	
Rolling Resistance (RR)	5	%	
Shovels	3		On level 1 (150 m)
	4		On level 2 (200 m)
	2		On level 3 (250 m)
	2		On level 4 (300 m)

Fleet requirements are calculated using Talpac™ software. The average of TR in this case is 15% therefore, FC_{Index} and CO_2-e_{Index} can be measured by using Figure 3-6 and Table 3-4, respectively. The total cost is calculated based on the cost of fuel consumption and CO_2-e emissions in 2015 that is illustrated in Figure 3-3 and Table 3-5, respectively. The price of fuel and CO_2-e is assumed constant during the years of operation. The results of calculation are presented in Table 3-7.

Table 3-7: Case study results

Parameter	Value		Unit
	Max (σ=30)	Min (σ=0)	
FC $_{Index}$	0.98	0.38	L / (hr.tonne)
CO_2-e $_{Index}$	2.65	1.02	Kg / (hr.tonne)
Cost $_{Index}$	1.10	0.42	$ / (hr.tonne)
Truck Fuel Consumption (Empty)	175		L / hr
Truck Greenhouse Gas emission (Empty)	682		Kg / hr
Truck Cost of Fuel and Greenhouse Gas (Empty)	209		$ / hr
Average Truck Payload	142		tonne
Fleet Size	15		Truck
Total Production per Year	19		M tonne / Year
Truck Availability	80		%
Loader Availability	85		%
Queue Time at Loader	3.05		Min / Cycle
Spot Time at loader	0.95		Min / Cycle
Average Loading Time	2.06		Min / Cycle
Travel Time (Hauling)	16.13		Min / Cycle
Travel Time (Returning)	6.03		Min / Cycle
Spot Time at Dump	0.76		Min / Cycle
Average Dump Time	1.02		Min / Cycle
Average Cycle Time	30.00		Min
Average No. of Bucket Passes	3		
Rate of Fuel Consumption (Fleet)	3774.9	2429.7	L / hr
Rate of Greenhouse Gas Emission (Fleet)	11795.4	8124.6	Kg / hr
Rate of Cost (Fleet)	4349.1	2821.5	$ / hr
Total Fuel Consumption Annually	18.12	11.66	M L / Year
Total greenhouse gas emission Annually	56.61	38.99	M kg / Year
Total cost of fuel consumption and Greenhouse Gas emission Annually	20.87	13.54	M $ / Year
Saving cost percentage	35		%
Total Saveable Cost	7.33		M $ / Year

The results show that in this case by reducing one unit of payload variance, $0.02 per (hr. tonne) is saveable. The case study mine is under 8 hours of operation in each shift and there is one shift in each day. This mine has 360 working days at year. The calculation shows that, maximum 35% of total fuel and CO_2-e cost is saveable by reducing standard deviation from 30 to zero. This amount of saving is equal to $7.33 M annually.

3.8 Conclusions

This paper aimed to develop a model to find saving opportunities based on the reduction of payload variance in surface mines. There is a significant payload variance in loading process in surface mines. This variance needs to be considered in analysing the mine productivity, diesel energy consumption, greenhouse gas emissions and associated costs. This paper investigated the effects of payload variance on diesel energy consumption, greenhouse gas emissions and their associated cost in surface mining operations. This study examined CAT 793D model truck, which is one of the mostly used haul trucks in surface mining operations. Based on the technical specifications of this truck, the variation range of payload was assumed to be between 0 and 30%. All data in Rimpull-Speed-Grade ability curve for examined truck were digitalised by DataThief® software. The correlations and equations to calculate the maximum truck velocity and fuel consumption were defined. To investigate the effects of payload variance on fuel consumption, greenhouse gas emissions and associated costs, main indexes were presented. The associated cost of greenhouse gas emissions and cost of diesel consumption were determined based on models presented by US Energy Information Administration. The results showed that the fuel consumption, rate of greenhouse gas emissions and their costs non-linearly increase as the payload variance rises for all haul road conditions. The correlation between the payload variance and cost saving was developed. This correlation is independent of haul road condition and presents the cost saving for different kinds of payload variance reduction. Presented model was utilised in a real mine site in Australia as a case study. The results of this project indicated that there is a great cost saving opportunity by decreasing the payload variance in surface mines that used truck and shovel method for mining operation. This can be achieved by using a truck on-board payload measurement system and on-line fleet monitoring.

Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P., **A Discrete-Event Model to Simulate the Effect of Payload Variance on Truck Bunching, Cycle Time and Hauled Mine Materials.** International Journal of Mining Technology, (2016).

Abstract

Payload variance is one of the most important parameter in payload management. This parameter must be considered to investigate about mine productivity and energy consumption. Payload variance, causes significant differences in gross vehicle weights. Heavily loaded trucks travel slower up ramps than lightly loaded trucks. Faster trucks are slowed by the presence of slower trucks, resulting in ‘bunching’, production losses and increasing fuel consumptions. This paper simulates the truck bunching phenomena in large surface mines to improve truck and shovel systems’ efficiency and minimise fuel consumption. The study concentrated on completing a practical simulation model based on a discrete event method which is most commonly used in this field of research in other industries. The simulation model has been validated by a dataset collected from a large surface mine in Arizona state, USA. The results have shown that there is a good agreement between the actual and estimated values of investigated parameters. [126]

Keywords: Discrete-Event Model; Simulation; Truck Bunching; Payload Variance; Cycle Time; Fuel Consumption

CHAPTER 4

4. A Discrete-Event Model to Simulate the Effect of Payload Variance on Truck Bunching, Cycle Time and Hauled Mine Materials.

4.1 Introduction

Improving the efficiency of haulage systems is one of the great challenges in mining engineering and is the subject of many research projects undertaken in both study and industry [127-129]. For mining, it is important that haulage systems are designed to be as efficient as possible, in order to minimise haulage cost, improve profitability and increase the total mine value. Haulage system inefficiency is typically derived from inadequate engineering, which results in poor haul road design, machinery standby and downtime, and circuit traffic [130-132]. According to the literature, haulage costs can be some of the largest in a mining system [133, 134]. In various case studies it was found that material transportation represents 50 per cent of the operating costs of a surface mine [135].

The main effective parameters on material transport when a truck and shovel system is used in surface mines are mine planning, road condition, truck and shovel matching, swell factors, shovel and truck driver's ability, weather condition, payload distribution and payload variance [58, 103, 119, 136]. Based on the literature among all above mentioned parameters, truck payload variance is one of the most important parameters in this field [106, 107]. The payload variance not only affects the production rate, but also it is an important parameter in the analysis of fuel consumption. The main source of the payload variance in truck and shovel mine operation is the loading process. Loading is a stochastic process and excavator performance is dependent on parameters such as swell factor, material density and particle size distribution [109]. Variation of these parameters causes variation of bucket and consequently truck payloads, affecting productivity. Reducing truck payload variance in surface mining operations improves productivity by reducing bunching effects and machine wear from overloaded trucks [108]. In large surface mines having long ramps, bi-directional traffic and restrictions on haul road widths negate the possibility of overtaking. Overloaded trucks are slower up ramp in comparison to under-loaded trucks. Thus faster trucks can be delayed behind slower trucks in a phenomenon known as truck bunching [106]. This is a source of considerable productivity loss for truck haulage systems in large surface mines.

There are some investigations about the payload variance simulation and the effect of this event on other mining operational parameters. A study conducted by Hewavisenthi, Lever and Tadic [107] is concerned with using a Monty-Carlo simulation to study the effect of bulk density, fill factor, bucket size and number of loading passes on the long term payload distribution of earthmoving systems. The focus of their study is on simulation of payload distribution and variance in large surface mines. A study conducted by Knights and Paton [106]is concerned with truck bunching due to load variance. This study was conducted to provide an analysis of the effect of load variance on truck bunching. In this project a GPSS/H model was constructed which simulates a haulage circuit designed using data inputs from a real mine site. The model was used to run haul circuit simulations with different levels of payload variance. From empirical data, haul route travel times were estimated to be dependent on payload based on a linear relationship with an additional stochastic component modelled by a normal distribution. The data was insufficient to determine the dependence of changes in haul route travel time on changes in payload variance. In this project a simulation was also conducted to investigate the haul circuit throughput difference if single truck overtaking was permitted. Webb [110] investigated the effect that different bucket load sizes had on truck cycle times and the inherent costs. The research project being undertaken will focus primarily on the effect of load variance on truck bunching.

Based on the condition of truck and shovel mining operations in surface mines, the best simulation for this event can be simulated by discrete event methods. Discrete event simulation can be used to model systems which exhibit changes in state variables at a discrete set of points in time [137]. The models can be static or dynamic. Static models represent a system at a specific time, while dynamic models represent a system as it evolves over a period of time [138]. A mining operation is a dynamic system which is very difficult to model using analytical methods. When simulation is used, the model input can be based on probabilistic data which better characterise the input variables and a given number of variables can be described by selecting appropriate distributions [139].

The trucks utilised in the haulage operations of surface mines consume a great amount of fuel [3] and this has encouraged truck manufacturers and major mining corporations to carry out a number of research projects on the fuel consumption of haul trucks [49]. There are many parameters that affect the rate of fuel consumption for haul trucks such as payload, velocity of truck, haul road condition, road design, traffic layout, fuel quality, weather conditions and driver skill [127]. A review of the literature indicates that understanding of energy efficiency of a haul truck is not limited to the analysis of vehicle-specific parameters; and mining companies can often find greater energy saving opportunities by expanding the analysis to include other effective parameters such as payload distribution and payload variance [140].

This paper aims to present a new simulation model based on the discrete event methods to investigate the effect of truck bunching due to payload variance on average cycle times, the rate of loading materials and fuel consumption.

4.2 Payload variance

Loading performance depends on different parameters such as bench geometry, blast design, muckpile fragmentation, operators' efficiency, weather conditions, utilisation of trucks and shovels, mine planning and mine equipment selection [107, 111]. In addition, for loading a truck in an effective manner, the shovel operator must also strive to load the truck with an optimal payload. The optimal payload can be defined in different ways, but it is always designed so that the haul truck will carry the greatest amount of material with lowest payload variance [106]. The payload variance can be illustrated by carrying a different amount of overburden or ore by the same trucks in each cycle [141]. The range of payload variance can be defined based on the capacity and power of the truck. The increase of payload variance decreases the accuracy of the maintenance program. This is because the rate of equipment wear and tear is not predictable when the mine fleet faces a large payload variance [108]. Minimising the variation of particle size distribution, swell factors, material density and fill factor can decrease the payload variance but it must be noted that some of the mentioned parameters are not controllable. Hence, the pertinent methods to minimise the payload variance are real-time truck and shovel payload measurement, better fragmentation through optimised blasting and improvement of truck-shovel matching. The payload variance is indicated by its standard deviation (σ). Standard deviation measures the amount of variation from the average. A low standard deviation indicates that the data points tend to be very close to the mean; a high standard deviation indicates that the data points are spread out over a large range of values.

Figure 4-1 shows the Theoretical normal payload distribution for different standard deviations (CAT 793D).

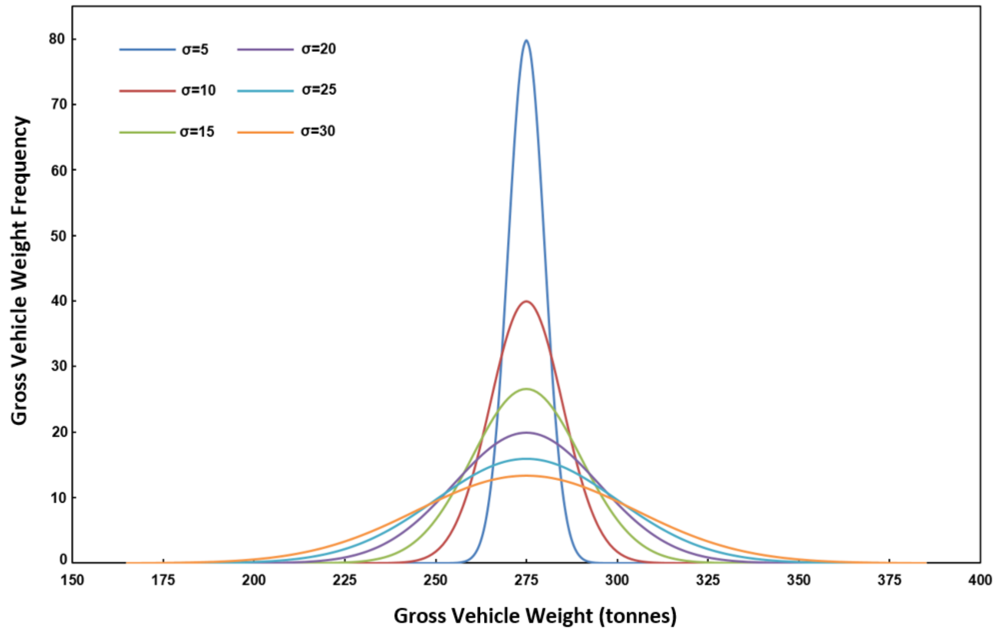

Figure 4-1: Theoretical normal payload distribution for different standard deviation (CAT 793D)

In this figure Gross Vehicle Weight (GVW) is the total weight of empty truck and payload. Based on the CAT 793D technical specifications, the range of GVW variation is between 165 tonnes (empty truck) and 385 tonnes (maximum payload). Hence, the maximum σ for this truck can be defined as 30; that is because for higher standard deviations, the minimum GVW is less than the weight of empty truck and the maximum GVW is more than the maximum capacity of truck.

4.3 Discrete simulation modelling

Based on the condition of truck and shovel mining operation in surface mines, the best simulation for this event can be by discrete event methods. Discrete event simulation can be used to model systems which exhibit changes in state variables at a discrete set of points in time [137, 142]. The models can be static or dynamic. Static models represent a system at a specific time, while dynamic models represent a system as it evolves over a period of time [143]. A mining operation is a dynamic system which is very difficult to model using analytical methods. There are different kinds of discrete simulation models used for modelling the systems in industrial projects. In this study, some of the most popular models have been investigated and a new model to simulate the truck bunching event in surface mining operation has been developed.

The first investigated model is AutoMod. This model is a simulation system which is designed for use in material movement systems developed by Applied Materials, USA [144]. It can be used for simulation of truck haulage circuits and transport circuits, conveyors, load dumping and retrieval, cranes and robots. Simulations with AutoMod have the ability for simulation of complex movement with stochastic inputs. AutoMod models can contain multiple systems (e.g. interacting truck and shovel circuits). To produce a simulation, the user constructs a series of action statements which allows the incorporation of elements such as machinery, queues, loading, delays and input values/variables. Simulations also allow the use of conditional tests. Load inputs can be deterministic or stochastic. AutoMod offers control variables for queuing, wait times and traffic which are crucial for haul circuit simulation bunching analysis. Visualisation of simulation is powerful and extensive in AutoMod. Graphical model outputs can be represented in three dimensions and is industry leading in terms of animation and realism.

The second studied model is SIMUL8. This model is a graphically oriented simulation package developed by the SIMUL8 Corporation [145]. This software is a discrete event simulation package, meaning it simply executes tasks in queue based on time, which then triggers the activity of new tasks. SIMUL8 can be used in simulation of multiple haulage systems, but is more effective at single circuit simulations.

The third analysed model is GPSS/H. The general purpose simulation system (GPSS) language was originally released in 1961 and became a popular means of simulation since it could be operated without the requirement for the user to be knowledgeable in programming. GPSS/H was derived from the evolution and expansion of GPSS and became the more widespread and superior package. GPSS/H was released in 1977 by Wolverine Software Corporation who still develop and sell GPSS/H today [106]. GPSS/H can be used with a wide range on models due to its simplicity and flexibility. It is based on a flowchart type system using “transactions” which move between “blocks”. It involves the creation of blocks and control statements to generate a system. Transactions move throughout the system based on the tick of an internal clock. Each tick of the clock corresponds to one-time unit worth of action. GPSS/H is stochastic in nature, such that it can execute Monte Carlo style randomisation to apply statistical distributions. GPSS/H is particularly adept at simulating queuing and bunching. GPPS/H can be applied to several systems including haulage circuits, data flow or a production line. The language is based on text entry, and does not provide visualisation without the use of Proof animation.

The fourth studied model in this project is WITNESS. This model is a discrete event simulation suite developed by Lanner. WITNESS is capable of producing haulage system simulations in a dynamic animated computer model [146]. The suite consists of four separate modules, the main WITNESS simulation module, an experimentation optimiser, a scenario manager for analysis and a three dimensional visual output.

The last but not least inspected model is ARENA. This model is a simulation software package developed by Rockwell Automation based on the SIMAN programming language [147]. SIMAN is a Discrete Event Simulation package which can be used in process or event scheduling mode. SIMAN is most commonly used in conjunction with ARENA in industry today. SIMAN can alternatively be used in conjunction with CINEMA, a visualisation package. The ARENA system can produce scale models of circuits and other simulations.

4.4 Truck bunching model

4.4.1 Developed algorithm

Hauling operations in surface mines consists of different kinds of components. These components are loading, hauling, manoeuvring, dumping, returning and spotting (see Figure 4-2).

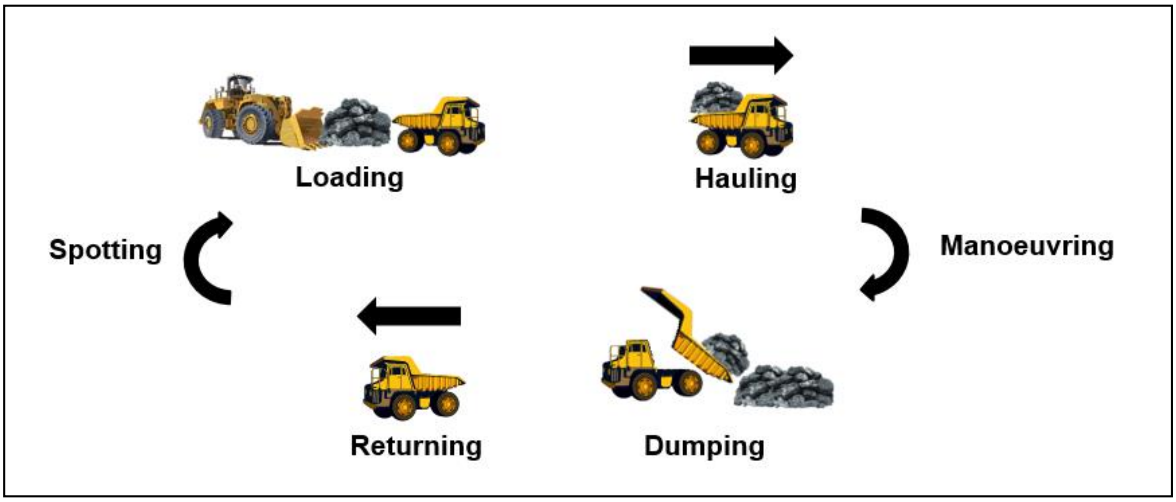

Figure 4-2: Schematic of hauling operation in surface mines

In the standard hauling operation loading time is the time taken to load the truck, hauling and returning time are traveling time for each truck between loading zone and dumping area. Spotting time is the time during which the loading unit has the bucket in place to dump, but is waiting for the truck to move into position. Spotting time will depend on the truck driver’s ability and the loading system. Double-side loading should almost eliminate spot time. Dumping time is the time taken for the truck to manoeuvre and dump its payload either at a crusher or dump.

Based on the above mentioned hauling operation components, four main times can be defined; fixed time, travel time, wait time and cycle time.

Fixed time is sum of the loading, manoeuvring, dumping and spotting time. It is called 'fixed' because it is essentially invariable for a truck and loading unit combination. Travel time is the time taken to haul and return the payload. Wait time is the time the truck must wait before being served by the loading unit, waiting in a queue for dumping and the waiting time in line behind the overloaded trucks in large surface mines (truck bunching). Cycle time is the round trip time for the truck. It is the sum of the fixed, travel and wait times. Figure 4-3 illustrates the proposed algorithm to complete a discrete event model in this project.

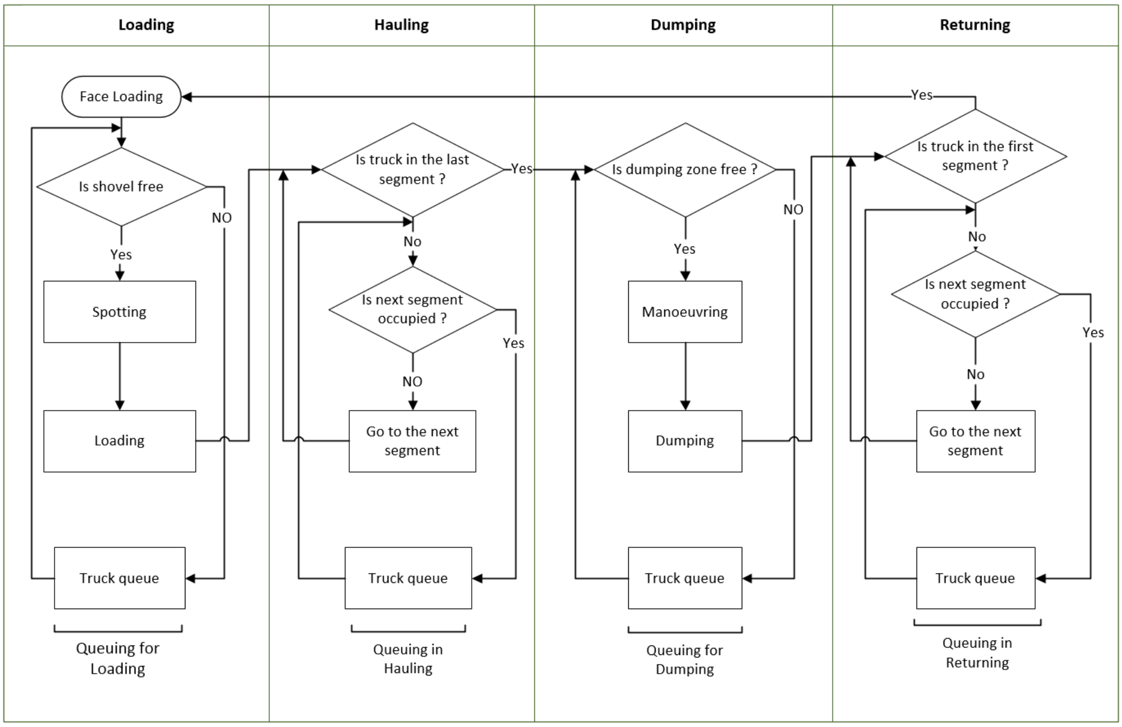

Figure 4-3: Truck bunching algorithm

This algorithm consists of four main subroutines to cover all processes in the hauling operation. These main components are loading, hauling, dumping and returning. Based on the developed model, each component has a waiting time. The main reason for waiting time in hauling is payload variance.

4.4.2 Payload distribution and variance simulation

A main part of the truck bunching model is simulating the payload distribution and variance. In this study, a simulation model was designed to estimate the distribution of truck and bucket payloads based on several of input parameters. These parameters are bucket size, number of loader passes (to fill the truck tray), distribution of bucket bulk density and distribution of bucket fill factor.

