Chapter

Energy Efficiency Improvement in Surface Mining

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Abstract

This chapter aims to provide an overview of energy efficiency in the mining industry with a particular focus on the role of fuel consumption in hauling operations in mining. Moreover, as the most costly aspect of surface mining with a significant environmental impact, diesel consumption will be investigated in this chapter. This research seeks to develop an advanced data analytics model to estimate the energy efficiency of haul trucks used in surface mines, with the ultimate goal of lowering operating costs. Predicting truck fuel consumption can be accomplished by first identifying the significant factors affecting fuel consumption: total resistance, truck payload, and truck speed. Second, developing a comprehensive analysis framework. This framework involves generating a fitness function from a model of the relationship between fuel consumption and its affecting factors. Third, the model is trained and tested using actual data from large surface mines in Australia, obtained through field research. Finally, an artificial neural network is selected to predict haul truck fuel consumption. The visualized results also clarify the general minimum areas in the plotted fuel consumption graphs. These areas potentially open a new window for researchers to develop optimization models to minimize haul truck fuel consumption in surface mines.

Keywords: energy efficiency, fuel consumption, surface mining, artificial intelligence, prediction

1. Introduction

Energy consumption in the last decade represents an increasing trend. Energy demand is growing across many countries globally as the population grows and human needs expand [1, 2]. As a consequence, fossil fuel consumption has also increased. Additionally, industrial activities have contributed directly and indirectly to annual greenhouse gas emissions [3, 4]. Australian energy consumption, for instance, grew by 0.7% a year on average for the past decade and reached 6014 PJ in 2019–2020, according to the Australian Bureau of Statistics [5, 6]. Fossil fuels (coal, oil, and gas) accounted for 93% of Australia's primary energy source in 2019–2020. Oil accounted for the most significant proportion of Australia's primary energy mix in 2019–2020, at 37%, followed by coal (28%), gas (27%), and renewable energy 8% [5].

Therefore, in recent years, the effects of sustainability on energy production and use have been well understood, and sustainability studies have recently considered enhancing energy efficiency. This is not an outlier trend to be found within the mining industry.

For many countries, mining is a crucial industry. Minerals, coal, metals, sand, and gravel are needed for construction and production and provide employment, taxes, and dividends that fund hospital, schools, and public facilities. To put it another way, mining is first and foremost a source of valuable mineral raw materials that are considered essential by all countries for national security, wealth creation, maintaining and improving the living standards of individual citizens [7].

Mining operations consume vast amounts of energy. For example, Mining in Australia consumes more than 9% of the nation's total energy consumption, which amounts to 570 petajoules per year [8]. Approximately 41% of mining's energy is derived from diesel, 33% from natural gas, and 22% from grid electricity, with the remainder being derived from coal, LPG, renewables, and biofuels. It is worth noting that diesel consumption has recently decreased from 49 to 41% in a decade [9]. It has been replaced mainly by natural gas and grid electricity due to infrastructure development and fluctuations in oil prices.

The mining industry appears to have benefited from rising fuel prices in the 1970s, as evidenced by studies on improving energy efficiency and using sustainable energy sources in the industry. As a result, reducing energy consumption has gradually become a priority for many countries with significant mining operations. Several projects have been conducted by the United States, Australia, Germany, Canada, and China that reduce energy consumption in mining operations [10–12]. Moreover, some governmental moves make industries pay for carbon taxes and similar regulatory costs, leading to the unprofitable and unsustainability of energy-intensive processes.

There are several aspects in the mining value chain where energy efficiency can be improved, such as managing electricity demand, capturing waste heat, improving ventilation, reducing mine drainage, and generating energy from by-products [13]. Numerous authors examined the energy consumption of various mining equipment. Oskouei and Awuah-Offei [11] studied energy consumption and dragline parameters. Peralta and colleagues demonstrate in their research that a maintenance policy based on equipment reliability can significantly reduce energy consumption [14]. Kuzin and colleagues proposed a method for estimating the energy consumption of process equipment and the relationship between energy consumption and vibration parameters and the temperature of the equipment surfaces [15]. According to research, blasting and material handling operations such as loading and hauling have the most significant potential for improving energy efficiency and lowering operating costs [16–20]. Based on numerous studies that have been conducted comparing energy efficiency improvements in mineral processing plants and material handling to other processes, this statement is confirmed.