This simulation was implemented as a MATLAB workbook and a commercially available Monte-Carlo simulation engine was used to run the simulation. In this model, the truck payload is calculated by

$$m_k = \rho_k \sum_{q=1}^{P} v_b f_q \tag{4-1}$$

where m_k is truck payload (for the k^{th} truck), V_b is bucket rated capacity, f_q is fill factor, ρ_k is bucket density (one value for all of the passes in one truck), q is bucket pass and P is the maximum bucket pass to fill the truck tray. In this simulation bucket bulk density (ρ_k) and fill factor (f_q) are randomly selected by the Monte-Carlo simulation engine.

4.4.3 Model considerations

In the model, the total length of haul and return (L) road is divided in segments based on the variation of Total Resistance (TR). TR is equal to the sum of the Rolling Resistance (RR) and Grade Resistance (GR). The haul and return road are analysed using the same approach. However, on haul roads, the grade resistance is positive and on the return road it is negative (see Figure 4-4). The main reason for truck bunching on haul road is payload variance and the reason for truck bunching on return roads is the driver's supposed ability and mine traffic management.

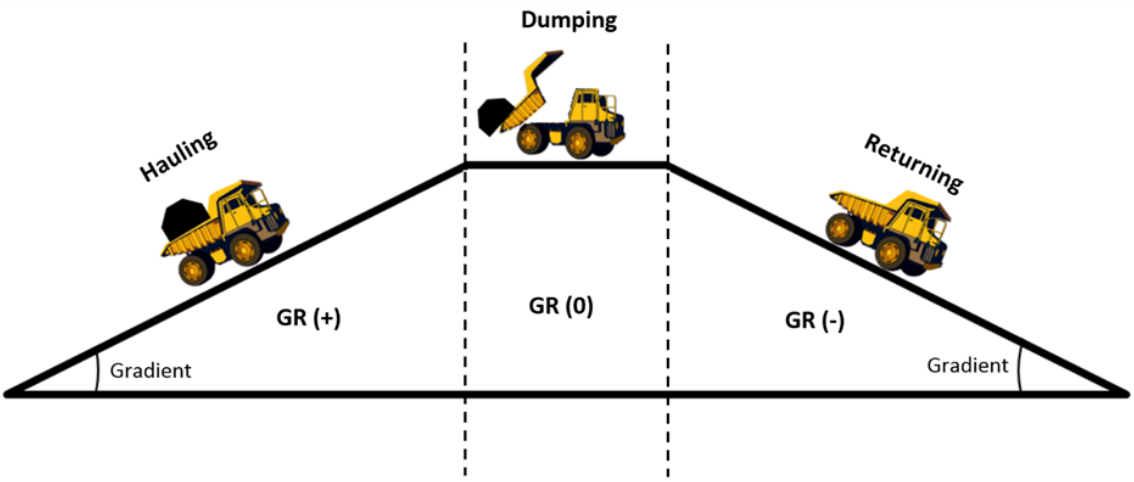

Figure 4-4: Grade Resistance (GR)

4.4.4 Decision variables

In completed discrete event model three decision variables have been defined. The variables are U_k, S_k and $n_{i,k}$.

$$U_k = \begin{cases} 1 & \text{If Truck "k" is in first segment} \\ 0 & \text{Otherwise} \end{cases} \tag{4-2}$$

$$S_k = \begin{cases} 1 & \text{If Truck "k" is in last segment} \\ 0 & \text{Otherwise} \end{cases} \tag{4-3}$$

$$n_{i,k} = \begin{cases} 1 & \text{If } V_{i,k} > V_{i,(k-1)} \\ 0 & \text{Otherwise} \end{cases} \tag{4-4}$$

To create a practical model, it is necessary to define some functions based on the above mentioned decision variables. V is truck speed in Equation 4-4.

4.4.5 Objective functions

In this section, the objective functions for cycle time, travel time and hauled mine materials have been presented in following equations.

$$(\text{Cycle Time})_k = t_S + t_L + \sum_i t_{(T)_i} + t_M + t_D + (t_S + t_L)W_{okj}U_k + (t_M + t_D)W_{Lkj}S_k \tag{4-5}$$

where:

t_S Spotting time;

t_L Loading time;

t_T Travel time;

t_M Manoeuvring time;

t_D Dumping time;

W_{0kj} Number of trucks at queue in front of truck k at time j in the first segment;

W_{Lkj} Number of trucks at queue in front of truck k at time j in the last segment;

U_k First decision variable; and

S_k Second decision variable.

$$(\text{Travel Time})_{i,k} = t_{(T)_{i,k}} = \sum_{i} \frac{2l_i (V_{(i+1),(k-1)} - V_{(i-1),k})}{V^2_{(i+1),(k-1)} - V^2_{(i-1),k}} n_{i,k} + \frac{2l_i (V_{i,k} - V_{(i-1),k})}{V^2_{i,k} - V^2_{(i-1),k}} (1 - n_{i,k}) \tag{4-6}$$

where:

$t_{(T)i,k}$ Travel time for truck k in segment i;

l_i The length of segment i;

$V_{i,k}$ The velocity of truck k in segment i;

$V_{(i-1),k}$ The velocity of truck k in segment i-1; and

$n_{i,k}$ Decision variable.

$$\text{Hauled mine materials} = \sum_{r} \sum_{k} \text{payload}_{k,r} / \text{shift time} \tag{4-7}$$

where:

Payload $_{k,r}$ is the payload of truck k in cycle r.

4.4.6 Constraints

There are three main constraints in the presented model.

$$\sum_{i} l_i = 2L = \text{Lengh of Haul Road} + \text{Lenght of Return Road} \tag{4-8}$$

$$n_{i,k} = n_{k,i} \tag{4-9}$$

$$W_{i,j,k} = W_{i,k,j} \tag{4-10}$$

4.4.7 Data processing

The developed truck bunching model uses two matrices at the same time (parallel processing) to create and process data. The first matrix is used to generate the truck payload based on Equation 4-3. In this process the truck payload in all steps of the model will be generated randomly by a Monte-Carlo simulation engine. A simplified version of payload matrix is presented in Table 4-1. In this table, k represents the number of trucks and r represents the number of cycles in each shift. $P_{k,r}$ in this table is the payload of truck k in cycle r.

Table 4-1: A simplified version of the payload matrix

	Truck (k)	k=1	k=2	…	k=N
Cycle(r)					
r = 1	→	$P_{1,1}$	$P_{2,1}$		$P_{N,1}$
r =2	→	$P_{1,2}$	$P_{2,2}$	$P_{k,r}$	$P_{N,2}$
.		.	.		.
.		.	.		.
.		.	.		.
r=M	→	$P_{1,Z}$	$P_{2,Z}$		$P_{N,Z}$

The presented model calculates the best performance velocity of each truck in each segment based on the payload generated by the payload matrix and truck Rimpull curve. This model can apply the truck bunching effects on the velocity and hauled mine material by trucks in each cycle and each segment. A very simplified version of velocity matrix is presented in Table 4-2.

Table 4-2: A simplified version of velocity matrix

	Truck (k)	k=1	k=2	…	k=N
Segment (i)					
i=1	→	$P_{1,1}$ $V_{1,1}$ $t_{(T)\ 1,1}$	$P_{2,1}$ $V_{2,1}$ $t_{(T)\ 2,1}$	$P_{k,i}$	$P_{N,1}$ $V_{N,1}$ $t_{(T)\ N,1}$
i=2	→	$P_{1,2}$ $V_{1,2}$ $t_{(T)\ 1,2}$	$P_{2,1}$ $V_{2,1}$ $t_{(T)\ 2,1}$	$V_{k,i}$	$P_{N,2}$ $V_{N,2}$ $t_{(T)\ N,2}$
.	.				.
.	.				.
.	.				.
i=2L	→	$P_{1,2L}$ $V_{1,2L}$ $t_{(T)\ 1,2L}$	$P_{2,1}$ $V_{2,1}$ $t_{(T)\ 2,1}$	${t_{(T)}}_{k,i}$	$P_{N,2L}$ $V_{N,2L}$ $t_{(T)\ N,2L}$

In this table k is the number of trucks in the fleet, i is the number of segments in haul and return roads, $P_{k,i}$ is the payload of truck k in segment i, $V_{k,i}$ is the velocity of truck k in segment i and $t_{(T)\ k,i}$ represents the travel time for truck k in segment i.

The developed parallel data processing in this model can simulate complicated fleets in large surface mines. There is not any limitation for the number of trucks and haul road segments. However, in completed case study for model validation the number of trucks was ten and model run for three haul road segments.

4.4.8 Fuel consumption simulation

Haul truck fuel consumption is a function of various parameters. The key parameters that affect the fuel consumption of haul trucks include the payload management, the model of the truck, the grade resistance and the rolling resistance, according to a study conducted by the Department of Resources, Energy and Tourism [49]. In the present study, the effects of GVW, the Velocity of Truck (V) and the TR on the fuel consumption of the haul trucks were examined. The truck fuel consumption can be calculated from Equation 4-11 [118].

$$FC = 0.3\,(LF.\,PW) \tag{4-11}$$

where LF is the engine load factor and is defined as the ratio of average payload to the maximum load in an operating cycle [58]and PW is the truck power (kW). The developed model, in this project, can simulate the fuel consumption by haul trucks based on the Equation 4-11.

4.4.9 Model validation

To validate the developed model, a dataset collected from a large open pit mine in central Arizona, USA has been applied. This dataset included measuring average loader payloads, truck payloads, average bucket bulk density, loader bucket fill factor and average swell factor (Table 4-3).

Table 4-3: Data collected for model validation (Sample)

NO	Average Loader Payload (tonne/pass)	Truck Payload (tonne)	Average Bucket Bulk Density (tonne/m^3)	Loader Bucket Fill Factor	Average Swell Factor
1	47.23	218.21	2.01	0.937	1.25
2	45.12	217.46	1.98	0.978	1.22
3	38.14	209.42	1.96	0.919	1.18
4	42.15	210.36	2.03	0.954	1.27
5	46.58	216.78	2.14	0.984	1.19
6	47.56	217.96	1.86	0.927	1.26
7	39.87	218.04	2.07	0.946	1.24
8	38.47	218.43	2.18	0.992	1.25
9	42.58	217.69	2.05	0.957	1.20
10	40.59	216.97	1.99	0.939	1.25

In this mine, the volume of material loaded into the bucket was determined by comparing loaded and empty laser scan profiles of the buckets. Fill factors were calculated by dividing the material volume by the rated volume of the bucket and bulk densities were calculated by dividing the payload by the loaded volume. On-board payload monitoring systems were used to measure payloads. The validation of the model was completed for average cycle times and the average mine material hauled by one type of truck (CAT 793D) after truck bunching. Table 4-4 and Figure 4-5 present sample values for the estimated (using the developed model) and the independent (tested) cycle time and hauled mine material in order to highlight the insignificance of the values of absolute error in the analysis.

Table 4-4-a: Values for estimated (Model) and independent (Tests) cycle time (Sample)

No	Estimated value of Cycle time (Model) (Sec)	Independent Value of Cycle time (Tests) (Sec)	Absolute error (%)
1	1520	1560	2.56
2	1650	1680	1.78
3	1410	1380	2.17
4	1620	1680	3.57
5	1990	2040	2.45
6	1910	1860	2.69
7	1465	1500	2.34
8	1350	1380	2.17
9	1910	1860	2.69
10	1390	1440	3.48

Table 4-4-b: Values for estimated (Model) and independent (Tests) hauled materials (Sample)

No	Estimated average value of Hauled mine materials (Model) (tonne/cycle)	Independent average value of Hauled mine materials (Tests) (tonne/cycle)	Absolute error (%)
1	203	198	2.46
2	205	200	2.44
3	207	202	2.42
4	209	206	1.44
5	212	208	1.89
6	214	218	1.87
7	214	209	2.34
8	223	228	2.24
9	229	224	2.18
10	233	238	2.15

The results indicate good agreement between the actual and estimated values of average cycle time and average hauled mine materials.

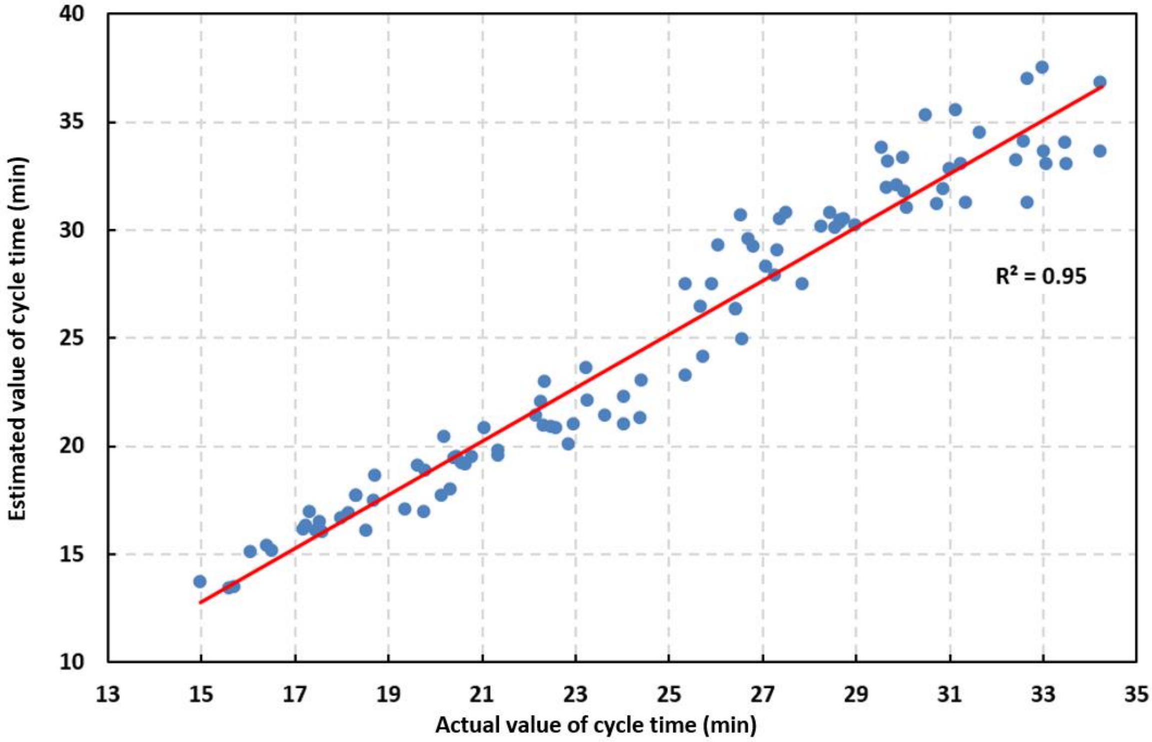

Figure 4-5-a: Comparison of actual values of cycle time with model outputs for test data

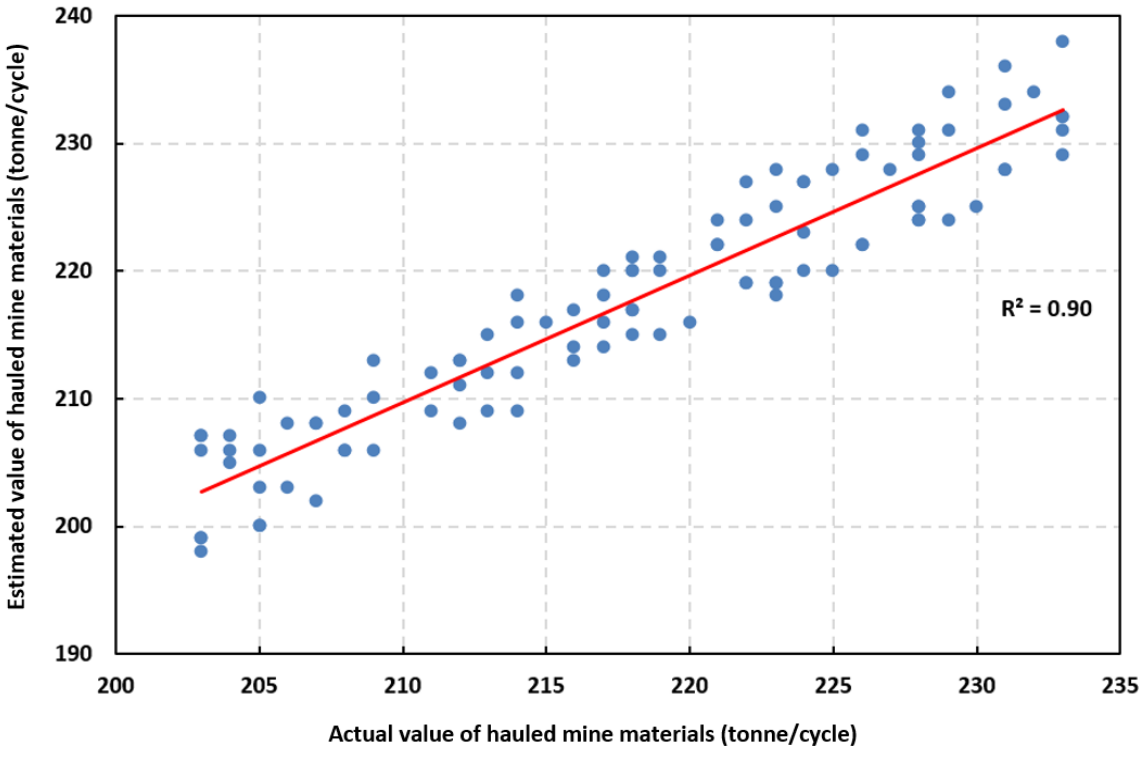

Figure 4-5-b: Comparison of actual values of hauled mine materials with model outputs for test data

4.5 Case study

In this project, a real mine site dataset that was collected from a large surface mine in central Queensland, Australia has been analysed. A sample of real mine site parameters are tabulated in Table 4-5.

Table 4-5: A sample of real mine site parameters (Case study)

	Parameter		Value	Unit
Material	Insitu Bank Density		2.5	tonne/m^3
	Swell factors	Bank to Loader Bucket	1.25	tonnes/m^3
		Bank to Truck Tray	1.25	
	Lose density	Bank to Loader Bucket	2	
		Bank to Truck Tray	2	
	Product Ration		1	tonne of product per tonne hauled
	Loader Bucket Fill Factor	Heaped	0.978	
		Struck	0.978	
Roster	5 day Week - 8 Hour Shifts			
	Mon - Fri		3 Shift	Daily
	Total Shift		783	shifts/year
	Scheduled Lost Shifts		27	shifts/year
	Scheduled Shifts		756	shifts/year
	Loading Unit Maintenance		113	shifts/year
	Unscheduled Lost Shift		42	shifts/year
	Fleet Operating Shifts		601	shifts/year
	Shift Duration		08:00:00	hh:mm:ss
	Non-Operating Shift Delays		01:00:00	hh:mm:ss
	In Shift Operating Time		07:00:00	hh:mm:ss
	Operating Shift Delays		00:30:00	hh:mm:ss
	In Shift Working Time		06:30:00	hh:mm:ss
Loading	Bucket Capacity		25.2	m^3
	Bucket Cycle Time		0.5	minute
	Mechanical Availability		85%	
	Truck Positioning		Single Sided	
	Bucket Fill Factor		0.98	
	First Bucket Pass Delay		50%	minute
	Payload Distribution		Normal	Right skewed
Truck	Spot time at loader		0.5	minute
	Spot time at dump		0.5	minute
	Dumping Time		0.5	minute
	Mechanical Availability		80%	
	Motor Power		1743	kW
	Transmission Speed Factor		1:00	

Truck	Standard Body Capacity	129	m^3
	Empty Truck Weight	165.75	tonne
	Actual Truck Payload	218	tonne
	Full Truck weight	383.75	tonne
	Operating Hours per Year	4799.2	op.hr/year
	Average Payload	221.53	tonne
	Production per Operating Hour	560.21	tonne
	Production per Loader Operating Shift	3137.17	tonne
	Production per Year	2688552.13	tonne
	Queue Time at Loader	2.71	min/cycle
	Spot Time at loader	0.5	min/cycle
	Average Loading Time	1.95	min/cycle
	Travel Time	15.94	min/cycle
	Spot Time at Dump	0.5	min/cycle
	Average Dump Time	0.5	min/cycle
	Average Cycle Time	22.11	min/cycle
	Fleet Size	8	
	Average No. of Bucket Passes	5	
Haulage System	Production per year	21,508,417	tonne/year

The effect of truck bunching due to payload variance on average cycle time and average hauled materials for one mostly used model of haul truck in studied surface mine is illustrated in Figure 4-6.

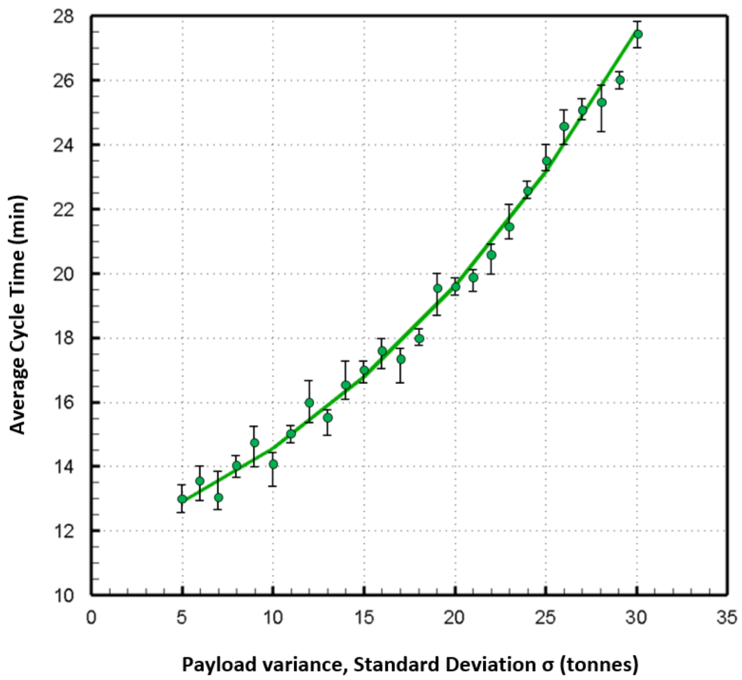

Figure 4-6: The variation of average cycle time with payload variance, standard deviation

This figure demonstrates that, there is a non-linear relationship between payload variance/standard deviation and average cycle time in the fleet. Based on the presented results of analysed data in Figure 4-6, it is clear that by increasing the payload variance the average cycle time increases dramatically. By maximum reducing of standard deviation from 30 tonnes to 5 tonnes, reducing average cycle time up to 15 min is possible. Another main effective parameter on mine productivity is average hauled materials. Figure 4-7 illustrates the relationship between the payload variance/standard deviation and average hauled materials. The correlation between mentioned parameters in this figure is non-linear. The minimum average hauled mine is obtain with maximum payload variance. The presented relationship between payload standard deviation and average hauled materials in studied mine shows that there is a great opportunity to improve productivity by reducing payload variance.

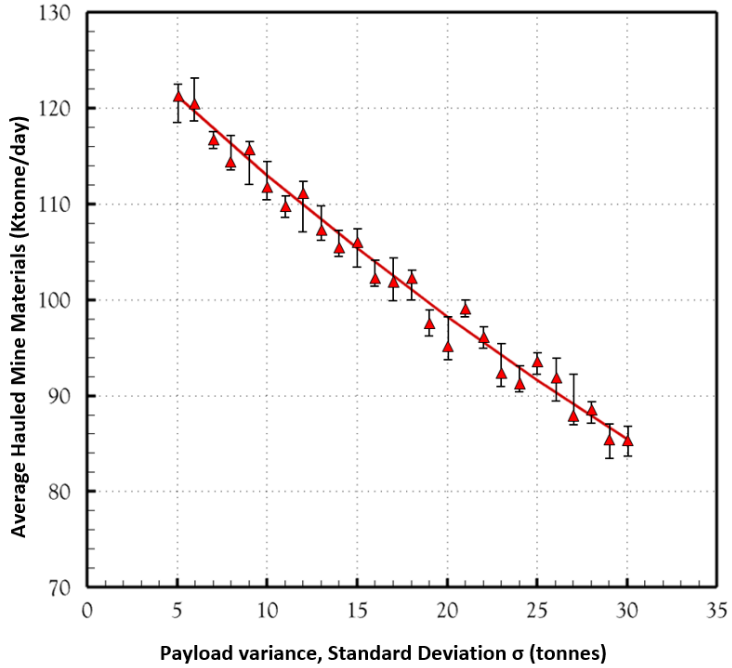

Figure 4-7: The variation of average hauled materials with payload variance/standard deviation

In this case study the effect of payload variance on haul truck fuel consumption in different haul road conditions for three models of haul truck has been investigated. It is noted that, to have a better understanding in this study, a fuel consumption index (FC_{Index}) has been defined. This index presents the quantity of fuel used by a haul truck to move one tonne of mine material (Ore or Overburden) in an hour. Truck specifications for studied haul trucks are presented in Table 4-6.

Table 4-6: Truck specification (case study)

Truck Specification		CAT 777F	CAT 785C	CAT 793D
Engine	Model	C32 ACERT™	3512B EUI	3516B HD EUI
	Gross Power	758 kW	1082 kW	1801
	Net Power	700 kW	1005 kW	1743 kW
Weights	Total Empty Operating Weight	64 tonnes	105 tonne	165 tonnes
	Nominal Payload Class	96 tonnes	144 tonnes	218
	Gross Machine Operating	160 tonnes	249 tonnes	383 tonnes

Haul trucks were selected based on their capacity and engine power. The maximum GVW for trucks are 160, 249 and 383 tonnes respectively. The results of completed investigation by developed truck bunching model are tabulated in Table 4-7.

Table 4-7: Fuel consumption index for three models of studied haul truck (case study)

Fuel Consumption Index (L/(hr.tonne))									
Standard Deviation (σ) (tonnes)	**CAT 777F**			**CAT 785C**			**CAT 793D**		
	TR=5%	**TR=10%**	**TR=15%**	**TR=5%**	**TR=10%**	**TR=15%**	**TR=5%**	**TR=10%**	**TR=15%**
σ = 5 tonnes	0.361	0.459	0.540	0.321	0.399	0.479	0.300	0.375	0.455
σ = 10 tonnes	0.456	0.543	0.619	0.416	0.482	0.563	0.399	0.466	0.546
σ = 15 tonnes	0.523	0.598	0.671	0.483	0.538	0.618	0.471	0.528	0.608

In this table FC_{Index} was calculated for three payload standard deviations (σ=5, 10 and 15 tonnes) in three different road conditions (TR=5, 10 and 15%). The results show that FC_{Index} increases not only by increasing the TR but also by increasing the payload variance for each truck. Figure 4-8 presents the FC_{Index} versus payload standard deviation for three studied model of trucks in same road condition (TR=10%).

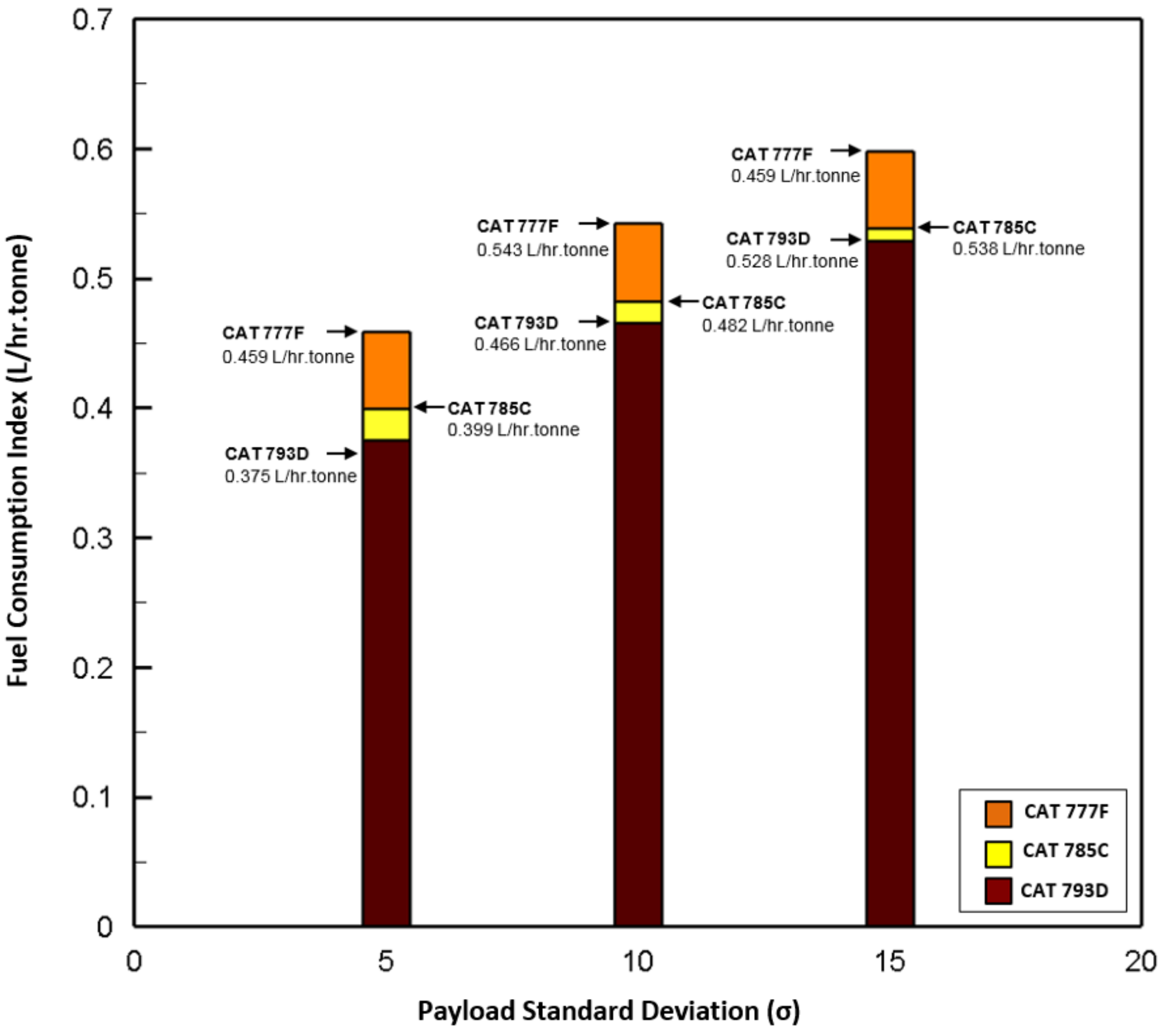

Figure 4-8: Fuel consumption index for three models of haul trucks, TR=10%

This figure shows that by increasing the capacity of truck, FC_{Index} can be reduced. In this case the maximum reduction of FC_{Index} can be achieved by changing the model of truck form CAT 777F to CAT 793D.

4.6 Conclusions

This paper aimed to develop a discrete event model to simulate the effect of payload variance on truck bunching to improve productivity and energy efficiency in surface mines. There is a significant payload variance in the loading process in surface mines. The main reason for truck bunching in this type of mine is the variance of payload. In this paper, an innovative simulation model was developed to investigate the effects of payload variance on truck bunching, mine operation efficiency and decreasing the fuel consumption by haul trucks. To validate the developed model a dataset collected from a large surface mine in Arizona, USA was used. Validation of the model was completed for the cycle time and the hauled mine materials by one type of truck (CAT 793D) after truck bunching. The results indicated a good agreement between the actual and estimated values of cycle time and hauled mine materials. The model was utilised in a real mine site in central Queensland, Australia as a case study. The results of this project showed that there is a non-linear relationship between payload variance and cycle time in the fleet. In this case study, a correlation between the payload variance and hauled mine materials was developed and the effect of truck bunching due to payload variance on energy consumption for three models of haul truck was studied.

Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P., **The Influence of Rolling Resistance on Haul Truck Fuel Consumption in Surface Mines.** Tribology International Journal, (2016).

Abstract

Rolling resistance as a part of total resistance plays a critical role in the productivity, fuel consumption, gas emissions, maintenance and safety of haul truck operations in surface mines. This paper aims to identify the most influential parameters on rolling resistance and complete an investigation about the effect of these parameters on the fuel consumption of haul trucks. In this paper, a comprehensive literature review has been completed to identify the parameters that are influential on rolling resistance. Through that process, 15 parameters have been identified and an online survey conducted to determine the most influential of these parameters on rolling resistance, based on the knowledge and experience of a number of professionals within the mining and haul road industries. In this survey, 50 industry personnel have been contacted with a 76% response rate. The results of the survey have shown that road maintenance, tyre pressure and truck speed are the most important effective parameters on rolling resistance. In this study based on the data collected from the literature review, the relationships between selected parameters and rolling resistance have been established. A correlation between the selected parameters and best performance fuel consumption for one type of common truck in Australian surface mines has been developed. As a case study, a computer model based on the nonlinear regression method has been created to find the correlation between fuel consumption and rolling resistance in a large coal surface mine in central Queensland, Australia. The relationships between the most influential parameters on rolling resistance and fuel consumption in this case study have also been developed. The results of the case study indicated that by decreasing the maintenance interval, increasing tyre pressure and decreasing truck speed, the fuel consumption of haul trucks can be decreased. [148]

Keywords: Rolling Resistance; Haul Truck; Surface Mine; Fuel Consumption

CHAPTER 5

5. The Influence of Rolling Resistance on Haul Truck Fuel Consumption in Surface Mines

5.1 Introduction

Globally, the world marketed energy consumption was approximately 600,000 PJ in 2013 [149]. Australia consumed roughly 6,000 PJ in the above mentioned period with a forecasted growth of 1.1% over the next 10 years [150]. The mining industry annually consumes vast amounts of energy in operations such as exploration, extraction, transportation and processing [3]. The Australian mining industry has observed a steady increase in energy consumption from 1976, consuming around 600 PJ of energy in 2013, or about 10% of the total energy consumption in Australia [150]. A large number of research studies and industrial projects have been carried out in an attempt to reduce energy consumption in Australian mining operations [49, 51]. Haulage operations are one of the main energy consumers within the mining industry [3]. Of the total energy expenditure, Loading, Hauling and Dumping (LHD) operations represent approximately 60% of the total energy consumption in the Australian mining industry [52]. 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 [151]. Trucks in surface mines are used to haul ore and overburden from the pit to the stockpile, 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 [129]. The trucks used in the haulage operations of surface mines consume a large amount of energy, encouraging truck manufacturers and major mining corporations to carry out a number of research projects on the energy efficiency of haul trucks [49]. 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 parameters that affect the energy use of trucks, such as effective parameters on haul road condition [152, 153]. There are a number of effective parameters on haul road condition 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. The consumption of fuel is dependent on many mine parameters including the grade of the haul road, the rolling resistance, payload, speed and truck engine characteristics [154]. By reducing the resistance a truck encounters during a hauling cycle, the overall fuel efficiency has the potential to be improved, without affecting cycle or productivity parameters [155, 156].

The aim of this paper is to investigate the effect of rolling resistance on haul truck fuel consumption as well as the key effective parameters affecting rolling resistance.

5.2 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 five main groups (see Figure 5-1). The key parameters that affect the energy consumption of haul trucks include the truck characteristics, fleet management, haul road condition, mine plan and environmental conditions, according to a study conducted by the Department of Resources, Energy and Tourism [49].

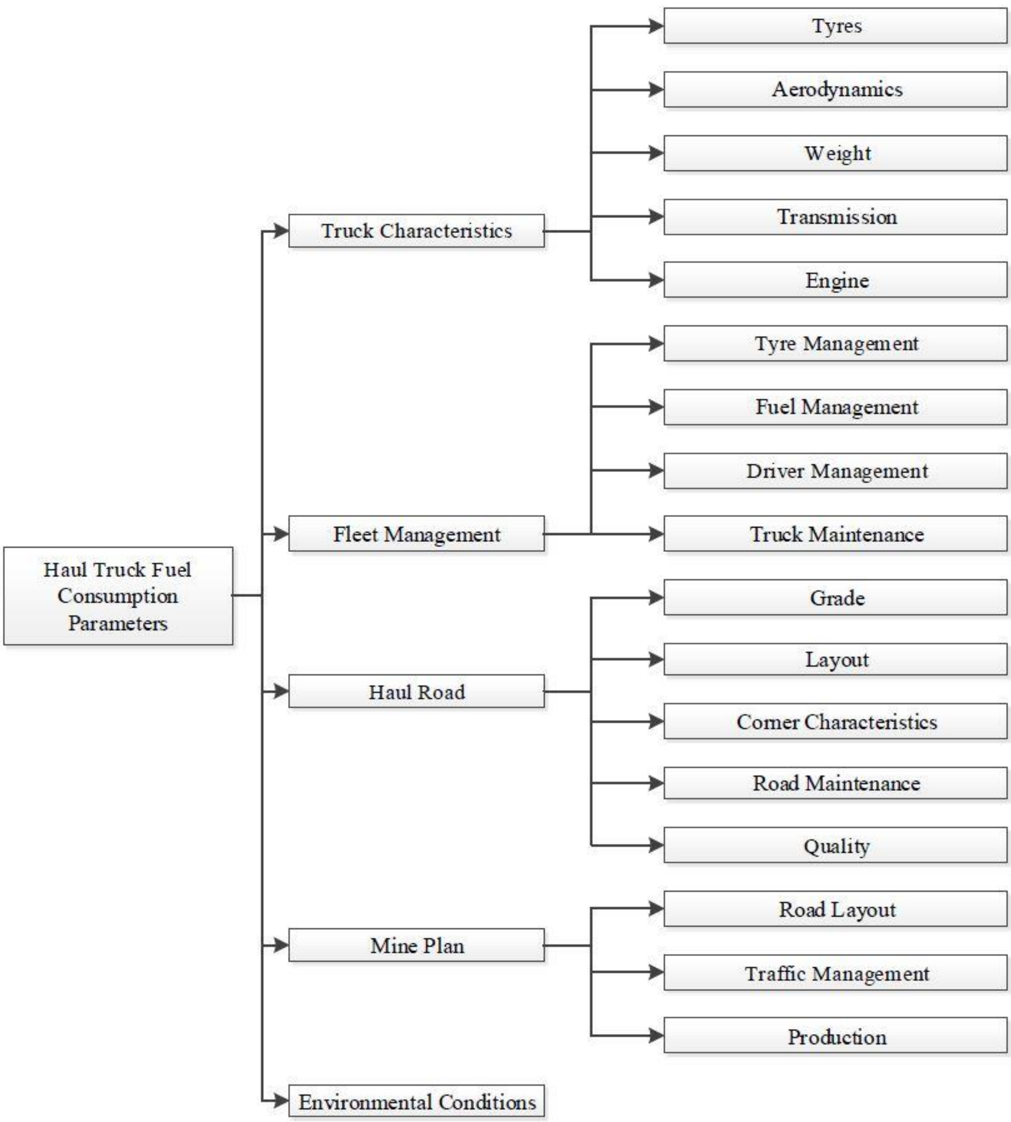

Figure 5-1: Parameters affecting haul truck fuel consumption

In the present study, the effects of the Rolling Resistance (RR) on the fuel consumption of the haul trucks were examined. The RR is one of the main components of Total Resistance (TR) and it is one of the main controllable effective parameter on haul truck fuel consumption. The TR is equal to the sum of the RR and the Grade Resistance (GR) when the truck is moving against the grade of the haul road [36].

$$\mathrm{TR} = \mathrm{RR} + \mathrm{GR} \tag{5-1}$$

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 motion when the truck tyre rolls on the haul road. 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 (see Figure 5-2).

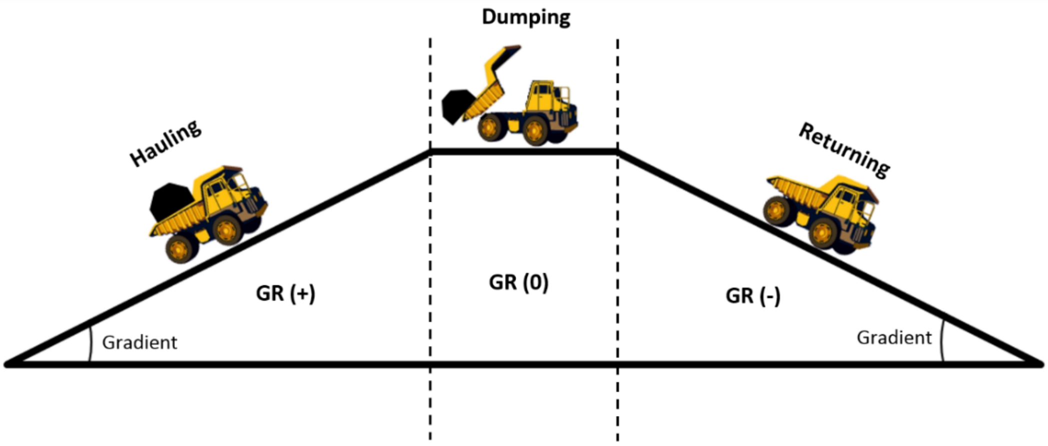

Figure 5-2: Grade Resistance (GR)

For example, a section of the haul road that rises 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.

Figure 5-2 presents a schematic diagram of a typical haul truck and the key parameters that affect the performance of the truck, such as the Gross Vehicle Weight (GVW) (representing the sum of the empty truck weight and the payload), RR, Gradient (G), Rolling Friction Force (RFF) and Rimpull Force (RF). RF is the force available between the tyre and the ground to propel the machine. 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) [157].

$$\mathrm{RF} = \frac{\mathrm{T}}{\mathrm{r}} \tag{5-2}$$

Estimation of the fuel consumption rate requires a number of assumptions as well as calculations. Figure 5-3 illustrates the relationship between the haulage operation parameters and truck fuel consumption.

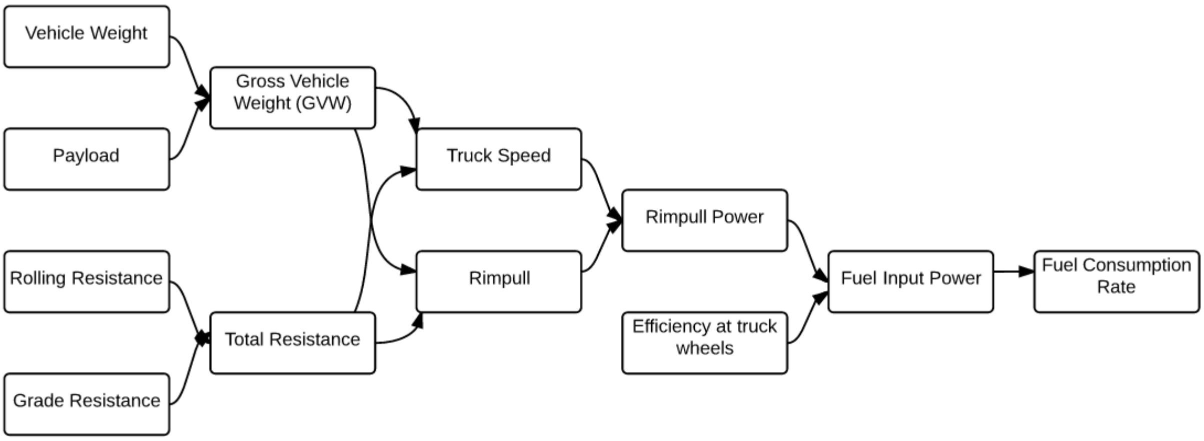

Figure 5-3: Variable relationships required for truck fuel consumption estimation

It illustrates the variables to be initially defined and the values to be calculated to estimate energy consumption. Several input variables are initially required and include the vehicle weight, defined as the weight of the unloaded truck and payload, or the weight of the material hauled by the truck. RR and GR are also required, and are both measured as a percentage. RR can be estimated for the road, or measured where possible.

In this study, a new parameter representing the fuel consumption by haul trucks has been defined. This parameter is the Fuel Consumption Index (FC_{Index}). This index represents the quantity of fuel burnt by a haul truck to move one tonne of mined material (Ore or Overburden) in an hour (L/ (hr. tonnes)). The FC_{Index} can be estimated using following equations.

$$FC_{Index} = \frac{F_i}{3600 \times P} \tag{5-3}$$

where F_i is Fuel Input Rate (L/s) and P is payload hauled by the truck (tonne) [51];

$$F_i = \frac{PO_f}{38600} \tag{5-4}$$

where PO_f is Fuel Input Power (kW) [51];

$$PO_f = \frac{PO_r}{EEF} \tag{5-5}$$

where PO_r is Rimpull Power and EEF is Energy Efficiency Factor [51];

$$PO_r = 0.28 \times S \times R \times g \tag{5-6}$$

where S is Truck Speed (km/hr), R is Rimpull and g is the acceleration due to gravity (m/s^2).

5.3 Rolling resistance

RR is defined as a measure of the force required to overcome the retarding effect between the tyres and road [158, 159]. This resistance is predominantly measured as a percentage of the GVW, but can also be expressed as energy divided by a distance, or a force [160, 161]. Tyre RR can also be characterised by a Rolling Resistance Coefficient (RRC), a unit-less number [162, 163]. RR manifests itself predominantly in the form of hysteresis losses described as the energy lost, usually in the form of heat, when a section of vulcanised rubber is deformed regularly, such as during the operation of a haul truck [164].

RR is able to be measured by a number of different methods, some of which are detailed in the British Standard for Measuring Rolling Resistance [165]. Measurements can be made under laboratory conditions, generally on ‘test drum surfaces’. This is a testing rig consisting of the tyre to be tested and a drum with a varying outer surface which is able to rotate, simulating the movement of the tyre over a road surface. A number of mathematical methods can then be applied to the values of Drum Torque, Power and Tyre Force measured during testing to determine the RR experienced by the tyre [166].

Measurements of RR can also be obtained for a specific mine haul roads using on site testing. This method generally uses a specially designed trailer towed behind a truck to measure RR. A series of sensors attached to the trailer measure the force between the truck and trailer, used to pull it across the road surface. They also measure the grade of the haul road and acceleration. This data is then used with the relevant mathematical expression to determine the RR of the haul road [44].

There are a number of effective parameters affecting RR, which are able to be categorised into four groups. These groups are Road, Tyre, System and Weather properties. Figure 5-4 illustrates the most influential parameters on RR. Haul road and tyre properties are predictably, properties of the haul road and truck tyres. System properties encompass operational parameters of the haul truck and weather properties envelopes all parameters associated with weather conditions.