Companies in the mining industry have recently begun implementing advanced Information Technologies (IT) to improve processes and simultaneously reduce energy consumption and operating costs. The mining industry deals with a large amount of data with layers of hidden knowledge. Since data analytics involves the science of analyzing raw data to derive information, it is a very effective technique for bringing disparate data sources together. Furthermore, data analytics provides cost savings, faster and better decision-making, and the development of new products and services, among other benefits [21]. As a result, data analytics is widely used, and it has a wide range of applications that many people may not have previously considered.

This chapter discusses advanced data analytics techniques to enhance mining energy efficiency. Open-pit haulage is the main target of the discussion. One of the objectives of this research is to develop a sophisticated data analytics model for assessing haul truck energy efficiency in surface mining. Concerning energy consumption in surface mining, the primary focus of this research is on the application of Artificial Neural Networks (ANNs) for prediction in the investigation of energy efficiency.

2. Energy consumption in mining

Mining is a crucial part of the global economy. In 2020, the top 40 mining companies made approximately 656 billion dollars [22]. Every year, hundreds of millions of raw materials are delivered to factories, the construction industry, utilities, and other commercial enterprises in the United States. Coal, metals, minerals, as well as sand and gravel are examples of such resources.

Research conducted in this area focuses on mining in Australia, which has also been a cornerstone of the Australian economy. Australia is the world's largest producer of lithium and is one of the world's top five producers of gold, iron ore, lead, zinc, and nickel, as well as some other minerals. In addition, the country has the most significant uranium and fourth-largest black coal resources in the world, respectively. Minerals are also one of Australia's major exports. Depending on their location, they are mined through open-cut mining on the earth's surface or underground mining techniques.

About the population, the energy consumption of Australia's industrial sector is among the highest. However, partly due to lower energy prices and lower rates of capital investment in the manufacturing industry, the rate of improvement in Australia's industrial development has lagged behind that of other countries [23, 24].

According to the most recent statistics, the sectors with the highest energy consumption in 2019–2020 were manufacturing and mining [8]. The mining industry in Australia consumes about 570 Pita Joules (PJ) of energy each year. However, Approximately a tenth of it can be savable [18]. Due to the significant energy savings opportunities, mining firms and the government have conducted many studies on cutting this industry's energy consumption (see **Table 1**).

The amount of energy consumed by a mine depends on various factors, including the minerals it mines, the production processes it employs, and the extraction technologies it employs. **Figure 1** illustrates the relative amounts of energy used by the world's three most energy-intensive mining sectors.

A mine's fuel type will vary depending on its type (underground or open-pit mine) and its process. Mining operations use diesel fuel, electricity, natural gas, coal, and gasoline, which account for 34%, 32%, 22%, 10%, and 2% of total energy consumption, respectively (see **Table 2**).

Table 3 shows how much energy is currently being used by various types of mining equipment. The most energy is used in material handling by diesel equipment (17%) and grinding equipment (40%).

Case study	2015–2016 (PJ)	2016–2017 (PJ)	2017–2018 (PJ)	2018–2019 (PJ)	2019–2020 (PJ)
Agriculture[a]	109	115	117	118	104
Mining	524	529	547	562	570
Manufacturing	964	928	938	915	910
Electricity[b]	136	130	132	130	133
Construction	135	142	148	140	144
Transport[c]	646	665	688	693	606
Commercial and services	330	337	345	354	347
Households	1247	1255	1274	1279	1228

[a]*Includes Forestry and fishing.*
[b]*Includes Gas, water supply, and waste services.*
[c]*Includes Postal and warehousing.*

Table 1.
Energy consumption by industries and households in Australia [8].

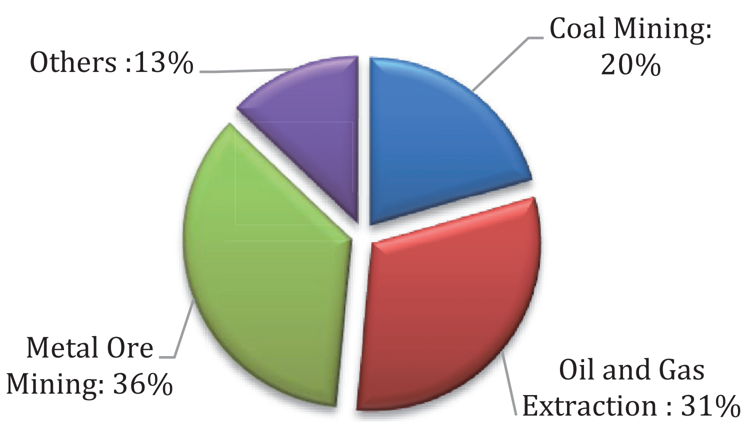

Figure 1.
Energy use by mining sub-division (PJ/year) [6, 25].