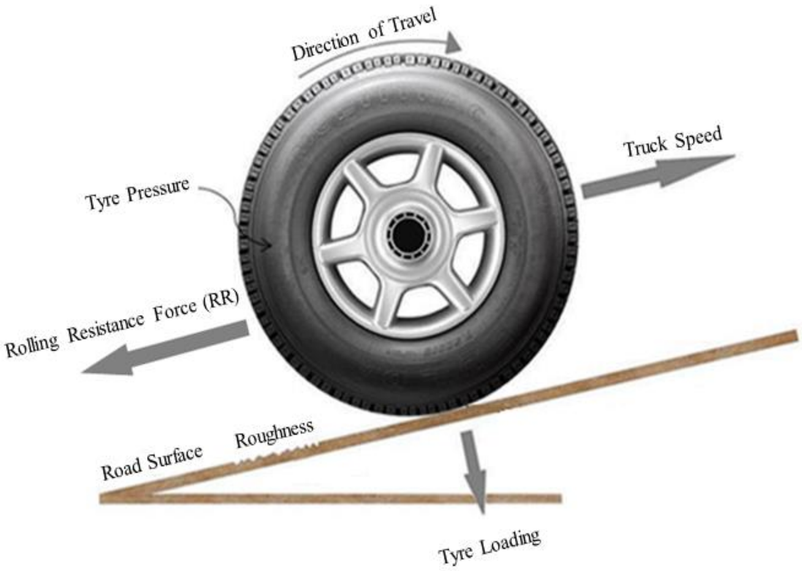

Figure 5-4: Rolling resistance and the most influential parameters

These parameters are also categorised as a Design (D), Construction (C), Operational (O) or Maintenance (M) parameter. Table 5-1 illustrates the parameters affecting RR, and the category to which it belongs to.

Table 5-1: Influential parameters on rolling resistance

	Group	**Category***				**Parameter**
		D	C	O	M	
	Road	✓			✓	Roughness
		✓	✓		✓	Defects
		✓	✓		✓	Material Density
				✓		Moisture Content
					✓	Road Maintenance
	Tyre	✓		✓	✓	Tyre Penetration
Rolling Resistance		✓				Tyre Diameter
				✓		Tyre Pressure
			✓	✓	✓	Tyre Condition
				✓		Tyre Loading
				✓		Tyre Temperature
	System			✓		Truck Speed
				✓		Driver Behaviour
	Weather			✓		Humidity
				✓		Precipitation
				✓		Ambient Temperature

* **D**:Design **C**:Construction **O**:Operational **M**:Maintenance

5.4 Road properties

Road properties are associated with the haul road itself, primarily the material forming the top layer or 'wearing course' of the road [164, 167]. A number of road properties have been identified in numerous studies as affecting the RR experienced by trucks using the road.

The surface material of the haul road is identified as a major contributor to RR. Numerous studies have found that softer road surfaces with looser under-footing resulted in increased RR [44, 45, 168-171]. Table 5-2 shows the results of one of these studies, displaying RR associated with surface type.

Table 5-2: Surface type and associated rolling resistance

Type of Surface	Rolling Resistance (%)
In-situ clay till	4 - 6.7
Compacted gravel	2-2.7
Compacted clay-gravel	3.9
Subsoil stockpile	4.4 - 8.3
Compacted clay till	4.1
Subsoil on mine spoil	7.3

A study conducted by Sandberg [172] is concerned with effective parameters on RR. The focus of this study is on the road roughness. Another study in this area completed by Mukherjee [173] shows that increasing the road roughness resulted in increasing RR.

A study conducted by Thompson and Visser [152] is concerned with the impact of defects on RR. This study shows that by increasing the Mean Profile Depth (MPD), the RR is also increased. Ajoy [174] presented an investigation about the estimation of RR. The presented results show that a higher degree of road compaction can decrease the RR. Thompson and Visser in another study [160] investigated the effect of haul road maintenance on RR. The results of this study show that road maintenance plays a critical role in RR. The main objective of maintenance is to repair defects, identified as significant contributors to RR, as well as prevent them from occurring. The results obtained from Thompson's study showed that decreases in maintenance intervals, or period of time between maintenance resulted in a decrease in RR.

5.5 Tyre properties

Tyre properties are those associated with the tyres of a haul truck and can be associated with the internal condition, tread properties or the operational characteristics. A number of these properties have been identified in a number of studies as being influential on RR [37, 172, 173, 175-179].

A study about the effect of tyre penetration as an influential parameter on RR has been completed by the Caterpillar research and development team [37]. In this study a correlation between tyre penetration and RR has been developed. The results show that by increasing the tyre penetration, the RR increases. Tyre penetration is also affected by a number of parameters, and varies depending on their influence. These parameters included tyre pressure, where a lower pressure generally corresponds to increased tyre penetration.

Tyre diameter has been identified in several studies as a contributor to RR [165, 180]. The contact patch, or area of the tyre in contact with the road changes with tyre diameter and so this change in geometry results in a change in RR. A study by Sandberg [172] found that as tyre diameter increased, RR decreased. The relationship was found to be constant among a number of different types of tyres.

Tyre pressure is a significant parameter when assessing RR, with under or overinflated tyres displaying large changes in RR. A study found that increasing tyre pressure resulted in decreasing RR [180]. Tyre pressure is also affected by temperature, with a study by Paine, Griffiths and Magedara [176] finding increasing tyre temperature responsible for increased tyre pressures.

Tyre condition is also an important parameter when considering RR, mainly manifesting itself in tread wear [181]. A study by Sandberg [172] found tyres in the worn condition with low tread height exhibited decreased RR. This relationship was observed among a number of different types of tyre.

Tyre loading is also considered in assessments and is the subject of several studies. Loading of a tyre is affected by a number of other parameters including the vehicle and payload weights as well as operational parameters of trucks. Studies by Hall and Moreland [177]found that increasing tyre load resulted in increased RR. The results of study completed by Ma, Xu and Cui [178] showed significant increases in RR with increasing tyre load. Tyre temperature has been the subject of several studies with its relationship with RR being the focus of experimental analysis [176, 180, 182, 183]. A study conducted by Janssen and Hall [183] found that increasing tyre temperature resulted in decreased RR. The study used a unit-less parameter, RRC, as the measurable representation of RR, and was found to decrease significantly with increasing tyre temperature.

5.6 System properties

System properties are those related to operational parameters of the truck as well as environmental parameters affecting truck operation. These are generally uncontrollable, or dependent on the operation of the truck, and have been linked to RR by a number of different studies.

Truck Speed (S) is a studied truck parameter, with experimental studies finding that increasing S resulted in increased RRC. Driver behaviour has not been the subject of extensive study in relation to its direct effect on RR. It can however be linked to other parameters such as tyre loading, through basic physics. As a truck corners, it generates centripetal force, which is dependent on the mass of the truck, velocity and radius of the turn [180]. Both turn radius and velocity are dependent on the driver behaviour. As a result, this behaviour affects centripetal force which affects tyre loading [184].

5.7 Weather properties

Weather properties are parameters associated with local conditions at a mine site. In surface mining these are generally uncontrollable parameters and include temperature and the presence of rain or other environmental influences.

Ambient temperature or environmental temperature is an uncontrollable parameter in open surface mines and is considered due to its effect on tyre pressure. Tyre pressure has been identified as having an effect on RR. As a result, ambient temperature affects RR through its effects on tyre pressure [183]. The results of a study conducted by Michelin in France [179] found that an increase in ambient temperature resulted in decreased RR.

5.8 Rolling resistance parameters selection

An online survey was conducted to determine the most influential parameters on RR, based on the knowledge and experience of a number of professionals within the mining and haul road industries. Fifty industry personnel were contacted with a 76% response rate. Of the personnel surveyed, 12% worked in the area of haul road planning, 48% in maintenance, 24% in design and 16% in operations.

This survey allowed participants to estimate the influence of parameters identified as affecting RR. A score was assigned to each parameter between 0 and 100 representing the influence of a particular parameter on RR, where 0 is not influential and 100 is highly influential. The results of the survey show that tyre diameter has the lowest influence on RR with a result of 40%. Defects, Tyre Condition, Tyre Temperature, Driver Behaviour and Ambient Temperature were all given rankings of approximately 50%. Maintenance, Tyre Pressure and Truck Speed were all identified as having the greatest influence on RR, with scores between 80 and 90%. The remaining parameters all scored between 50 and 70% (see Figure 5-5).

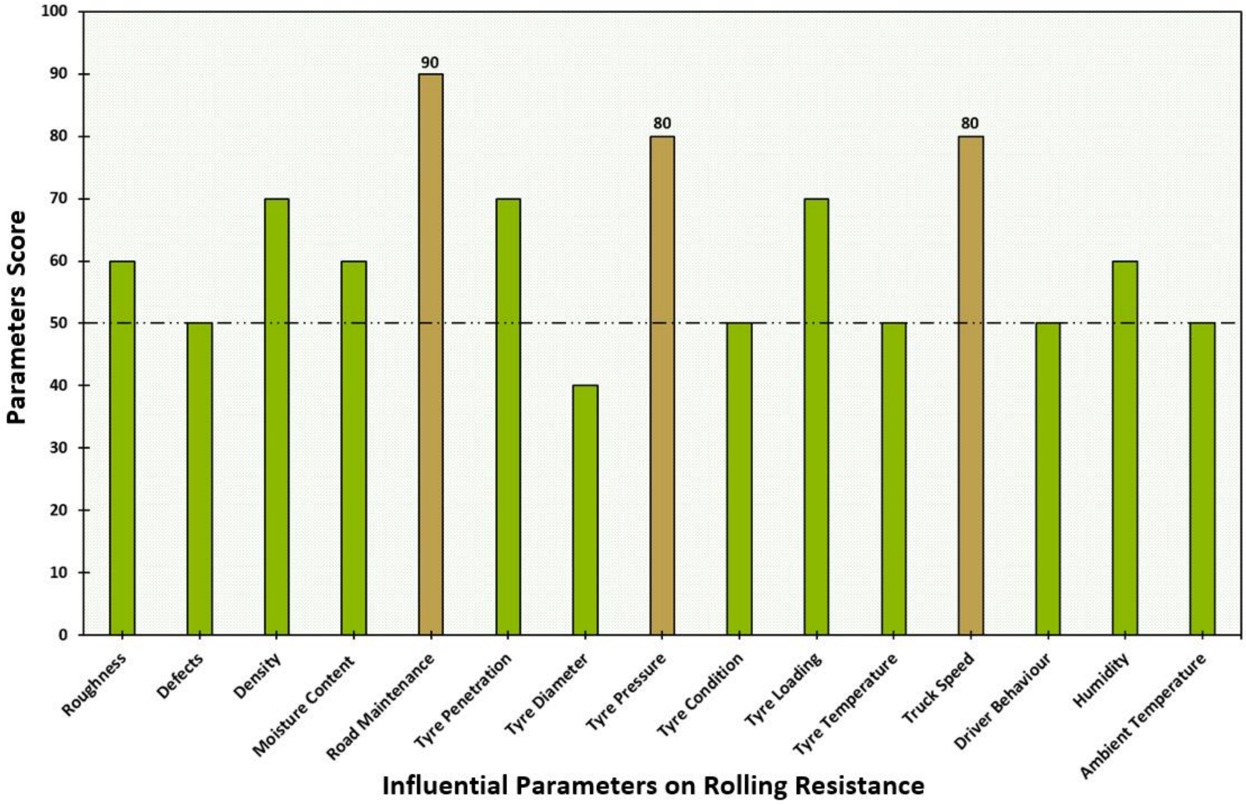

Figure 5-5: Survey results

Based on the collected data from literature, the relationships between RR or RRC and Maintenance Interval (M) [160], Tyre Pressure (TP) [172] and Truck Speed (S) [180] can be found in Figure 5-6, Figure 5-7 and Figure 5-8, respectively.

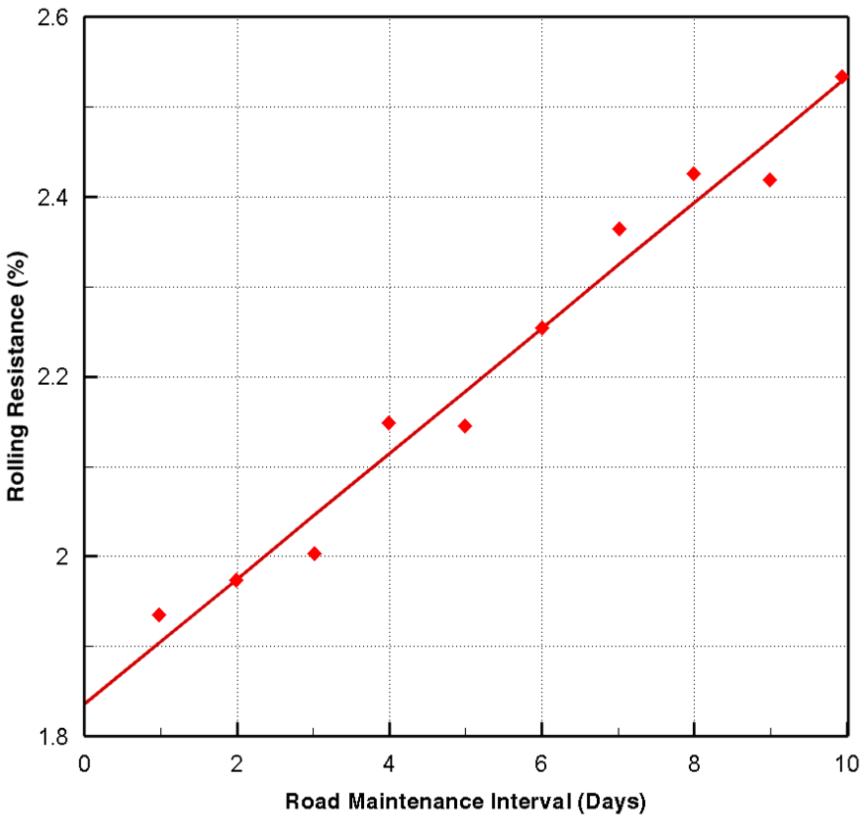

Figure 5-6: Rolling resistance vs. road maintenance interval

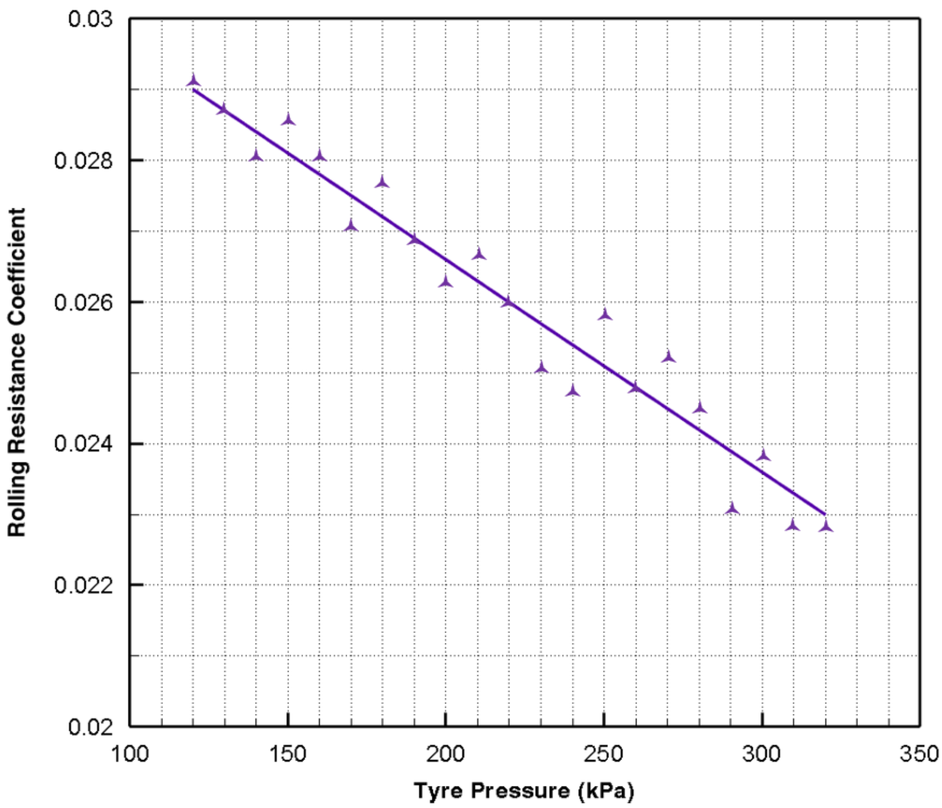

Figure 5-7: Rolling resistance coefficient vs. tyre pressure

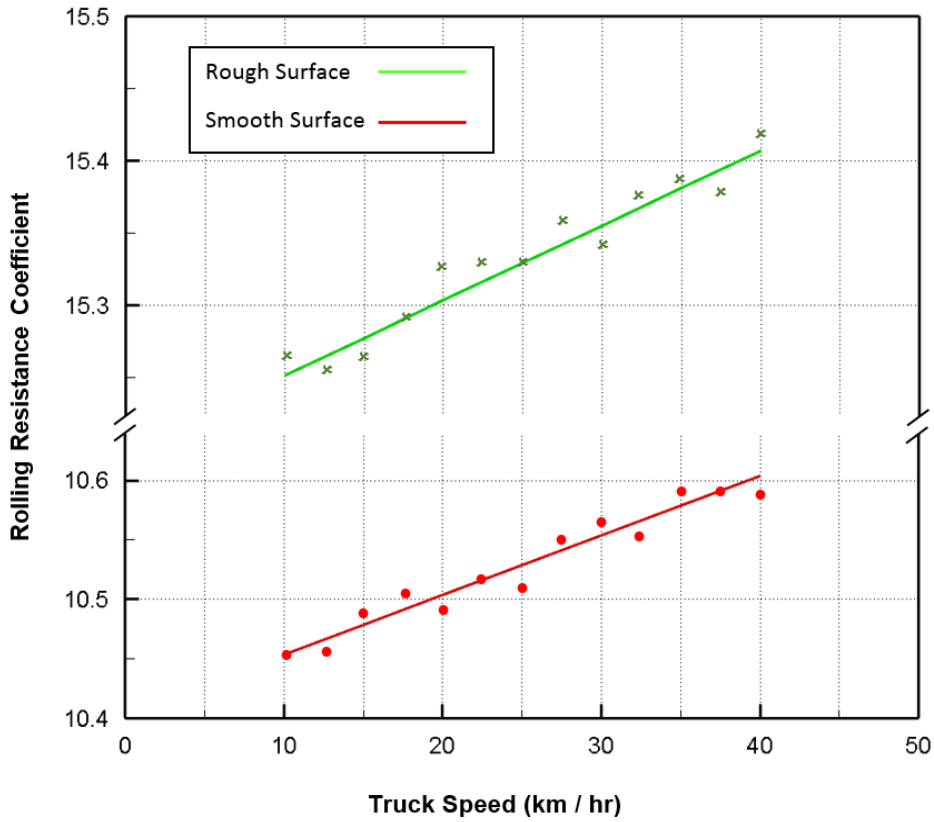

Figure 5-8: Rolling resistance coefficient vs. truck speed

5.9 Fuel Consumption completed correlations

In this project, a real mine site dataset collected from a large surface mine in central Queensland, Australia has been analysed. A sample of the collected mine site data are tabulated in Table 5-3.

Table 5-3: A sample of dataset collected from a surface coal mine in Queensland, Australia (CAT 793D)

Date	Payload (tonne)	Truck Speed (km/hr)	Cycle Time (hh:mm:ss)	Cycle Distance (km)	Rolling Resistance (%)	Grade Resistance (%)	Total Resistance (%)	Fuel Consumption (L/hr)
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

Caterpillar trucks are the most popular vehicles of the different brands used in the studied mine. Based on the power of vehicle, mine productivity, haul truck capacity and other key parameters, the CAT 793D (Table 5-4) was selected for the analysis presented in this study. Figure 5-9 presents the Rimpull-Speed-Grade curve extracted from the manufacturer's catalogue [120].

Table 5-4: CAT 793D specifications

Feature	Value
Gross Machine Operating Weight (GMW)	383,749 kg
Maximum Payload Capacity	218 tonnes
Top Speed - Loaded	54.3 km/h
Body Capacity	129 m^3
Tyres	40.00 R57

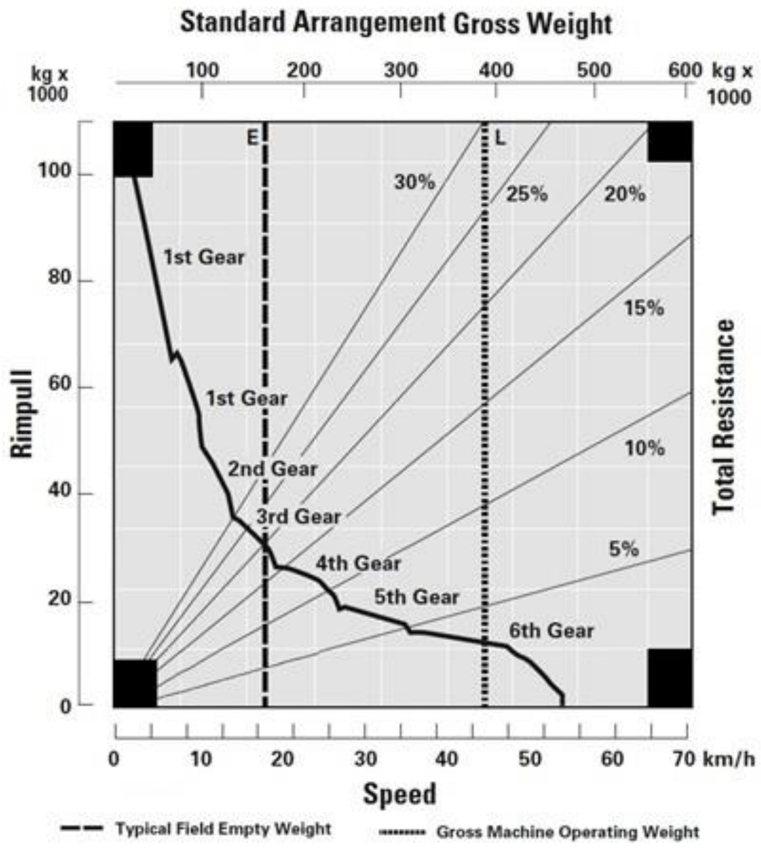

Figure 5-9: Caterpillar 793D Rimpull Curve [120]

This curve was used to determine the Rimpull (R) and the Maximum Truck Speed (S_{max}) based on different values of TR for the different values of GVW.

Figure 5-10 demonstrates the relationship between Maintenance Interval and FC_{Index}. This relationship shows that a main solution for increasing the energy efficiency in haulage operation is decreasing the maintenance interval.