Fuel type	Amount (PJ/year)	Percentage
Gasoline	12.1	2%
Coal	60.7	10%
Natrural gas	133.5	22%
Electricity	194.2	32%
Diesel	206.4	34%

Table 2.
Fuel consumed in the mining industry [6, 26, 27].

Fuel type	Amount (PJ/Year)	Percentage
Electric Equipment for Material Handling	9	4%
Separations	9	4%
Ancillary Operations	19	8%
Crushing	9	4%
Ventilation	23	10%
Digging	14	6%
Blasting	5	2%
Drilling	12	5%
Grinding	93	40%
Material Handling Diesel Equipment	40	17%

Table 3.
Energy consumption in the mining industry [6, 26, 27].

3. Truck energy consumption

The hauling of mined material from a pit to a stockpile, dumpsite, or the next step in the mining process is accomplished by trucks at a surface mining operation. Their use may be combined with other types of machinery, such as loaders, diggers, and excavators, depending on the layout and production capacity of the site [28–31]. Surface mines in Australia use a considerable amount of diesel and are costly to purchase, maintain, and operate [28].

It is insufficient to analyze only the parameters specific to a haul truck to estimate its energy efficiency. By expanding the analysis of how energy is used throughout an entire fleet, companies can often find more significant benefits [32, 33]. This chapter is concerned with the identification and optimization of these parameters.

A fleet's energy efficiency can be affected by a variety of factors, including the rate of mining at a particular site, the age and condition of its equipment, the payload, the truck speed, and truck cycle time, the mine layout and plan, the idle time, tire wear, rolling resistance, dumpsite design, engine operating parameters, and shift patterns. By combining this knowledge with mine planning and design procedures, energy efficiency can be improved [34–38].

3.1 Mine operating parameters

Trucks in mines can use a variety of parameters that can influence how much energy they use, some of which are listed in **Table 4**.

3.2 Truck travel time

The time spent hauling and returning the payload is referred to as the travel time. There are four methods for calculating travel time: time study, Rimpull curves, empirical calculations, and computer simulation. Time study is the most common method.

Fuel type	Amount (PJ/year)
Truck model and type	Each type and model of the truck has unique characteristics, and these can be effective on energy consumption by truck.
Material	Material that is hauled
Bucket density	The density of the material being loaded.
Swell factor	The 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 how many bucket loads (passes) are required to fill the truck to its nominal capacity.
Calculated truck payload	The 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 is taken for a loading unit to complete one pass.
Load time	Time is taken to load the truck.
Spot time	The time during which the loading unit has the bucket in place to dump but is waiting for the truck to move into position. Spot time will depend on the truck driver's ability and the loading system. Double-side loading should almost eliminate spot time.
Dump time	Time is taken for the truck to maneuver 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 is taken to haul and return the load.
Wait time	Duration of time spent waiting for the loading unit to arrive.
Cycle time	The truck's round trip time is the sum of fixed, travel, and wait times.
Efficiency	The amount of productive time achieved in one hour of operating time is measured. The following activities are included in the efficiency factor: Cleaning up by the loading unit or dozer and grading. All aspects to consider are slowdowns in the crusher and dump, fueling, inspections, loading unit movement, and operator experience. Under the heading of trucking, Weather-related delays have occurred more frequently than usual.
Queue factor	It keeps track of the time that has been lost due to queuing. It is yet another way of expressing the length of time spent waiting.
Productivity	Tonnes of production hauled in an operating hour (t/h) Productivity = Efficiency/(Cycle time × Truck payload × Queuing factor)
Mechanical availability	Depending on the type of machine, its age, and the maintenance philosophy,
Utilization	Operating time divided by available time
Production	Hourly Productivity × Operating Hours

Table 4.
Parameters that influence the energy consumption of haul trucks [21, 39, 40].

3.3 Haul profile

Information that effectively estimates travel time, such as distance, vehicle weight, slope, and speed limit, is called a haul profile.

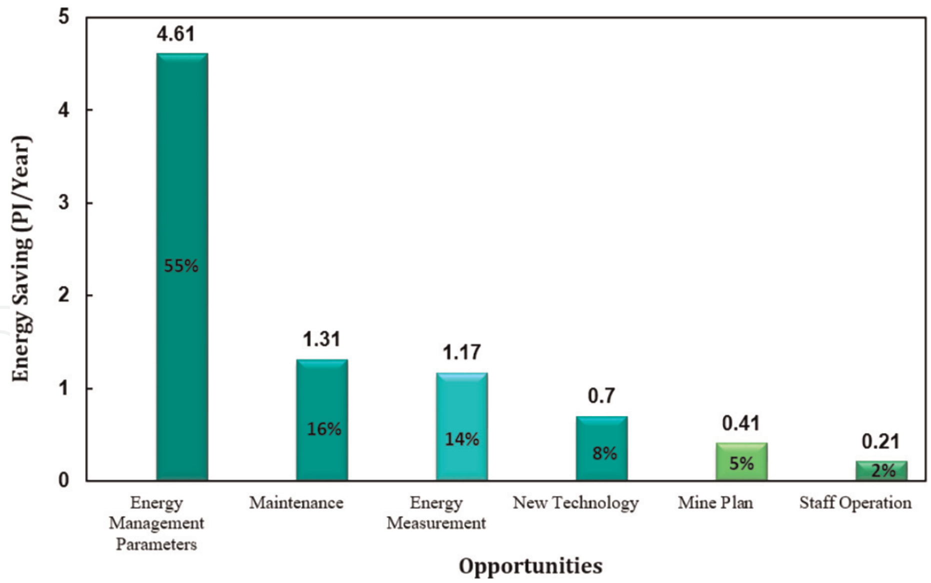

Figure 2.
Opportunities for energy conservation in the mining industry [41, 42].

4. Identifying the most influential parameters

A variety of variables influences the energy consumption of a truck. Because of the constraints of the project, it is not possible to model all of the parameters at this time. The model, therefore, includes the most important parameters. Mining energy savings opportunities can be categorized based on the latest government reports, staff operations, maintenance procedures, management systems, energy measurement, energy management parameters, and new technologies [41–43]. **Figure 2** represents the amount of energy saved and the percentage of total savings achieved by mining companies during the 2019–2020 period, based on the types of energy efficiency opportunities identified and implemented by the companies. The mining entities identified the most energy savings opportunities through energy management projects or 4.61 PJ. This accounts for 55 percent of the total potential savings determined by the mining companies.

Three main parameters have been identified as effective in reducing truck fuel consumption due to an online survey conducted for this research. The survey reached out to 60 industry professionals, who responded at a rate of 81 percent. According to the survey findings, the payload, truck speed, and the resistance of the road are the three most important factors influencing haul truck fuel consumption. Following identifying the primary effective parameters on haul truck fuel consumption in surface mines, a practical method for creating the model must be selected to predict the burnt fuel with the trucks in the mine site. ANN is the name of this method.

5. Artificial neural network (ANN)

ANNs or neural networks, also known as a simulated neural network (SNN), or what is known as 'parallel distributed processing,' represents how the brain uses various methods to learn. The ANN is a collection of mathematical models intended to mimic a few of the common characteristics of natural neural networks. In some cases,

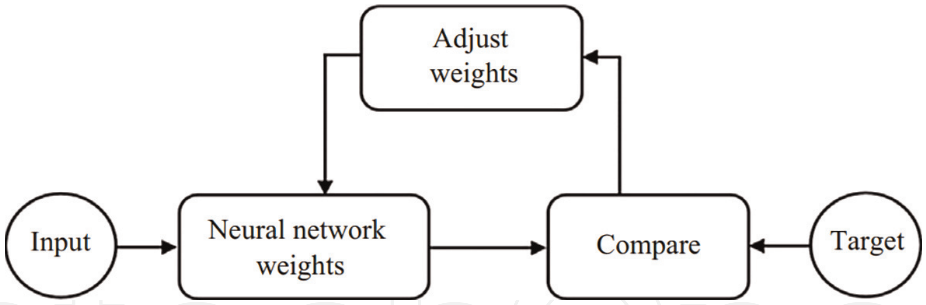

Figure 3.
An example of a typical artificial neural network procedure [44].

the unusual structure of the data processing system may be the most critical component of an ANN paradigm. **Figure 3** depicts an example of a neuronal model that consists of weighted connectors, an adder, and an activation function, among other components. These models are used in computer applications to solve complex problems that arise from user input. They do not require a mathematical description of the process-related phenomena, nor do they need any information to identify the factors that are associated with the process. Instead, they rely on acceptable errors and simple models [35, 36].

In neural networks, the node is the main component. Signals from various sources are summarized by biological nodes, which perform nonlinear operations on the results to produce output. When it comes to artificial neural networks, they are typically divided into three layers: an input layer, a hidden layer, and an output layer. According to its most basic configuration, each of the inputs and its associated weights is multiplied by the connected weight of its neighboring input. The resulting quantities and biases pass through activation functions to produce the output.