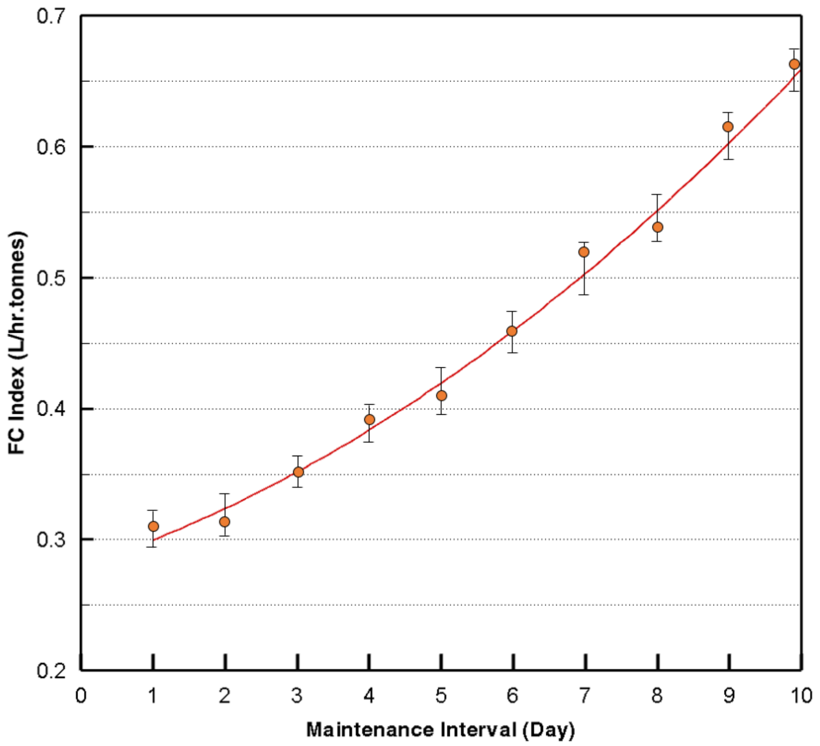

Figure 5-10: Relationship between maintenance interval and FC_{Index}

This Figure also shows that by reducing the maintenance interval from 10 to 5 days, FC_{Index} will be decreased from 0.65 to 0.4 L/ (hr. tonne). This amount of fuel savings can be a great opportunity for mine managers to reduce their operational costs.

Based on the completed on-line survey in this study, the second main effective parameter on RR is Tyre pressure. Figure 5-11 illustrates the correlation between FC_{Index} and Tyre Pressure for the CAT 793D in different conditions.

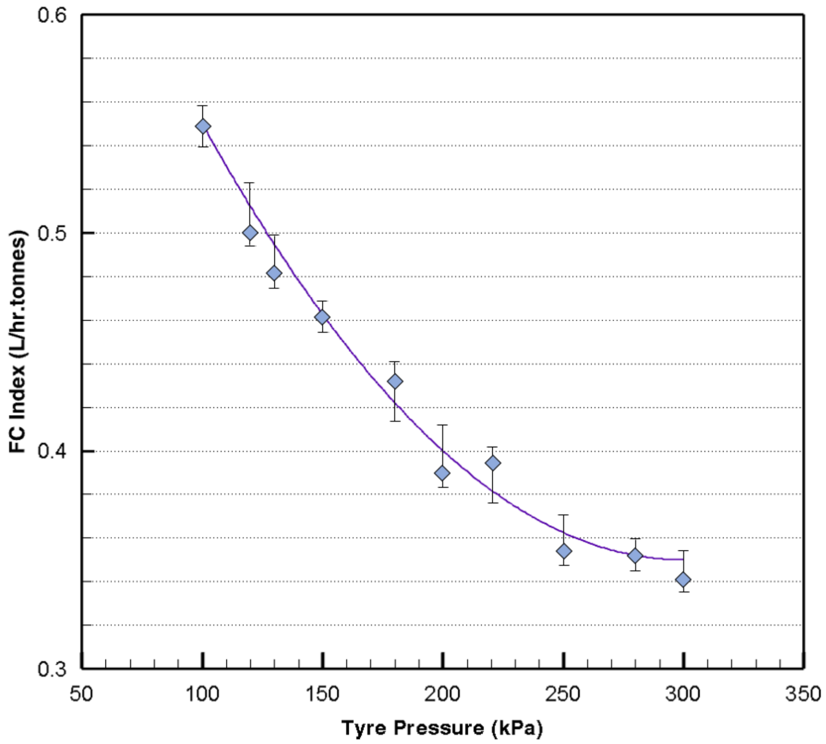

Figure 5-11: Correlation between FC_{Index} and Tyre Pressure

In this Figure the relationship between haul truck fuel consumption and tyre pressure has been completed for a normal range of tyre pressures found for trucks in the studied surface mine. This relationship shows that by increasing the tyre pressure, FC_{Index} will be decreased sharply. Therefore, it is obvious that by a regular pressure check, increasing the fuel efficiency in haulage operations will be possible. The effect of truck speed on FC_{Index} is illustrated in Figure 5-12.

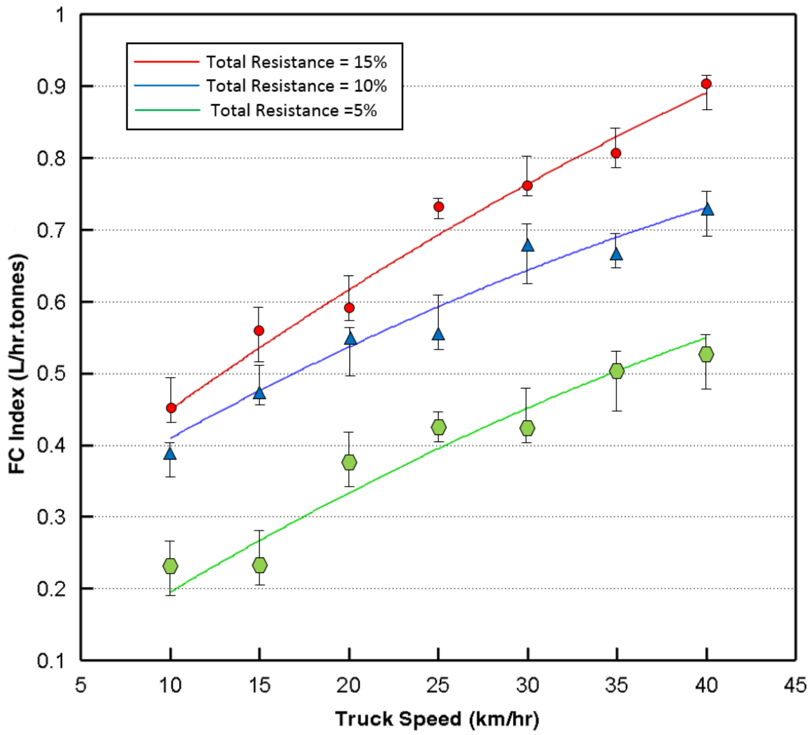

Figure 5-12: The effect of truck speed on FC_{Index}

The non-linear correlation between FC_{Index} and truck speed shows that by increasing the S, fuel consumption by the truck increases. This Figure also shows that a valid approach for decreasing the fuel consumption is to decrease the total resistance, in this case could be achieved by reducing RR.

5.10 Conclusions

In this study an investigation to identify the most influential parameters on rolling resistance was completed. After a comprehensive literature review, 15 parameters were identified and an on-line survey conducted to determine the most influential of the parameters on rolling resistance. In this survey, 50 industry personnel were contacted with a 76% response rate. Of the respondents, 12% worked in the field of road planning, 48% in maintenance, 24% in design and 16% in operations. The results of the survey revealed that road maintenance, tyre pressure and truck speed are the most important effective parameters on rolling resistance. The effect of these three main selected parameters were investigated on haul truck fuel consumption in a real mine site located in central Queensland, Australia. The non-linear relationships between the selected parameters in the survey and fuel consumption in the real studied mine were developed. The results indicated that by decreasing the maintenance interval, increasing tyre pressure and decreasing truck speed, the fuel consumption of haul trucks can be decreased.

Soofastaei, A., Aminossadati, S.M., Arefi, M.M. and Kizil, M.S., **Development of a multi-layer perceptron artificial neural network model to determine haul trucks energy consumption.** International Journal of Mining Science and Technology, (2016). 26(2): P. 285-293

Abstract

The mining industry annually consumes trillions Btu of energy. A large part of this energy is saveable. The considerable amount of potential saving has motivated both the mining industry and governments to conduct research on how to reduce the energy consumption in the mining industry. Diesel fuel is a significant source of energy in surface mining operations. Haul trucks are the major users of this energy resource. Based on the analysis on the data collected from mine sites, Gross Vehicle Weight (GVW), Maximum Truck Speed (V_{max}) and Total Resistance (TR) were identified to be the most influential parameters affecting the fuel consumption. The relationship between the three abovementioned parameters and the haul truck fuel consumption is complex. Thus, the development of a new approach using an artificial intelligence method is essential to create a reliable model for analysing the problem. In this paper, an Artificial Neural Network (ANN) model was developed to predict the fuel consumption of haul trucks in surface mines. The network was trained and tested using a dataset of samples where the values of GVW were collected from a mine site and the values of and were calculated. It was found that the configuration of 3 input variables, 15 hidden cells and 1 output for the synthesised ANN model provided excellent results. The sensitivity analysis showed that all the three input variables (GVW, V_{max} and TR) have noticeable effect on the haul truck fuel consumption. It was also found that V_{max} has the most influential parameter with the relative importance of 60%. The results of this study indicate that the artificial neural network modelling accurately predicts the haul truck fuel consumption based on the values of haulage parameters considered in this study. [185]

Keywords: Fuel Consumption; Haul Truck; Surface Mine; Artificial Neural Network

CHAPTER 6

6. Development of a Multi-Layer Perceptron Artificial Neural Network Model to Determine Haul Truck Energy Consumption

6.1 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 [48, 102, 113, 186]. Current investments in the improvement of mining equipment have resulted in a significant reduction of energy consumption [14, 100]. A large amount of energy can also be saved by improving mining technologies and energy management systems [25, 101]. 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 [99, 187]. 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 [96], which are highly energy-intensive, accounting for 87% of the total energy consumed in material handling [2, 3].

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 [103]. They are used in combination with other equipment, such as excavators, diggers and loaders, according to the production capacity and the site layout [95]. The trucks used in the haulage operations of surface mines use a great amount of energy [3, 188] 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 [39, 98, 104, 115, 188].

The study conducted by Antoung and Hachibli [98] 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 [39] 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, Bartlett and Kaboli [115] 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 parameters affecting the fuel consumption. Chingooshi, Daws and Madden [104] 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 parameters that affect the energy use of trucks, such as payload distribution [49]; 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 [50, 59-64], biochemical engineering [65], medicine [66] and mechanical engineering [67-70]. 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.

6.2 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 (see Figure 6-1).

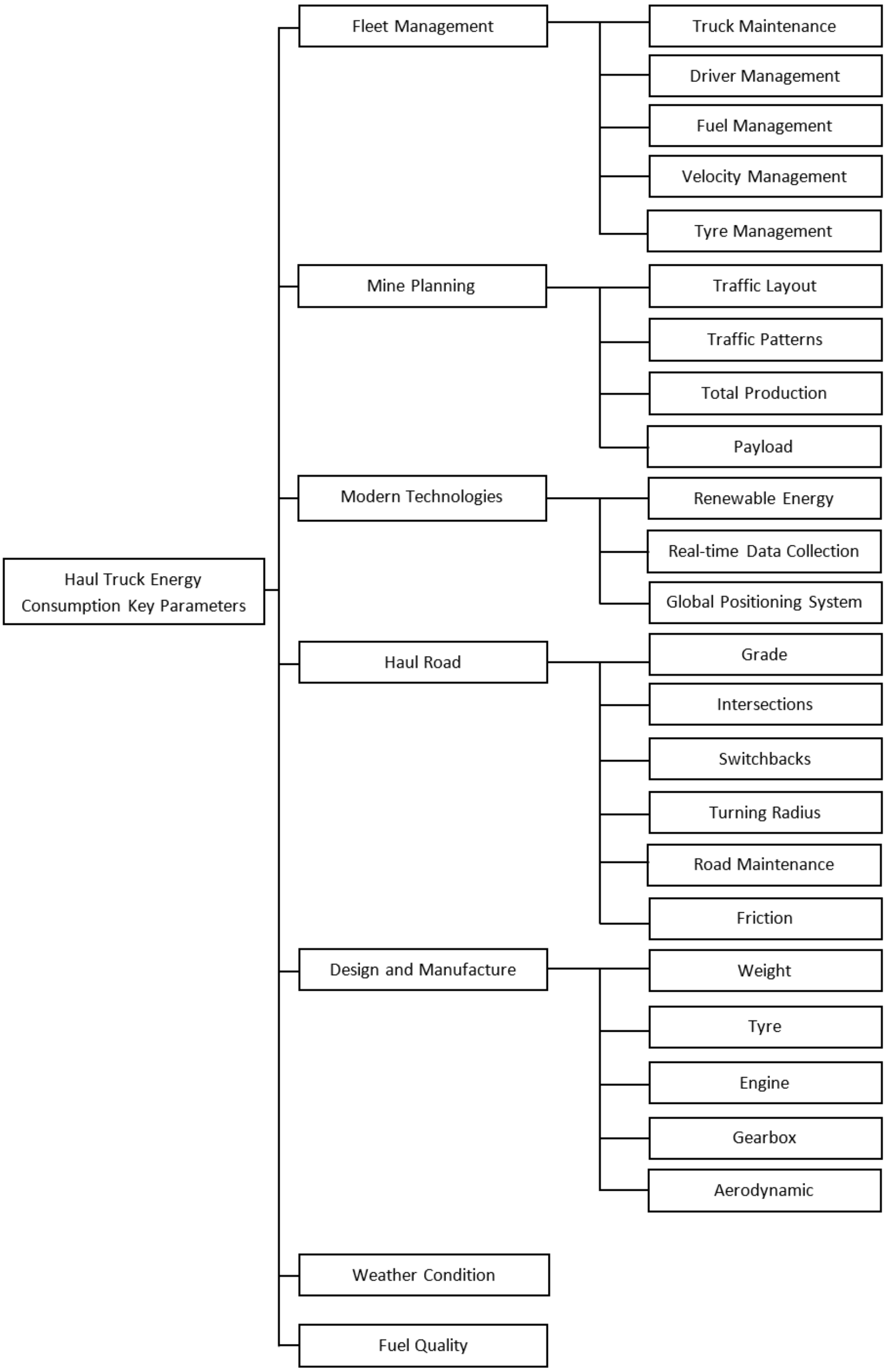

Figure 6-1: Haul truck energy consumption key parameters

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 [49]. 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.

$$\mathrm{TR} = \mathrm{RR} + \mathrm{GR}$$
(6-1)

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 (see Figure 6-2).

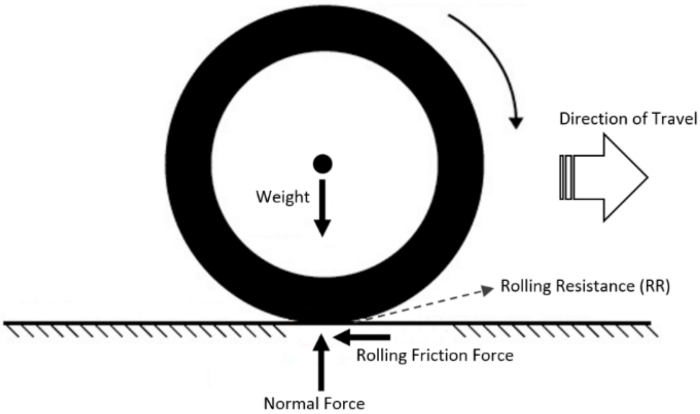

Figure 6-2: A schematic diagram of a truck tyre showing the forces

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 6-1 [189].

Table 6-1: Typical values for Rolling Resistance (RR) [190]

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	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

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 (see Figure 6-3). 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.

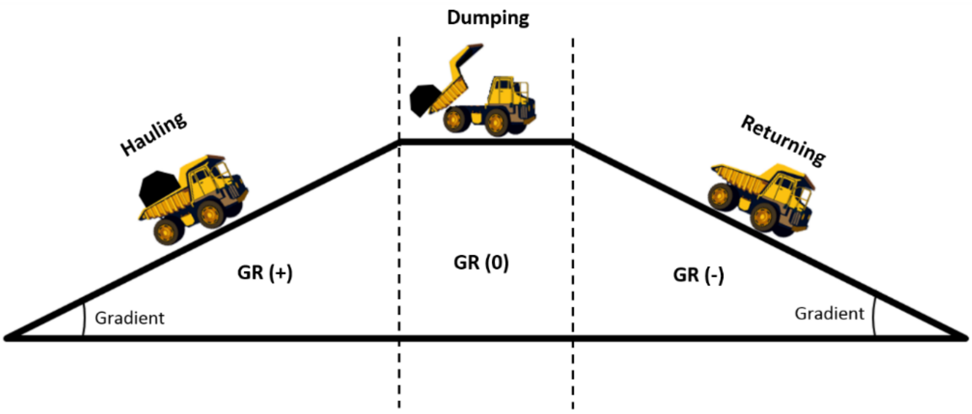

Figure 6-3: Grade Resistance (GR)

Figure 6-4 presents a schematic diagram of a typical haul truck and the key parameters that affect the performance of the truck, such as the GVW, RR, gradient, friction force and Rimpull Force (RF).

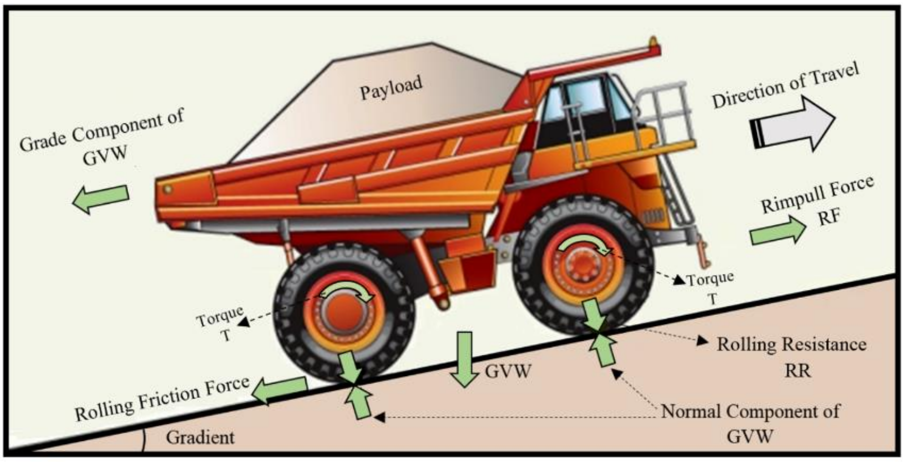

Figure 6-4: A schematic diagram of a typical haul truck and effective key parameters on truck performance

RF is the force available between the tyre and the ground to propel the machine (see Figure 6-5). 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).

$$RF = \frac{T}{r} \tag{6-2}$$

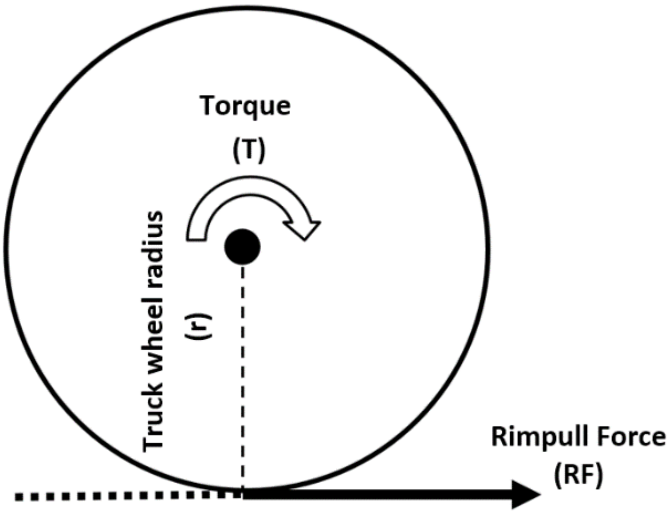

Figure 6-5: Schematic of the wheel showing the Rimpull Force (RF)

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 6-2) was selected for the analysis presented in this study.

Table 6-2: CAT 793D Mining truck specifications [120]

Specification	Value
Engine	
Engine Model	CAT 3516B HD
Gross Power	1801 kW
Net Power	1743 kW
Weights - Approximate	
Gross Weight	384 tonnes
Nominal Payload	240 tonnes
Body Capacity	
Struck	96 m^3
Heaped	129 m^3

The Rimpull-Speed-Grade ability curve presented in Figure 6-6 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/hr), cycle time (hh:mm:ss), cycle distance(km), RR(%), GR(%), TR(%) and truck fuel consumption (L/hr), A sample of the dataset is presented in Table 6-3.

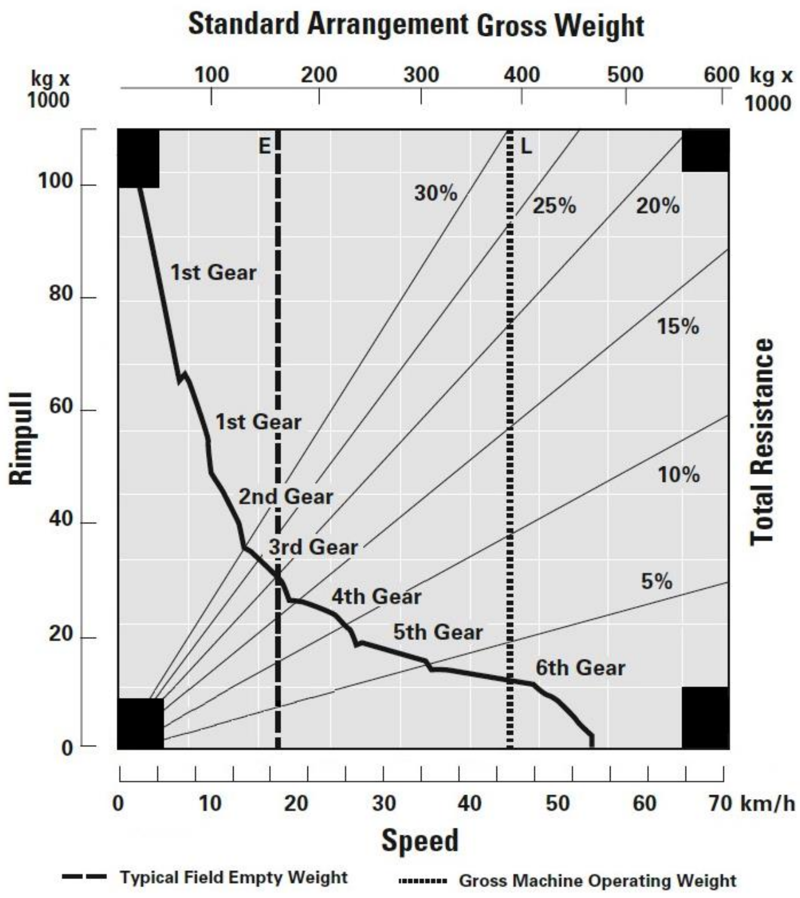

Figure 6-6: Rimpull-Speed-Grade Ability Curve for Truck CAT 793D [120]

Table 6-3: A sample of dataset collected from a surface coal mine in central Queensland, Australia

Date	Payload (tonne)	Truck Velocity (km/hr)	Cycle Time (hh:mm:ss)	Cycle Distance (km)	Rolling Resistance (%)	Grade Resistance (%)	Total Resistance (%)	Fuel Consumption (L/hr)
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

The cycle time, presented in Table 6-3, 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 (see Figure 6-7) [190]. 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.