6. Proposed model

Several different variables influence fuel consumption for haul trucks. The performance of a typical haul truck is illustrated in **Figure 4** by the key factors that influence it.

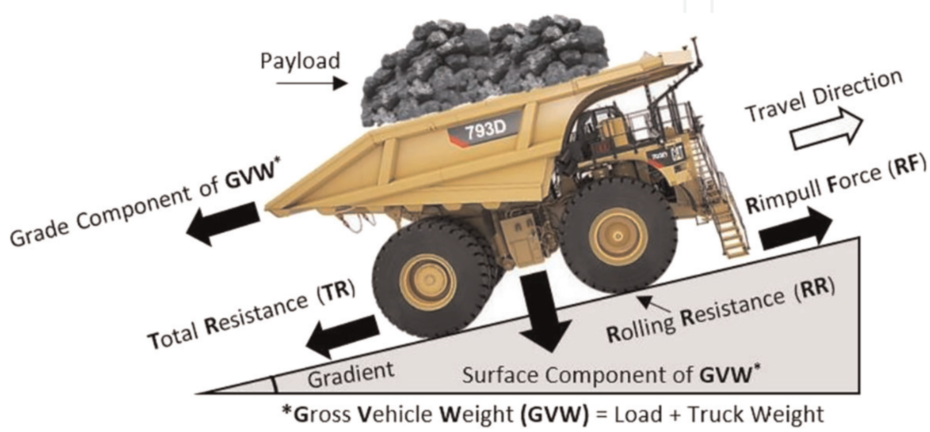

Figure 4.
Influential critical factors of performance of a typical haul truck.

The results of this study examined the effects of the Payload (L), Truck Speed (S), and Total Resistance (TR) on fuel consumption. Burt et al. define the TR as the sum of the Rolling Resistance (RR) and the Grade Resistance (GR) [45].

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

When the characteristics of the tires and the haul roads are considered, this RR can be used to calculate the Rimpull Force (RF). As the truck tire rolls down the haul road, the RF measures the resistance to motion in the tire. The GR denotes the gradient of the haul road. When expressed in percentage, it is determined by the relationship between the rise of the road and the horizontal length. The truck's Fuel Consumption (FC) can be calculated with the help of Eq. (2) [46]:

Eq. (2) (Filas 2002) can be used to calculate FC.

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

Where SFC is the engine Specific Fuel Consumption at full power (0.213–0.268 kg/kW hr) and FD is the Fuel Density (0.85 kg/L for diesel). The simplified version of Eq. (2) is presented by Runge [47]:

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

LF is the engine Load Factor and is defined as the ratio of average load to the maximum load in an operating cycle [48], p is the truck power (kW), and it is determined by:

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

The calculation mentioned above method does not work ideally in mine sites. The calculated consumed fuel by haul trucks using the simple formula same as Eq. (3) cannot help mine managers, operation team, and other related groups estimate fuel consumption. The accuracy of proposed straightforward approaches by researchers is not enough to allow the mine managers to make the correct decisions and improve the energy efficiency in surface mines. Based on the reasons mentioned above and to solve the business problem, this chapter introduces an innovative solution using ANN to predict truck fuel consumption based on the collected data for three effective parameters: payload, truck speed, and total resistance.

6.1 Developed ANN model

Biological nodes generate outputs by combining signals from various sources nonlinearly. A neural network is typically composed of three layers: an input layer, one or more hidden layers, and an output layer, among other things. In its most basic form, each input is multiplied by the weight of the connected input, and the result is passed through the activation functions to generate the output (see Eqs. (5)–(7)).

$$E_K = \sum_{J=1}^{Q}\left(W_{I,J,K}X_J + B_{I,K}\right) \qquad K\text{-}1,\ 2,\ \ldots,\ M \tag{5}$$