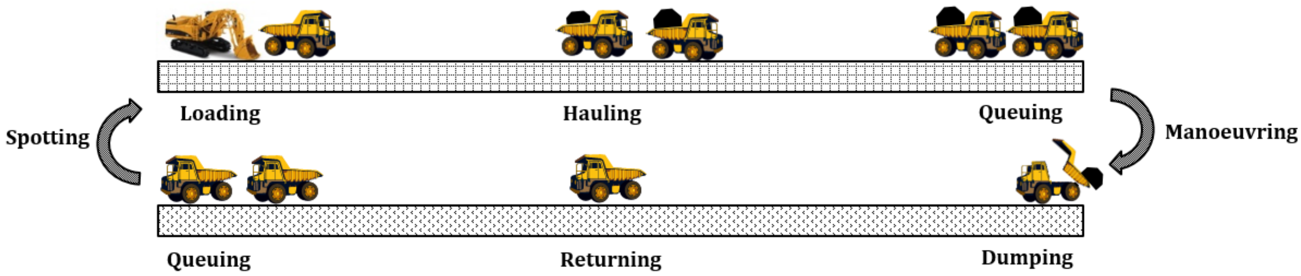

Figure 6-7: Hauling truck operations in a round trip

The truck fuel consumption can be calculated from Equation 6.3 (Filas [191]):

$$FC = \frac{SFC}{FD}(LF.\,P) \tag{6-3}$$

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 6-3 is presented by Runge [118]:

$$FC = 0.3\,(LF.\,P) \tag{6-4}$$

where LF is the engine load factor and is defined as the ratio of average payload to the maximum load in an operating cycle [113]. The typical values of LF are presented in Table 6-4 [37]. P is the truck power (kW). For the best performance of the truck operation, P is determined by:

$$P = \frac{1}{3.6}\,(RF \,.\, V_{max}) \tag{6-5}$$

where the RF is calculated by the product of Rimpull (R) and the gravitational acceleration (g). V_{max} is calculated by Equation 6-6, which is based on the relationship between R and V_{max} as presented in Figure 6-6 (Soofastaei [192]).

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

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 (see Figure 6-6).

$$R = 0.183\,GVW\,(0.006 + 0.053\,TR) \tag{6-7}$$

The relationship between V_{max} and GVW for six values of TR is illustrated in Figure 6-8. 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 6-4: 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

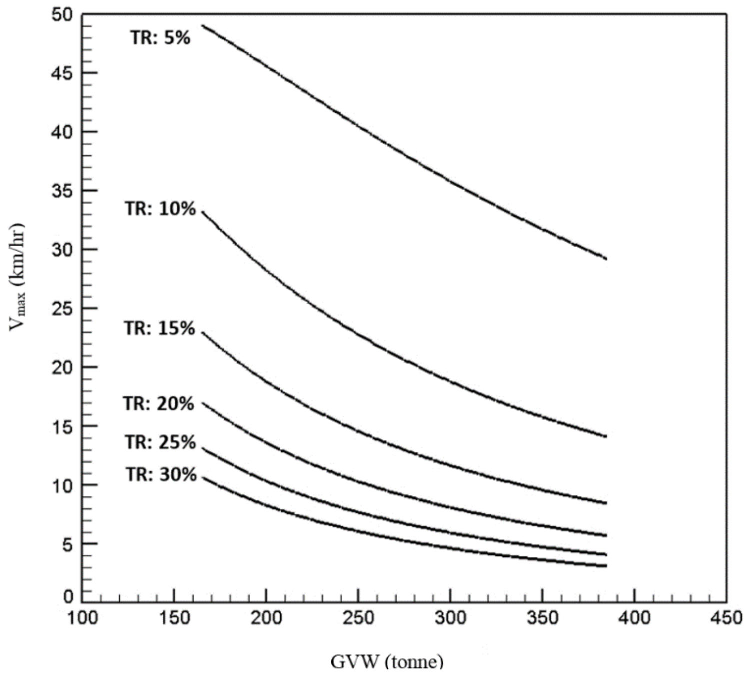

Figure 6-8: Variation of V_{max} with GVW for different TR

Table 6-5 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 Equation 6-3 and by using the values of R and V_{max}. For other values of TR in the range of 5%–30%, FC was calculated versus GVW, as presented in Figure 6-9. 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.

Table 6-5: Fuel Consumption (FC) by CAT 793D for TR=10% ± 0.1 (Sample)

GVW* (tonne)	Rimpull (tonne)	Truck Velocity (km/hr)	Power (kW)	LF	Fuel Consumption (L/hr)
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

* GVW=Payload + Empty Truck Weight

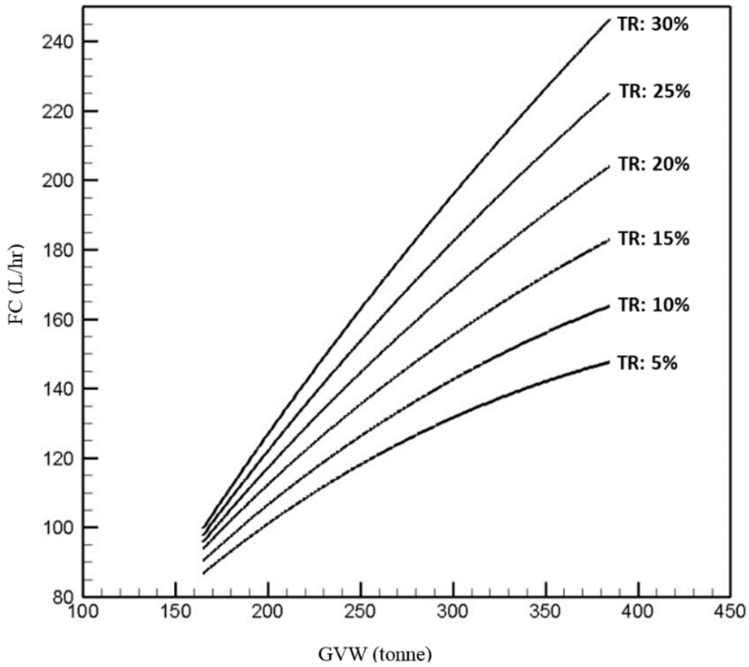

Figure 6-9: Variation of FC with GVW for different TR

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 (see Figure 6-6); 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 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.

6.3 Artificial neural network

6.3.1 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 [193]. 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 (see Figure 6-10).

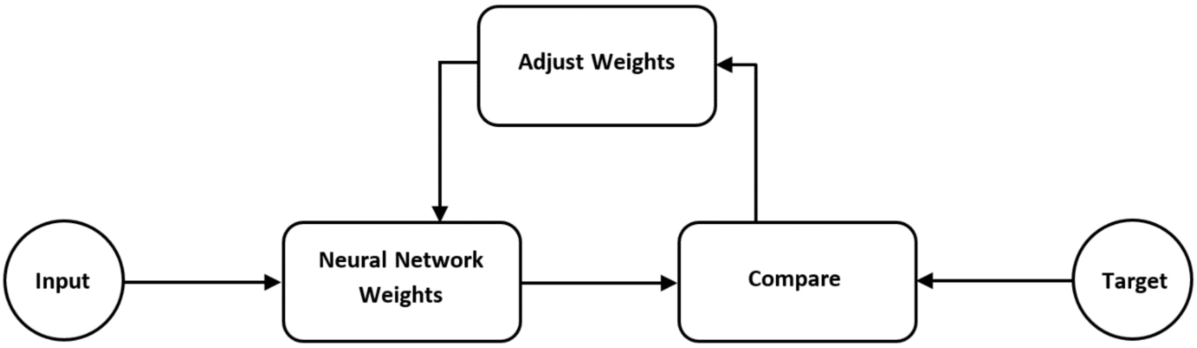

Figure 6-10: A typical procedure of an artificial neural network

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 parameters [194]and do not require the mathematical description of the phenomena involved in the process.

6.3.2 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 Equations 6-8, 6-9, 6-10). Figure 6-11 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).

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

(6-8)

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 $b_{i,k}$. Equation 6-9 can be used as the activation function between the hidden and the output layers (in this equation, f is the transfer function).

$$F_k = f(E_k) \qquad (6\text{-}9)$$

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 Equation 6-10.

$$\text{Out} = (\sum_{k=1}^{m} w_{o,k} F_k) + b_o \tag{6-10}$$

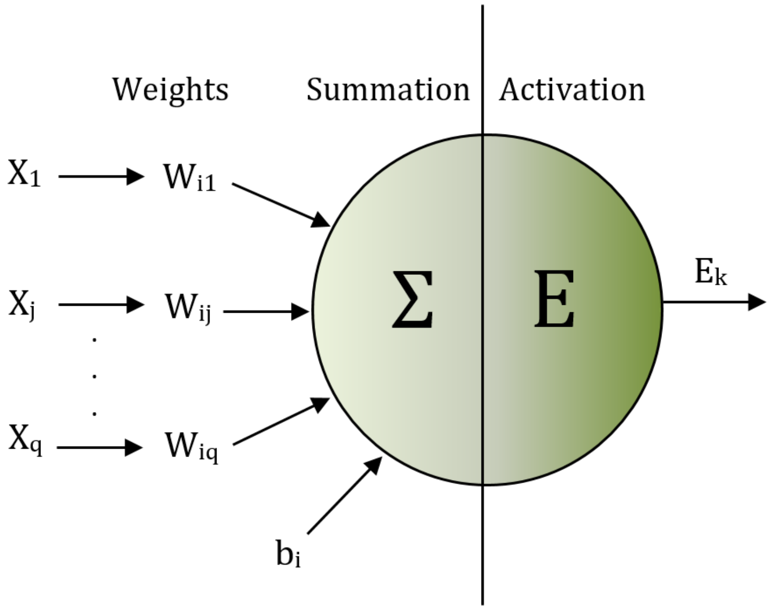

Figure 6-11: Data processing (treatment) in a neural network cell (node)

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 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 [195, 196]:

$$MSE=\frac{1}{p}\sum_{r=1}^{p}(y_r-z_r)^2 \tag{6-11}$$

$$RMSE=(\frac{1}{p}\sum_{r=1}^{p}(y_r-z_r)^2)^{\frac{1}{2}} \tag{6-12}$$

$$R^2=1-\frac{\sum_{r=1}^{p}(y_r-z_r)^2}{\sum_{r=1}^{p}(y_r-\bar{y})^2} \tag{6-13}$$

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 [197, 198].

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.

6.4 Proposed model

6.4.1 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 [199] .

The activation functions in the hidden layer (f) are the continuous differentiable nonlinear tangents sigmoid presented by Equation 6-14.

$$f=\mathrm{tansig}(E)=\frac{2}{1+\exp(-2E)}-1 \tag{6-14}$$

where E can be determined by Equation 6-8.

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 6-6 and Figure 6-12).

Table 6-6: 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

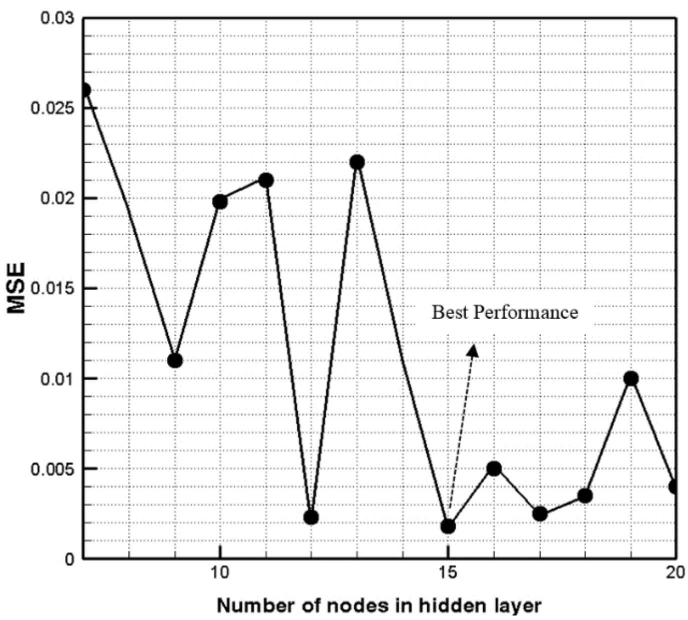

Figure 6-12: The performance of the network at different hidden nodes using LM algorithm

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 Figure 6-13.

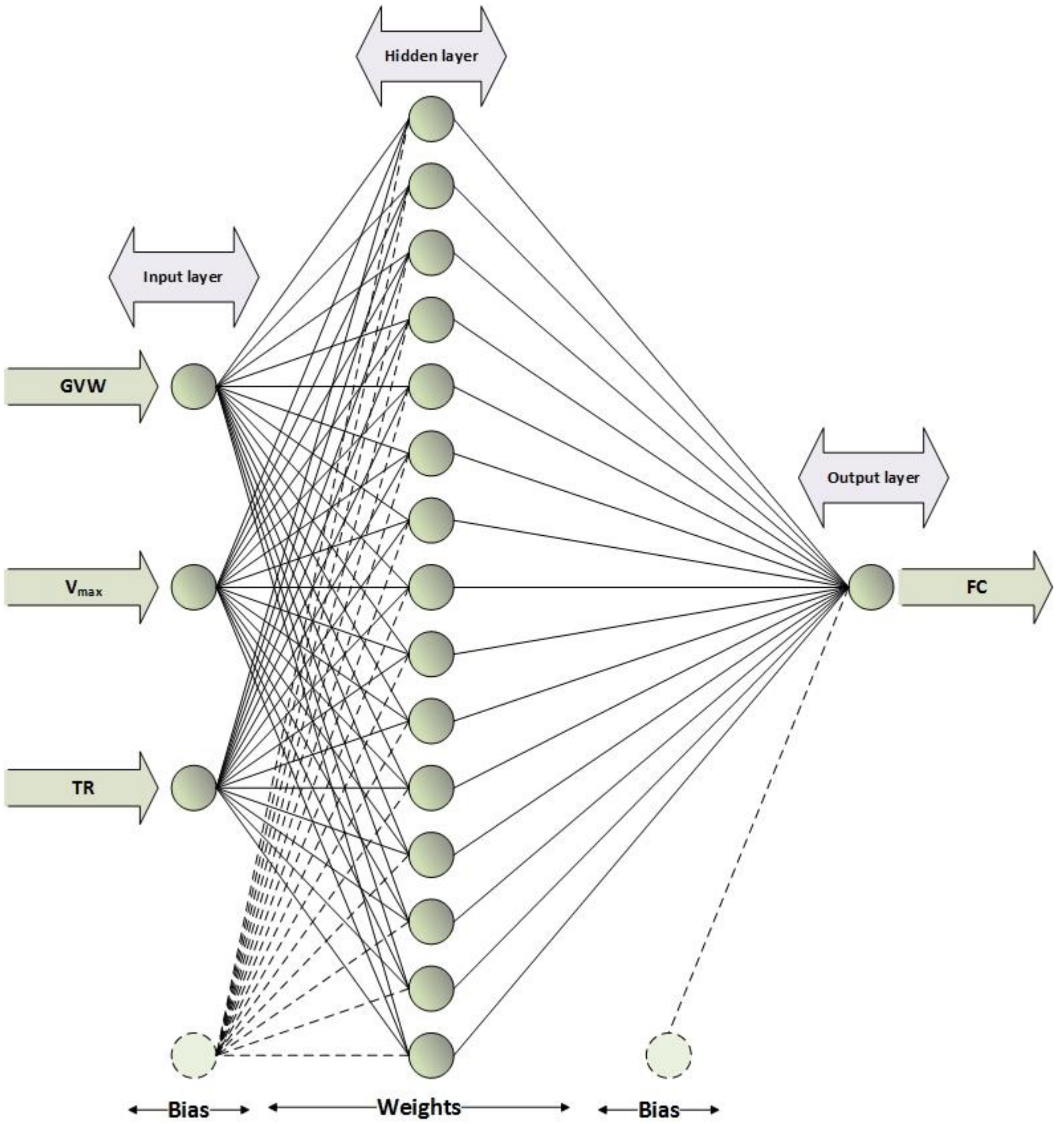

Figure 6-13: Schematic illustration of the designed neural network structure

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 6-7.

Table 6-7: Input and output variables statistical features

Statistical Features	Gross Weight (tonne)	Total Resistance (%)	Maximum Velocity (km/hr)	Fuel Consumption (L/hr)
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

6.4.2 Network training

In order to train the ANN model, 4600 pairing data were randomly selected from the 6630 values of the collected site data (A large surface mine located in central Queensland, Australia). 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 Equation 6-15:

$$FC_n = \sum_{k=1}^{m}\left[w_{o,k}\left(\frac{2}{1+\exp\left(-2\left(\sum_{j=1}^{q}\left(w_{i,j,k}x_j\right)+b_{i,k}\right)\right)}-1\right)\right]+b_o \tag{6-15}$$

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 Equation 15, are presented in Table 6-8.

Table 6-8: Adjustable parameters obtained (weights and bias) in the proposed model

m=15 (k=1… 15), q=3 (j=1, 2, 3)

Weight				Bias	
	$w_{i,j,k}$		$w_{o,k}$	$b_{i,k}$	b_0
$w_{i,1,1}$	$w_{i,2,1}$	$w_{i,3,1}$	$w_{o,1}$	$b_{i,1}$	b_0
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	

Figure 6-14 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.

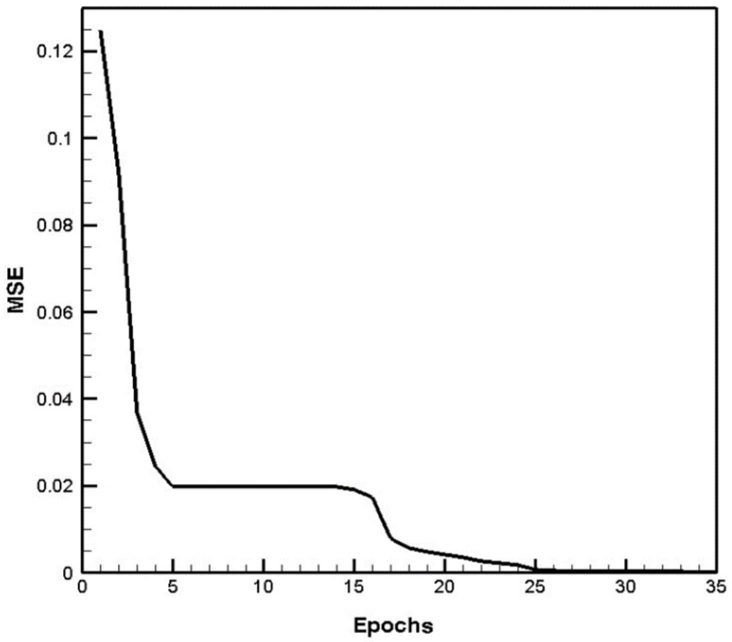

Figure 6-14: Neural network error diagram (MSE) during network training

6.4.3 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:

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

$$x_n = \left(\frac{x - x_{min}}{x_{max} - x_{min}} \times 2 \right) - 1 \tag{6-16}$$

Step 2: Calculating the E parameter for each hidden node

$$E_k = \sum_{j=1}^{q} (w_{i,j,k} x_j + b_{i,k}) \qquad k = 1, 2, ..., 15 \tag{6-17}$$

Step 3: Calculating the F parameters

$$F_k = \frac{2}{1 + \exp(-2E_k)} - 1 \qquad k = 1, 2, ..., 15 \tag{6-18}$$

Step 4: Calculating the normalised fuel consumption FC_n

$$FC_n = (\sum_{k=1}^{15} w_{o,k} F_k) + b_o \tag{6-19}$$

Step 5: Denormalising the fuel consumption

$$FC = 13.61 + \frac{(FC_n + 1)(237.92 - FC_n)}{2} \tag{6-20}$$

6.4.4 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 Figure 6-15 where the vertical and horizontal axes show the estimated fuel consumption values by the model and the actual fuel consumption values, respectively.

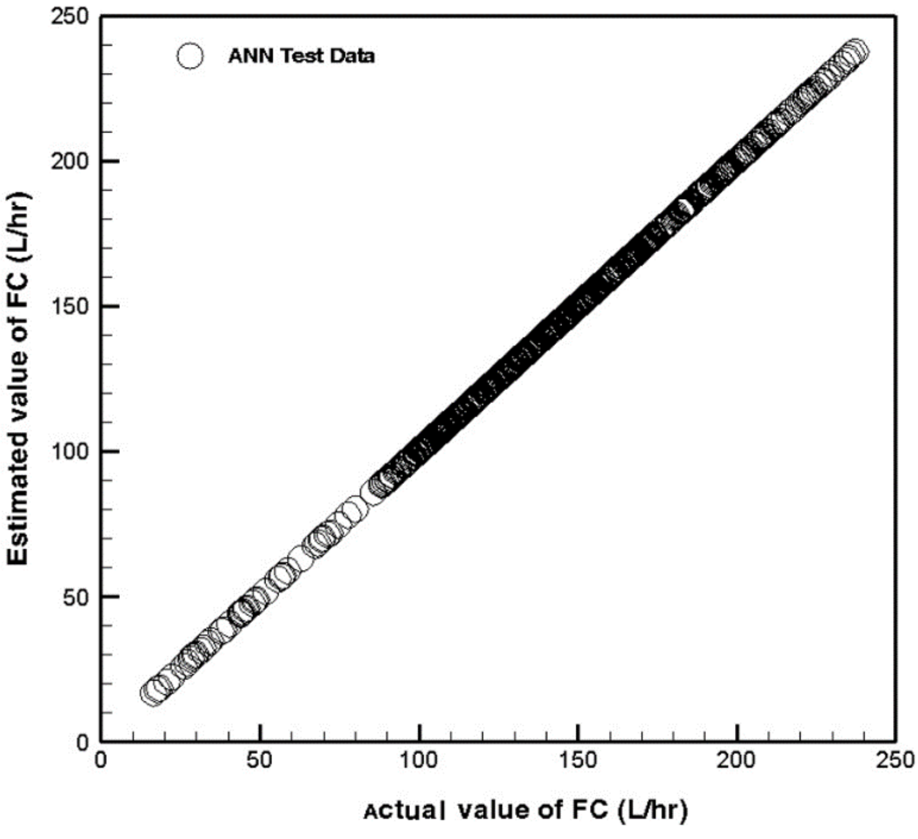

Figure 6-15: Comparison of actual values with network outputs for test data (First quarter bisector)

The results show good agreement between the actual and estimated values of fuel consumption. Table 6-9 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.

Table 6-9: Sample values for estimated (ANN) and independent (Tests) fuel consumption

Estimated value of FC (ANN) (L/hr)	Independent Value of FC (Tests) (L/hr)	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

6.4.5 Sensitivity analysis

To identify the critical parameters and their degree of significance in relation to the outputs of the model, a sensitivity analysis was carried out. There are many methods to assess the relative importance of the input variables in the ANN, such as 'PaD' [204-200] , 'Profile' [205], 'Stepwise' [202] and 'Weight' [206-208]. In this paper, the 'Weight' method, based on the neural net weight matrix and the Garson equation [205] was utilised. Garson proposed an equation based on the partitioning of connection weights, as illustrated in Equation (6-21):

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

(6-21)

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) (see Figure 6-16). $Q_{j,r}$ 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 [207].