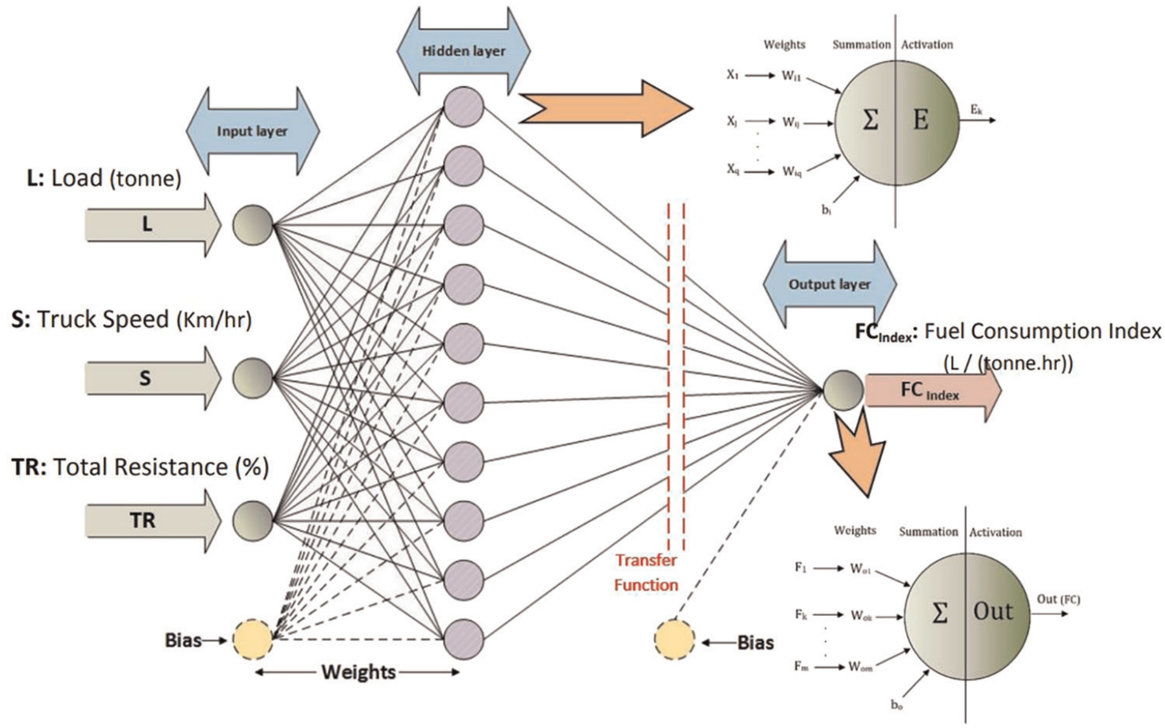

Figure 5.
Structure of ANN developed model.

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

Figure 5 depicts a simplified representation of the structure of the model developed in this research. It should be noted that the hidden layer nodes are free to generate their output using any differentiable activation function they choose.

In general, the activation functions are made up of both linear and nonlinear equations, depending on the situation. Matrixes $W_{i,j,k}$, and $b_{i,k}$ are used to organize the coefficients associated with the hidden layer in the hidden layer. As an activation function between the hidden and output layers, Eq. (6) can be used to achieve the desired result (in this Equation, f is the transfer function).

$$F_K = F(E_K) \tag{6}$$

During the output layer's computation, the hidden layer's signals are weighted summed, and the coefficients associated with these weights are organized into three matrices: $W_{o,k}$, and B_o. The network's output can be calculated using matrix notation, as shown in Eq. (7).

$$OUT = \left(\sum_{K=1}^{M} W_{O,K} F_K\right) + B_O \tag{7}$$

It is presented in this chapter the results of a study in which different types of algorithms were investigated to determine the best back-propagation generating algorithm. First, let us compare the Levenberg-Marquardt (LM) back-propagation generating algorithm to other similar algorithms. It has the lowest mean square error (MSE), Root mean square error (RMSE), and Correlation Coefficient (R^2) of any of the algorithms (see Eqs. (8)–(10)). In addition, network generation using the LM algorithm can be accomplished with the smallest possible Expanded Memory Specification (EMS) and a quick generating process by using the LM algorithm. The statistical criteria MSE, RMSE, and R^2 are used to evaluate the accuracy of the results in accordance with the following Equations (Ohdar and Pasha 2003 and Poshal and Ganesan 2008), which are as follows:

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

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

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

Where y denotes the target (actual), z denotes the output (estimated) of the model, (y denotes the average value of the targets, and p denotes the number of network outputs). To examine the error and performance of the neural network output, the MSE and R^2 methods were used. In addition, the LM optimization algorithm was used to determine the optimal weights for the network.