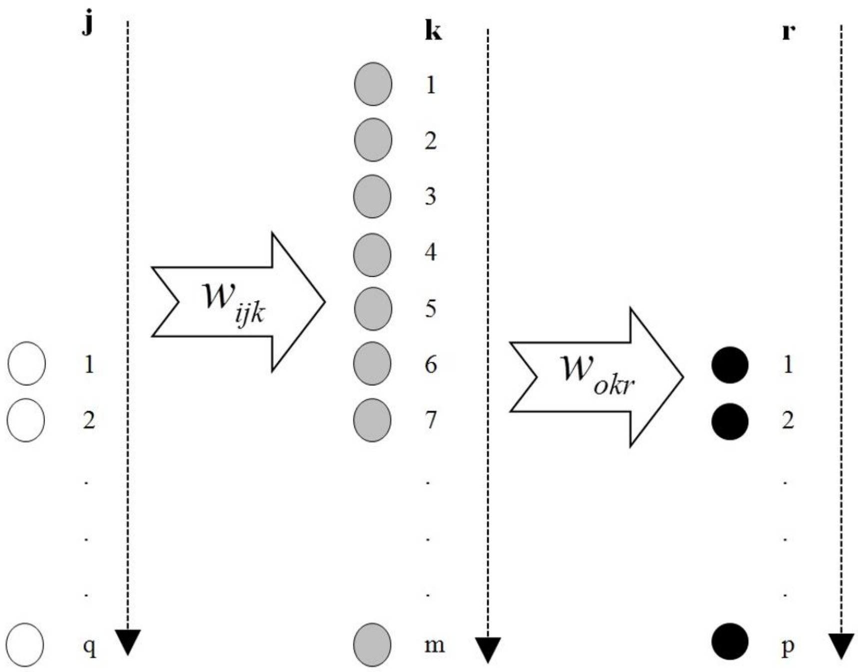

Figure 6-16: Weight method structure for sensitivity analysis

Table 6-10 presents the relative importance of the input variables calculated by Equation 6.21 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.

Table 6-10: 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

6.5 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.

Soofastaei, A., Aminossadati, S.M., Kizil, M.S. and Knights, P.,
Reducing Fuel Consumption of Haul Trucks in Surface Mines Using Genetic Algorithm. Applied Soft Computing, (2016).

Abstract

This paper aims to develop a comprehensive model based on artificial intelligence methods for reducing fuel consumption by surface mine haul trucks. Truck payload, speed and the haul road total resistance are key parameters that affect fuel consumption. The relationship between the key parameters and the haul truck fuel consumption is determined using an Artificial Neural Network (ANN) model. The ANN model is trained and tested using real data collected from a large surface mine in central Queensland, Australia. A fitness function for the haul truck fuel consumption is successfully generated by the ANN model. This function is utilised to generate a computerised learning algorithm based on a novel multi- objective genetic algorithm and estimate the optimum values of effective haulage parameters to reduce the diesel fuel consumption by haul trucks in surface mines. [209]

Keywords: Energy Efficiency; Haul Truck; Surface Mine; Genetic Algorithm

CHAPTER 7

7. Reducing Fuel Consumption of Haul Trucks in Surface Mines Using Genetic Algorithm

7.1 Introduction

The Mining industry consumed 450 PJ of energy in 2011-12 or 11% of the national energy end use in Australia [150]. Energy consumption and intensity in mining is rising at around 6% annually in Australia due to lower grade ores, located deeper underground [150]. Similar statistics are observed in other developed countries [210]. Mining operations use energy in a variety of ways, including excavation, material transfer, ventilation and dewatering [3]. Based on completed industrial projects, significant opportunities exist within the mining industry to reduce energy consumption [3]. The potential for energy savings has motivated both the mining industry and governments to conduct research into the reduction of energy consumption [2].

In surface mines, the most commonly used means of mining and hauling of materials is via a truck and shovel operation [39, 119]. The trucking of overburden constitutes a major portion of energy consumption [2]. The rate of energy consumption is a function of a number of parameters. The research presented by Carmichael et al.[115] is concerned with the effects of the geology of the site, the density of the load, road surfaces and gradients on the energy consumption of haul trucks. Cetin [127] examined the relationship between haul truck energy efficiency and loading rates, vehicle efficiency, and driving practices [127]. Beatty and Arthur [39] investigated the effect of some general parameters, such as cycle time and mine planning, on the energy consumed by haul trucks. They determine the optimum values of these parameters to minimise fuel consumption in hauling operations. The study conducted by Coyle [105] is concerned with the effects of payload on truck fuel consumption. In this study he shows the effect of load density variation based on the blasting procedures on fuel consumption by haul trucks.

To the authors' best knowledge, the studies reported in the literature are based mainly on the theoretical models used to calculate the fuel consumption of haul trucks. These models work based on the Rimpull-Speed-Grad curve prepared by the truck manufacturer for the performance of trucks [119, 120, 211-214].

In the present study, 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 above mentioned parameters 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 based on a comprehensive dataset collected from a large coal surface mine in Central Queensland, Australia. The model can estimate the energy consumption of one type of haul truck in surface mines using an Artificial Neural Network (ANN) and can also find the optimum value of P, S and TR using a Genetic Algorithm (GA).

7.2 Calculation of haul truck fuel consumption

Haul truck fuel consumption is a function of a number of parameters. Figure 7-1 presents a schematic diagram of a typical haul truck and the key parameters that affect the performance of the truck.

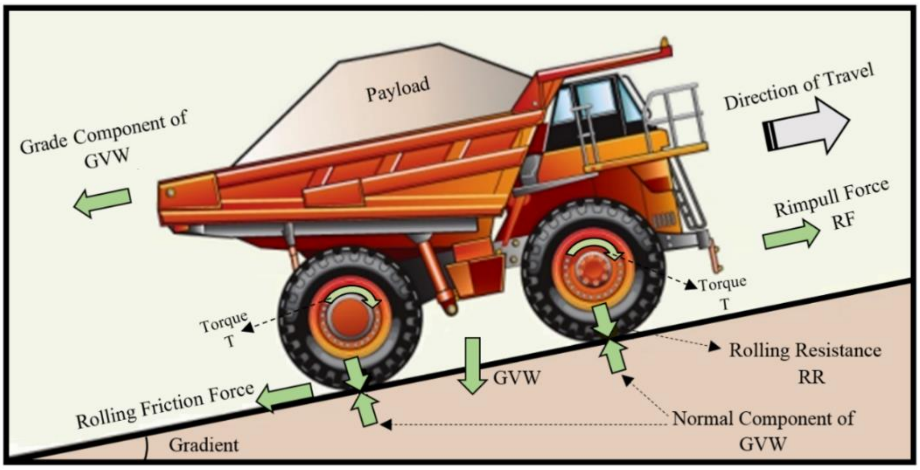

Figure 7-1: A schematic diagram of a haul truck and effective key parameters

In the present study, the effects of the P, S and TR on the fuel consumption of haul trucks were examined. The TR is equal to the sum of the rolling resistance (RR) and the grade resistance (GR) when the truck is moving against the grade of the haul road [37].

$$\mathrm{TR} = \mathrm{RR} + \mathrm{GR} \tag{7-1}$$

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 (see Figure 7-2) [49].

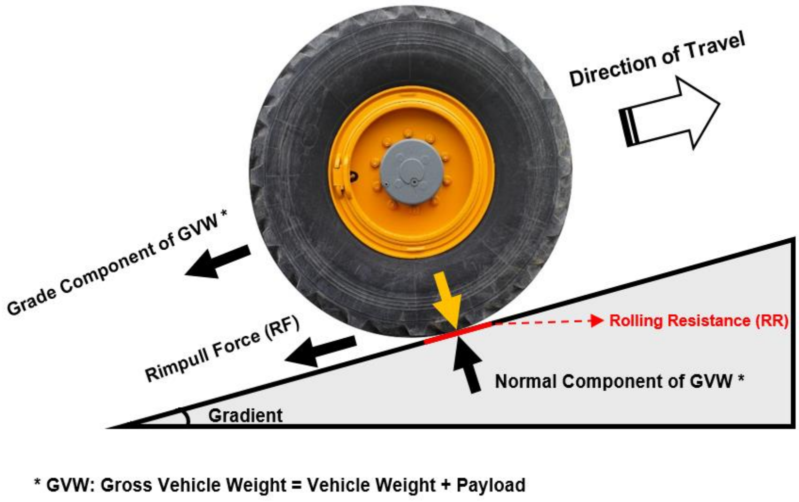

Figure 7-2: A schematic of haul truck tyre showing the Rolling and Grade Resistance (RR & GR)

The truck Fuel Consumption (FC) can be calculated from Equation 7-2 (Filas [191]):

$$FC = \frac{SFC}{FD}\,(LF.\,P_o) \tag{7-2}$$

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 7-3 is presented by Runge [118]:

$$FC = 0.3\,(LF.\,P) \tag{7-3}$$

where LF is the engine Load Factor and is defined as the ratio of average payload to the maximum load in an operating cycle [113]. The typical values of LF are presented in Table 7-1 [37]. P_o is the truck power (kW) and it is determined by:

$$P_o = \frac{1}{3.6}\,(RF\,.\,S) \tag{7-4}$$

Table 7-1: 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

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

7.3 Data collection

In this study, a completed dataset by mine engineers in a large coal surface mine in Australia collected from 01/07/2013 to 20/10/2014 was analysed to create all models presented in this paper. The real dataset includes 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 793D rigid body trucks. A sample of dataset is presented in Table 7-2. The collected data has been measured by a Vehicle Information Management System.

Table 7-2: A sample of real dataset collected from a surface coal mine in Queensland, Australia (01/07/2013 – 20/10/2014)

Date	Payload (tonne)	Average Truck Speed (km/hr)	Cycle Time (hh:mm:ss)	Cycle Distance (km)	Rolling Resistance (%)	Grade Resistance (%)	Total Resistance (%)	Fuel Consumption (L/hr)
23/01/2013	218.6	8.5	00:25:35	4.9	3.0	12.0	15.0	84.0
15/02/2013	219.4	11.5	00:16:17	5.1	3.0	9.0	12.0	90.0
13/03/2013	168.2	11.0	00:11:12	2.4	3.0	10.0	13.0	90.0
29/03/2013	158.9	14.0	00:17:42	5.1	3.0	9.0	12.0	94.0
22/04/2013	216.5	10.0	00:19:17	5.3	3.0	10.0	13.0	88.0
08/05/2013	202.1	12.0	00:18:45	5.3	3.0	9.0	12.0	91.0
25/06/2013	185.5	11.5	00:16:24	4.0	3.0	10.0	13.0	90.0
16/08/2013	175.9	12.0	00:18:48	4.6	3.0	10.0	13.0	91.0
07/10/2013	147.6	13.0	00:22:23	5.3	3.0	10.0	13.0	93.0
19/12/2013	214.3	11.5	00:17:55	5.1	3.0	9.0	12.0	90.0

VIMS is an electronic package consisting of a main processor and a network of sensors installed on all new Caterpillar equipment to generate a wide range of data to manage the performance of a given machine. In fact, today's CAT equipment generates huge volumes of data that help miners to monitor machine health and condition, track equipment hours and usage, optimise work flows and production cycles, maximise equipment uptime and finally, reduce costs per tonne [112].

The surface mine under study is located in central Queensland, Australia. Operational hours for this mine are around 5000 per year. This mine has 4 haulage routes and 2 ramps. The length of the longest ramp is 3 km. The width of the haul road is 35 m and the horizontal haulage distance is 60 m In-Pit and 120 m Ex-Pit. The truck down ramp speed is limited to 30 km/h due to safety considerations.

The relationship between truck fuel consumption and selected parameters in this study (P, S and TR) is complex and requires an artificial intelligence method to determine. The next section of this paper contains the details of an ANN model that was developed to determine how the truck fuel consumption varies with the variation of these parameters.

7.4 Estimation of haul truck fuel consumption

7.4.1 Artificial neural network model

Artificial Neural Networks (ANNs) are a popular artificial intelligence method to simulate the effect of multiple variables on one major parameter by a fitness function. 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 [50, 59-61, 63], biochemical engineering [65], medicine [66] and mechanical engineering [67, 68, 215]. 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 ANNs is that they can simulate both linear and nonlinear relationships between parameters, using the information provided to train the network. ANNs, also known as parallel distributed processing, are the representation of methods that the brain uses for learning [68]. They are a series of mathematical models that imitate a few of the known characteristics of natural nerve systems and draw 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. ANNs are utilised in various computer applications to solve complex problems.

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

7.4.2 Developed model

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 activation functions in the hidden layer (f) are the continuous differentiable nonlinear tangents sigmoid presented in Equation 7-5.

$$f = \tan\text{sig}(E) = \frac{2}{1+\exp(-2E)} - 1 \qquad (7\text{-}5)$$

Where E can be determined by Equation 7-6.

$$E_k = \sum_{j=1}^{q} (w_{ijk} x_j + b_{ik}) \qquad k = 1, 2, ..., m \tag{7-6}$$

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.

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

$$F_k = f(E_k) \tag{7-7}$$

The output layer computes the weighted sum of the signals provided by the hidden layer and the associated coefficients. The network output can be given by Equation 7-8.

$$Out = (\sum_{k=1}^{m} w_{ok} F_k) + b_o \tag{7-8}$$

In order to find the optimal number of nodes in the hidden layer, Mean Square Error (MSE) and Coefficient of Determination (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 10 nodes in the hidden layer (Table 7-3).

Table 7-3: 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	0.3377	0.9999
2	0.0631	1.0000
3	0.0301	1.0000
4	0.0212	1.0000
5	0.0181	1.0000
6	0.0156	1.0000
7	0.0145	1.0000
8	0.0170	1.0000
9	0.0164	1.0000
10	0.0101	1.0000
11	0.0150	1.0000
12	0.0129	1.0000
13	0.0323	1.0000
14	0.0147	1.0000

The schematic structure of the designed neural network based on three input variables, ten nodes in the hidden layer and one output is shown in Figure 7-3.

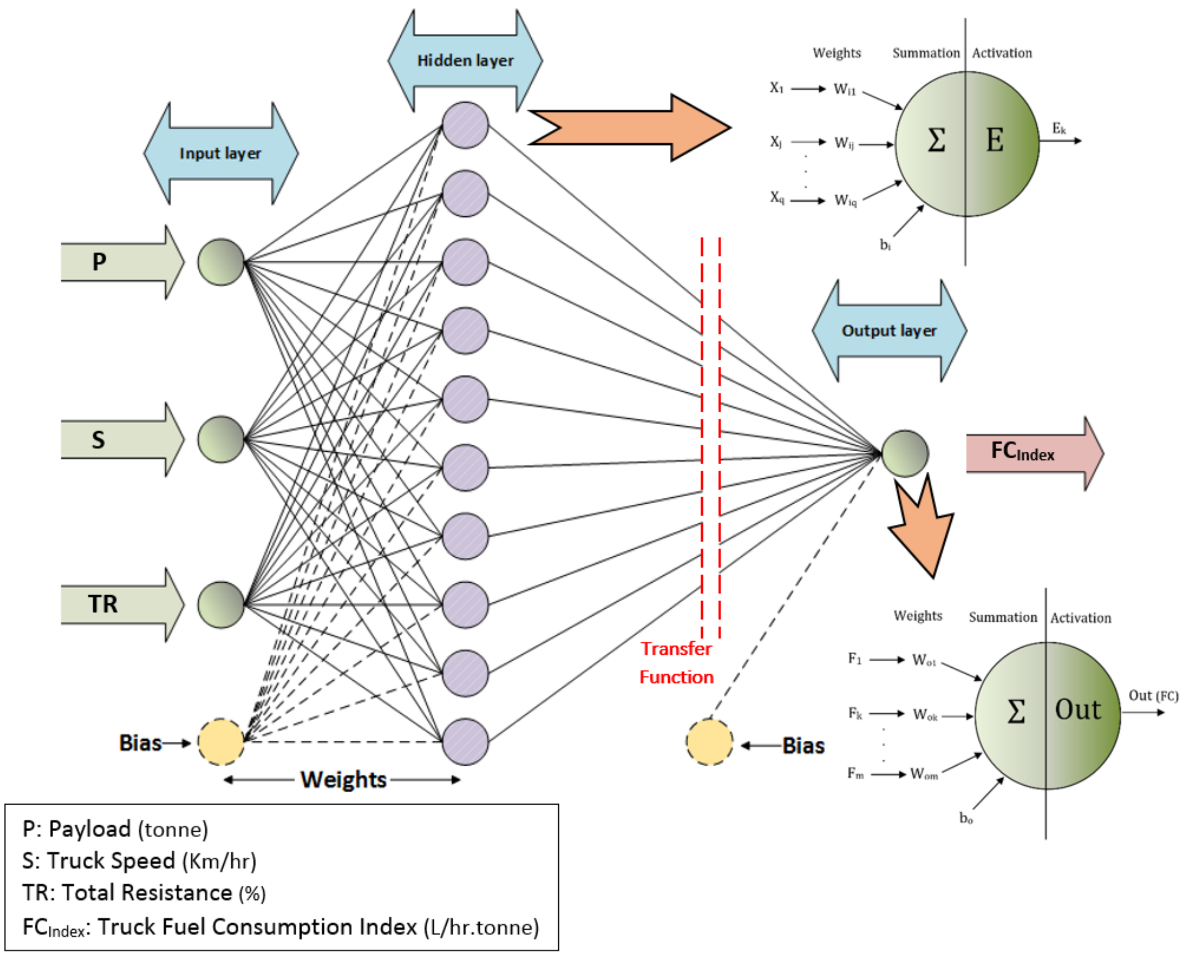

Figure 7-3: Schematic illustration of the designed ANN structure

7.4.3 ANN training and validation

In order to train the proposed ANN model, 8300 pairing data were randomly selected from the 16500 values of the collected site data. In order to test the network accuracy and validate the model, 8200 independent samples were used. All collected datasets had more than 100 columns of data for about 85 parameters. Selection data process was completed based on the scope of project. The results show good agreement between the actual and estimated values of fuel consumption. The test results of the synthesised network are shown in Figure 7-4 where the vertical and horizontal axes show the actual fuel consumption values and the estimated fuel consumption values by the model, respectively.

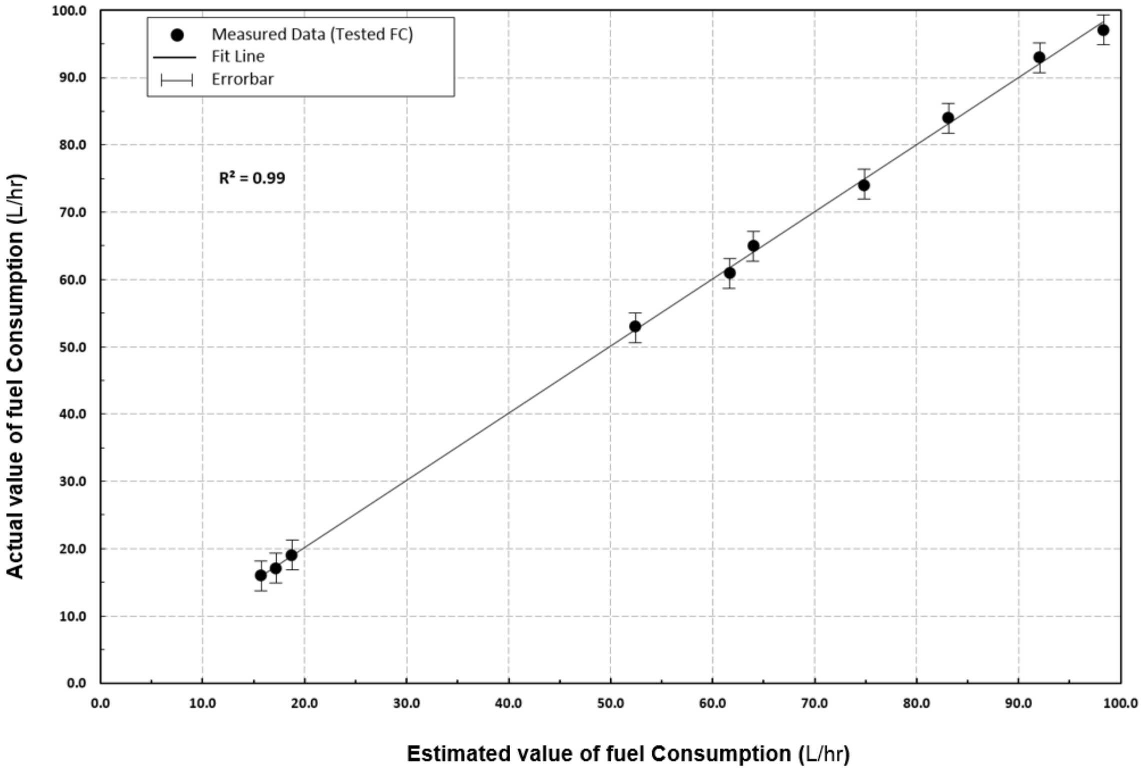

Figure 7-4: Comparison of actual values with estimated value of haul truck fuel

Table 7-4 presents sample values for the estimated (using the ANN) and the actual (tested) haul truck fuel consumption in order to highlight the insignificance of the values of absolute error in the analysis.

Table 7-4: Sample values for estimated (ANN) and actual (Tests) haul truck fuel consumption

Estimated value of FC (ANN) (L/hr)	**Actual value of FC (Tests) (L/hr)**	**Absolute error (%)**
15.75	16.00	1.58
18.75	19.00	1.33
17.20	17.00	1.16
52.45	53.00	1.05
61.70	61.00	1.13
64.00	65.00	1.56
74.85	74.00	1.13
83.10	84.00	1.08
92.00	93.00	1.09
98.31	97.00	1.33

7.4.4 Network application

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

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

$$x_n = \left(\frac{x - x_{min}}{x_{max} - x_{min}} \times 2 \right) - 1 \tag{7-9}$$

Step 2: Calculating the E parameter for each hidden node

$$E_k = \sum_{j=1}^{q} (w_{i,j,k} x_j + b_{i,k}) \qquad k = 1,2,...,15 \tag{7-10}$$

Step 3: Calculating the F parameters

$$F_k = \frac{2}{1 + \exp(-2E_k)} - 1 \qquad k = 1,2,...,15 \tag{7-11}$$

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

$$FC_{Index(n)} = (\sum_{k=1}^{15} w_{o,k} F_k) + b_o \tag{7-12}$$

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

$$FC_{Index} = 13.61 + \frac{(FC_n + 1)(237.92 - FC_n)}{2} \tag{7-13}$$

7.4.5 Network results

Figure 7-5 illustrates the correlation between P, S, TR and FC_{Index} created by the developed ANN model for a normal range of payloads.