The proposed ANN model for function approximation has the structure of a feed-forward multi-layer perceptron neural network with three input variables and a single output. One or more hidden layers of sigmoid nodes are frequently found in the feed-forward network, tracked by an output layer of linear nodes. Nodes with nonlinear activation functions are arranged in multiple layers, allowing the network to learn the linear and nonlinear connections between the input and output vectors over time. The linear output layer enables the network to generate values outside the [−1,+1] range using a linear function. The activation functions in the hidden layer (f) are the continuous differentiable nonlinear tangents sigmoid presented by Eq. (11).

$$f = \tan\ \operatorname{sig}(E) = \frac{2}{1 + \exp\left(-2E\right)} - 1 \tag{11}$$

When determining the optimal number of nodes in the hidden layer, MSE and R^2 were calculated for various hidden layer densities to determine their optimal number of nodes. For 15 nodes in the hidden layer, the minimum MSE and the maximum R^2 (best performance) were discovered, resulting in the best overall performance (as shown in **Figure 6**).

To train the ANN model, 4600 pairing data points were randomly selected from the 6630 values of the site data that had been gathered for this study (A large surface mine located in central Queensland, Australia). The values of payload, Vmax, and TR were calculated from the site data and used to train the ANN model, which was then used to calculate the fuel consumption from the site data.

As shown in **Figure 7**, the variation of MSE occurs during the network training process: it can be seen that the error approaches zero after 25 epochs, which indicates that the desired network convergence was achieved during the training process.

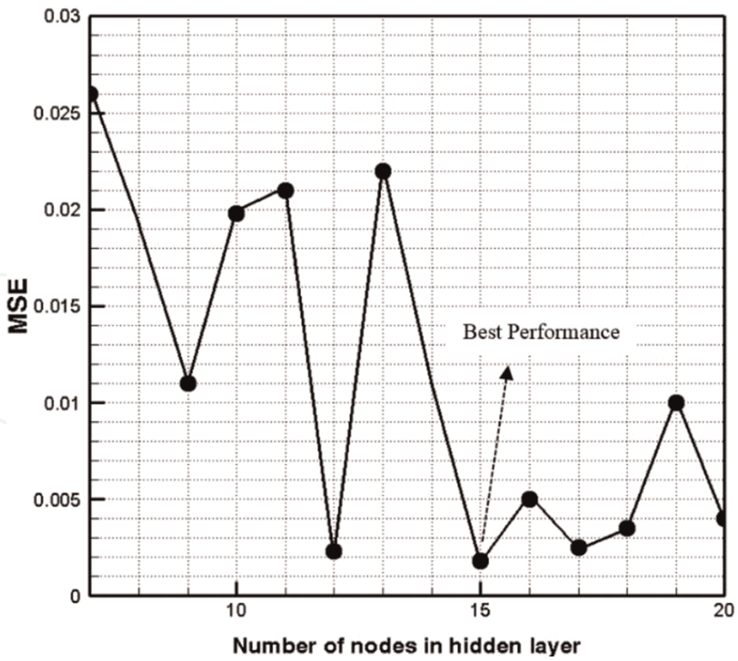

Figure 6.
The performance of the network at different hidden nodes using the LM algorithm.

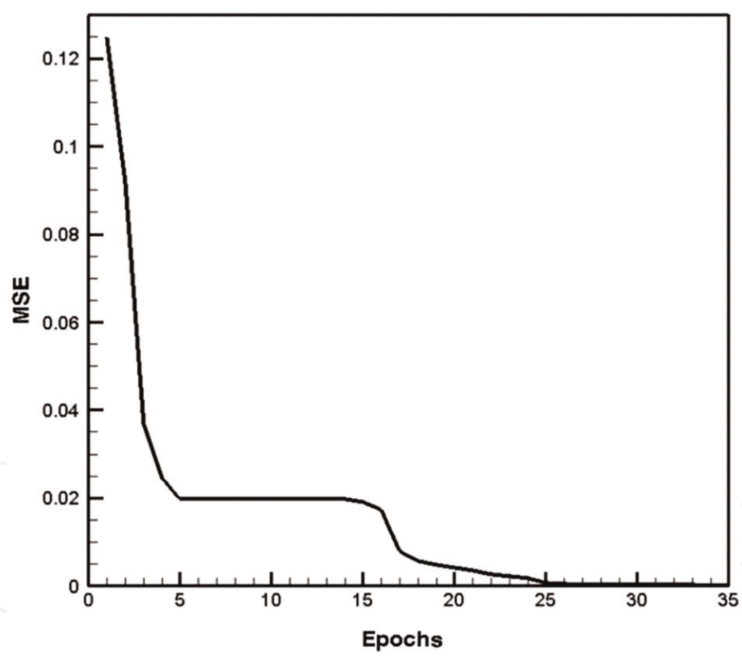

Figure 7.
Neural network error diagram (MSE) during network training.