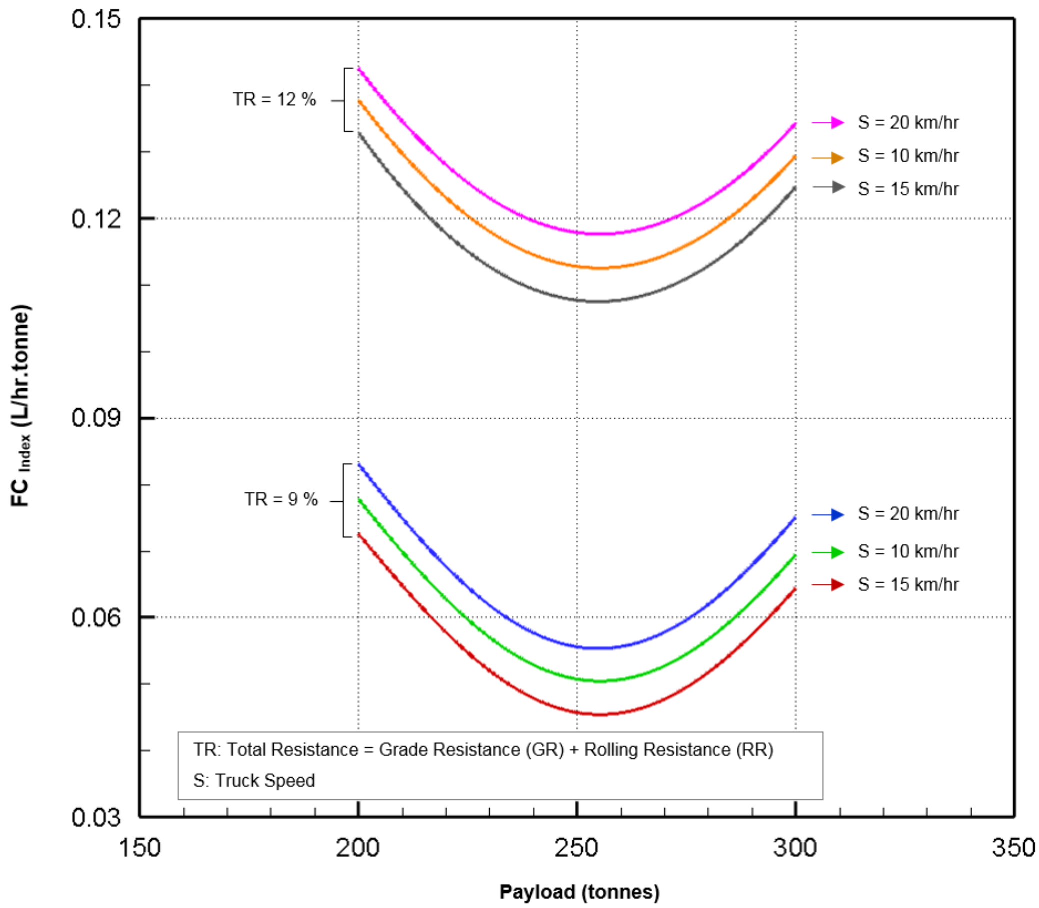

Figure 7-5: Correlation between P, S, TR and FC_{Index} based on the developed ANN model

The presented graph shows 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 S. The developed model also shows that the value of FC_{Index} changes by variation of S and P but there is no clear relationship between all effective parameters and fuel consumption. Therefore, completing another artificial intelligence method is essential to finding the optimum value of the selected effective parameters in order to minimise the haul truck fuel consumption.

7.5 Optimisation of effective parameters on haul truck fuel consumption

7.5.1 Optimisation

Optimisation is a part of computational science that is very effective way to find the best measurable solution for problems. To solve the problems, it is important to consider two components. The first one is search area and the second one is objective function. In the search area, all the possibilities of solution are considered and the objective function is a mathematical function that associates each point in the solutions area to a real value, applicable to evaluate all the members of the search area. Solving the complex computational problems has been a constant challenge in Engineering. Traditional optimisation methods are characterised by the stiffness of its mathematical models that they are very difficult to represent of real dynamic and complex situations (Stiffness mathematical model means non-dynamic and flexible model). Introducing the optimisation techniques based in Artificial Intelligence, as the heuristic search based ones, has reduced the problem of stiffness. Heuristic rules can be defined as practical rules, derived from the experience and observation of behaviour tendencies of the system in analysis. They are appropriate to solve all types of problems in engineering. Using analogies with nature, some heuristic algorithms were proposed during the 50s by trying to simulate biological phenomena in engineering. These algorithms, called Natural Optimisation Methods. One of the best advantages of using the mentioned algorithms is their random characteristic. By developing the computers during the 80s, the use of these algorithms for optimisation of functions and processes became practicable, when traditional methods were not successful in this area. During the 90s some new heuristic methods created by the previous completed algorithms, as Swarm Algorithms, Simulated Annealing, Ant Colony Optimisation and Genetic Algorithms.

7.5.2 Genetic algorithms

Genetic Algorithms (GAs) were proposed by Holland in 1975 as an abstraction of biological evolution, drawing on ideas from natural evolution and genetics for the design and implementation of robust adaptive systems [216]. The new generation of genetic algorithms are comparatively recent optimisation methods. They do not use any information of derivate, therefore, they have good chances of escape from local minimum. Their application in practical engineering problems generally brings to global optimal, 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. GAs have been applied to a diverse range of scientific, engineering and economic problems [63, 67, 216-218] due to their potential as optimisation techniques for complex functions. There are four major advantages when applying genetic algorithms 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 us with great flexibility to hybridize with domain dependent heuristics to allow an efficient implementation for a specific problem. Besides of genetic operators, 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 7-5.

Table 7-5: Genetic algorithm Parameters

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.

7.5.3 Developed model

In this project, a GA model was developed to improve three key effective parameters on the energy consumption of haul trucks. In this model P, S and TR are the individuals and the main function for optimisation of the fitness function is fuel consumption (Equation 7-12). In this model the fitness function was created by the ANN Model. All GA processes in the developed model are illustrated in Figure 7-6. In this model seven main processes were defined.

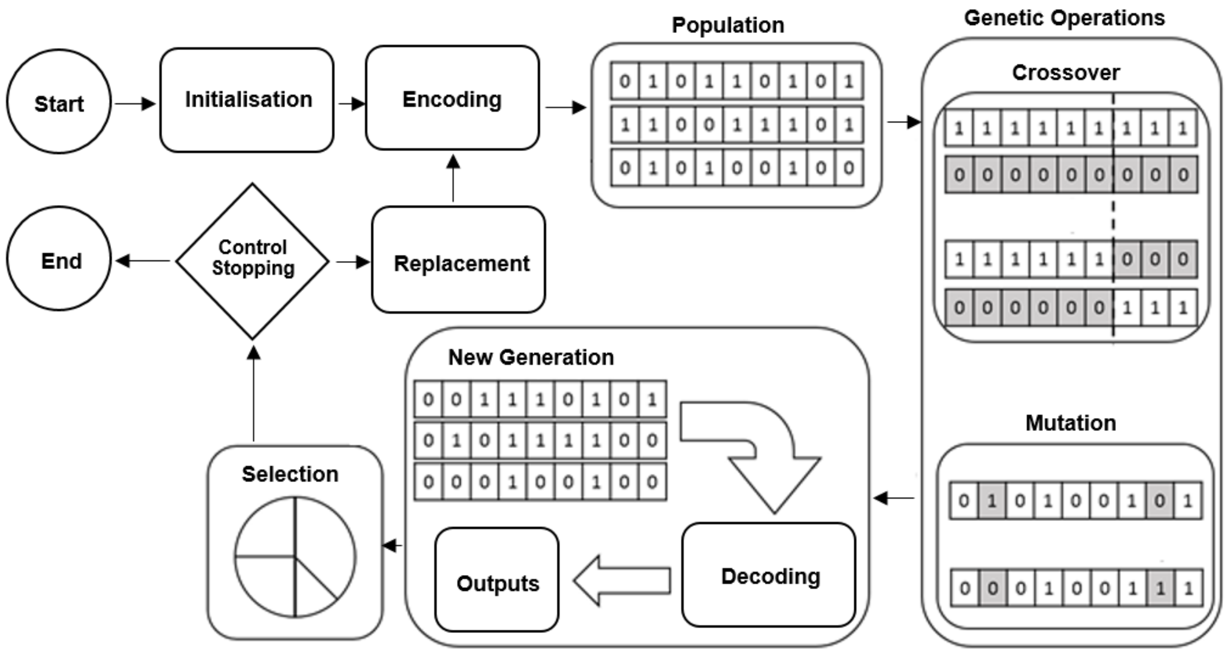

Figure 7-6: Genetic algorithm processes (Developed Model)

These processes are initialisation, encoding, crossover, mutation, decoding, selection, and replacement. The details of the above mentioned processes are presented in Table 7-6.

Table 7-6: Genetic algorithm processes

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

Technical details of the developed model are presented in Table 7-7.

Table 7-7: Technical details of genetic algorithm developed model

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

These parameters were defined based on the presented results in similar completed projects reviewed in this study. In this project, the completed ANN and GA model were developed by writing computer code in MATLAB software. P, S and TR are inputs of the code in first step. The completed code creates the fitness function based on the developed ANN model. This function is a correlation between the fuel consumption of the haul truck, P, 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 P, 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 a large surface mine in Australia, but the completed methods can be developed for other surface mines by replacing the data.

7.5.4 Results and discussions

The first step of running the developed GA model is defining the minimum and maximum values of all variables (individuals). The range of possible values for variables in the developed model is based on the collected dataset and presented in Table 7-8.

Table 7-8: The range of possible values for variables in developed model

Variables	Minimum	Maximum
Payload (P)	140 tonne	310 tonne
Total Resistance (TR)	8 %	15 %
Speed (S)	7 km/hr	30 km/hr

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 (see Figure 7.7).

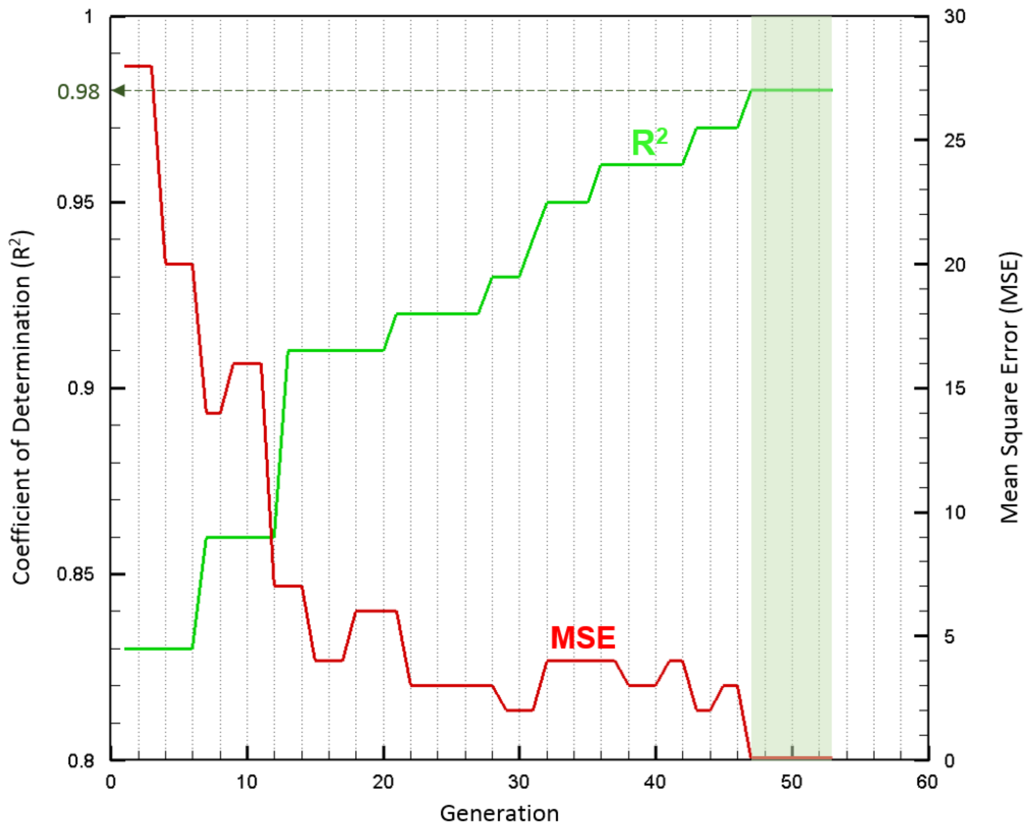

Figure 7-7: The coefficient of determination and mean square error for all generations

Figure 7-8 demonstrates the variation of these parameters in generations.

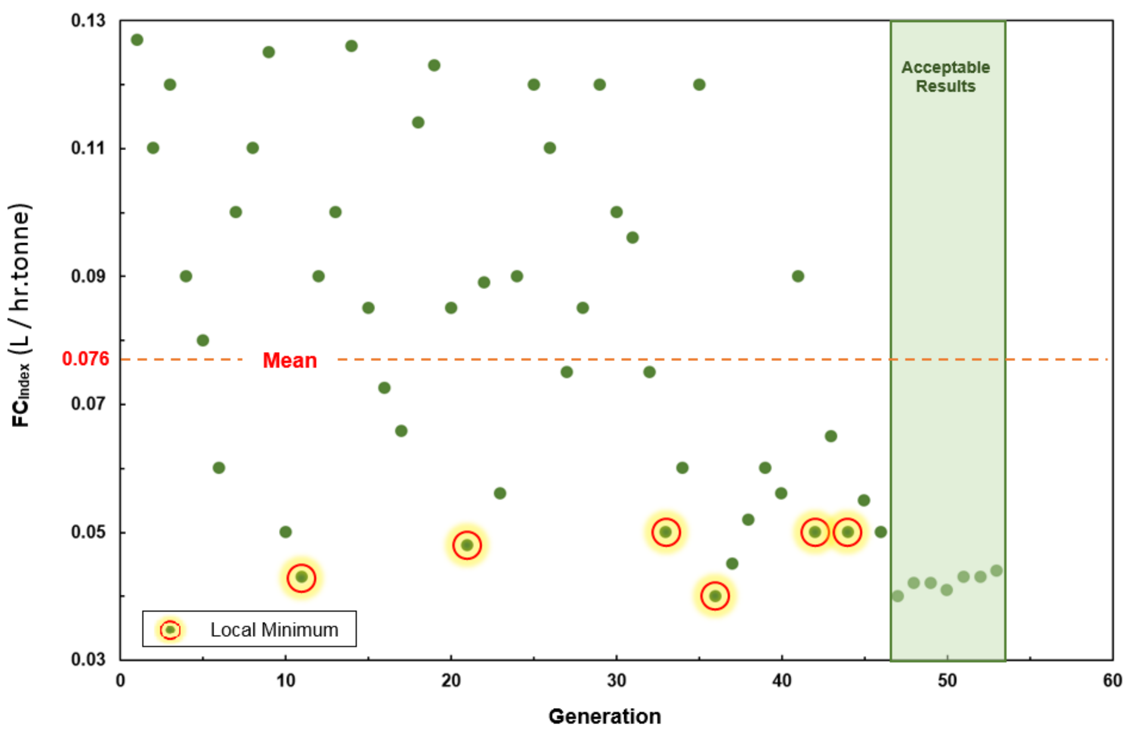

Figure 7-8: Fuel Consumption (Fitness Value) in all generations

The value of MSE was 0 and the value of R^2 was about 0.98 after the 47th generation. These values were not changed until the GA model was stopped in the 53rd generation. Also, the values of control parameters were constant after the 47th generation, but the model continued all processes until the 53rd. That is because a confidence interval was defined for the model to find reliable results. The value of the fitness function or FC_{Index} in all generations has been demonstrated in Figure 7-8. The simulated value of the fuel consumption of haul trucks varies between 0.03 and 0.13 L/(hr. tonne). The mean of the calculated results is 0.076 L/(hr. tonne) and more than 45% of results are located above the average line. The presented model could find some local minimised fuel consumption but the acceptable results can be found after the 47th generation. Figure 7-8 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 P, S and TR in the studied mine site, the minimum FC_{Index} for the CAT 793D is about 0.04 L/hr. tonne. The optimum range of variables to minimise fuel consumption by the selected haul truck in this case study is tabulated in Table 7-9.

Table 7-9: Optimum range of variables to minimise fuel consumption by haul trucks (GA Model)

Variables	Minimum	Maximum
Payload (P)	250 tonne	270 tonne
Total Resistance (TR)	8.5 %	9 %
Speed (S)	13 km/hr	15 km/hr

The results showed that the best value of payload for the CAT 793D in this mine is between 250 and 270 tonnes. This value of payload is close to the recommended value supplied by the manufacturer (Caterpillar) for this type of truck. The speed of the truck depends on different kinds of parameters such as safety, weather conditions, driver skill etc. The developed model recommends a truck speed between 13 and 15 km/hr for the CAT 793D in the analysed mine site. Driving in the recommended range of truck speeds can reduce the fuel consumption of haul trucks in this surface mine. Based on the data analysed by the GA model, the optimum range of TR to minimise the FC_{Index} is between 8.5% and 9%. This range of TR is achievable by changing the grade or rolling resistance in the studied mine site.

7.6 Conclusions

The aim of this study was to develop a GA model to improve haul truck fuel consumption based on the relationship between P, S 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, an ANN model was developed to find a correlation between P, S and TR with fuel consumption. The results showed that fuel consumption has a nonlinear relationship with the investigated parameters. The ANN was trained and tested using the collected real mine site dataset and the results showed that there was good agreement between the actual and estimated values of fuel consumption. In the last part of the study, to minimise the energy efficiency in haulage operations, a GA model was developed. The results showed that by using this model, optimisation of the effective parameters on energy consumption was possible. The developed model could estimate the local minimums for the fitness function. The presented genetic algorithm model 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 results showed that the best value of payload for the CAT 793D in this mine is between 250 and 270 tonnes. The developed model recommends a truck speed between 13 and 15 km/hr for the CAT 793D in the analysed mine site. Driving in the recommended range of truck speeds can reduce the fuel consumption of haul trucks in this surface mine. Based on the data analysed by the GA model, the optimum range of TR to minimise the FC_{Index} is between 8.5% and 9%.

Chapter 8

8. Conclusions and Recommendations

8.1 Conclusions

This research thesis aimed to develop an advanced data analytics model to improve energy efficiency for haul trucks in surface mines. This model consisted of Artificial Intelligence methods for developing a fitness function for haul truck fuel consumption, and optimising the important controllable parameters that result in minimum fuel consumption. In order to enhance the analysis, the effects of payload variance and rolling resistance on fuel consumption and gas emissions were investigated. In addition, the effect of truck bunching on cycle time, hauled mine materials and fuel consumption were examined. All completed models in this thesis were validated by collected data from four open-cut (coal0mines and four open-pit (Copper) mines in Australia and United States. All presented case studies were completed by collected data from surface mines and validations were completed for similar type of mines as well.

A comprehensive literature review was conducted on energy efficiency opportunities in mining industry, haul truck fuel consumption, Artificial Neural Network (ANN) and Genetic Algorithm (GA). The research on haul truck fuel consumption resulted in identifying the key parameters affecting the haul truck fuel consumption. An online survey was also conducted to identify the most important controllable parameters, namely payload, truck speed and total resistance. In this survey, 50 personnel from five surface mines in Australia and The United State were contacted with 63% response rate. The research on ANN and GA proved that ANN could be used to develop the fitness function for truck fuel consumption, and GA could be used to optimise the selected key parameters for minimising the fuel consumption.
(Chapter 2, Literature review).

The effects of payload variance on fuel consumption, greenhouse gas emissions and their associated cost in surface mining operations were examined. CAT 793D truck, one of the mostly used haul trucks in surface mines, was considered for the analysis. Based on the technical specifications of this truck, the variation range of payload was 0-30%. The correlations for the maximum truck speed and fuel consumption were determined by digitising Rimpull-Speed-Grade ability curve using DataThief®

software. The costs of consumed fuel and greenhouse gas emissions were determined based on models developed by US Energy Information Administration. The results showed that the fuel consumption, rate of greenhouse gas emissions and their costs non-linearly increase as the payload variance rises for all haul road conditions. The correlation between the payload variance and cost saving was also developed. This correlation presented the cost saving for different payload variance reductions regardless of haul road conditions. Real site data from a mine in Australia were used to test the correlation model. The results of this simulation indicated that there was a considerable cost saving opportunity by reducing the payload variance in surface mines.
(Chapter 3, Payload variance).

The payload variance is one of the main reasons for haul trucks to travel with different speeds causing truck bunching in large surface mines. An innovative model was developed to examine the relationship between truck bunching and payload variance. The effect of truck bunching on cycle time, hauled mine materials and fuel consumption was then examined. To validate the developed model, a dataset collected from a large surface mine in Arizona, USA was used. Validation of the model was completed for the cycle time and the hauled mine materials by one type of truck (CAT 793D). The results indicated a good agreement between the actual and estimated values of cycle time and hauled mine materials. The model was utilised in a real mine site for three models of haul truck in Australia as a case study. The results indicated that there was a non-linear relationship between payload variance and cycle time in the fleet for all considered truck models.
(Chapter 4, Truck bunching).

The most influential parameters on haul road total resistance were determined based on a comprehensive literature review. An on-line survey was conducted in order to determine the most influential parameters on the rolling resistance. In this survey, 45 industry personnel from four mines were contacted with a 76% response rate. The results of the survey revealed that the road maintenance, the tyre pressure and the truck speed were the most important effective parameters on the rolling resistance. The effects of these three parameters on haul truck fuel consumption in a real mine site located in central Queensland, Australia were investigated. The non-linear relationships between the selected parameters in the survey and the fuel consumption in the considered mine site were developed. The results indicated that the truck fuel consumption decreased as the maintenance interval and truck speed decreased and tyre pressure increased.
(Chapter 5, Haul road total resistance).

The relationship between truck fuel consumption and pertinent parameters (payload, truck speed and total resistance) is complex. This was concluded based on the real dataset obtained from surface mining operations. Therefore, an Artificial Neural Network (ANN) model was developed to simulate truck fuel consumption as a function of payload, truck speed and total resistance. This model was trained based on the truck's best performance characteristics using real values from a surface mine in Australia. The model was tested using the remaining values of the collected dataset. The results showed that there was good agreement between the actual and estimated values of fuel consumption. The sensitivity analysis showed that all the three input parameters significantly affected the truck fuel consumption. It was also found that the truck speed was 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.
(Chapter 6, Artificial neural network).

The fitness function for the truck fuel consumption generated by ANN was used in the development of a Genetic Algorithm (GA) model for minimising the haul truck fuel consumption based on the optimised values of payload, truck speed and total resistance. It was evident that the developed model could estimate the local minimums for the fitness function. The GA model identified the acceptable ranges of payload, truck speed and total resistance that result in minimum truck fuel consumption.
(Chapter 7, Genetic algorithm).

The developed methodology in this thesis (use of ANNs followed by optimisation using GAs) is widely applicable to other data analytics problems.

8.2 Recommendations for future works

- Investigation of the incorporation of additional constraints in the problem formulation (e.g. consideration of a desired production level).
- Investigation of how to incorporate the ANN and GA steps into a single process.
- Application of the fuel efficiency algorithm to other mining scenarios such as underground mining and/or maintenance prediction.

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