Approximately 2030 independent samples were used to evaluate the accuracy of the network and validate the model. The test results of the synthesized network are depicted in **Figure 8**, where the vertical and horizontal axes represent the estimated fuel consumption values by the model and the actual fuel consumption values, respectively, and the vertical and horizontal axes represent the actual fuel consumption values.

Figure 8 illustrates the accuracy of the developed model. The results show more than 85% accuracy, which is acceptable for a mining application using unstructured noisy data collected from a real mime site.

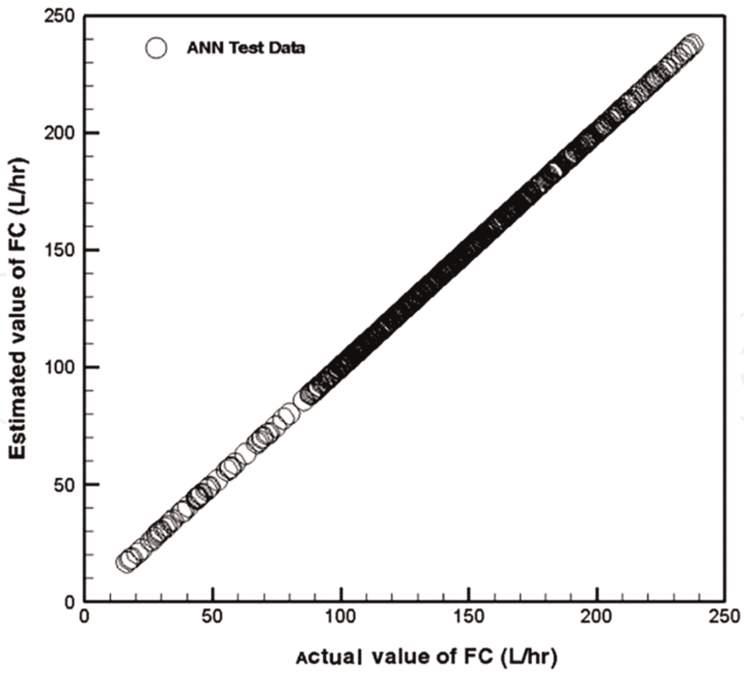

Figure 8.
Comparison of actual values with network outputs for test data (first quarter bisector).

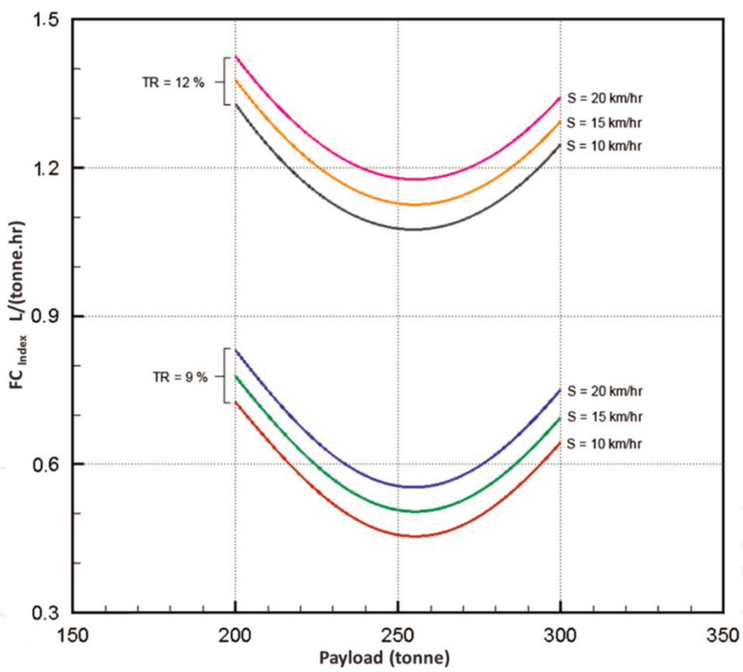

Figure 9.
Correlation between Payload, S, T.R., and FC_{Index} based on the developed ANN model for CAT 793D.

For a standard range of loads, **Figure 9** shows the correlation between Payload, Truck Speed, Total Resistance, and FC_{Index} created by the constructed ANN model for CAT 793D tested in a coal surface mine in central Queensland, Australia.

The results show that ANN could correctly predict the fuel consumed by haul trucks in different conditions. As a result, there are different ranges of consumed fuel for different haul road conditions. **Figure 9** also shows that there is the minimum area for consumed fuel in all tested scenarios. This minimum area is located close to the maximum recommended payload for the truck. It means that loading the truck with the recommended weight can help the mine managers to reduce fuel consumption.

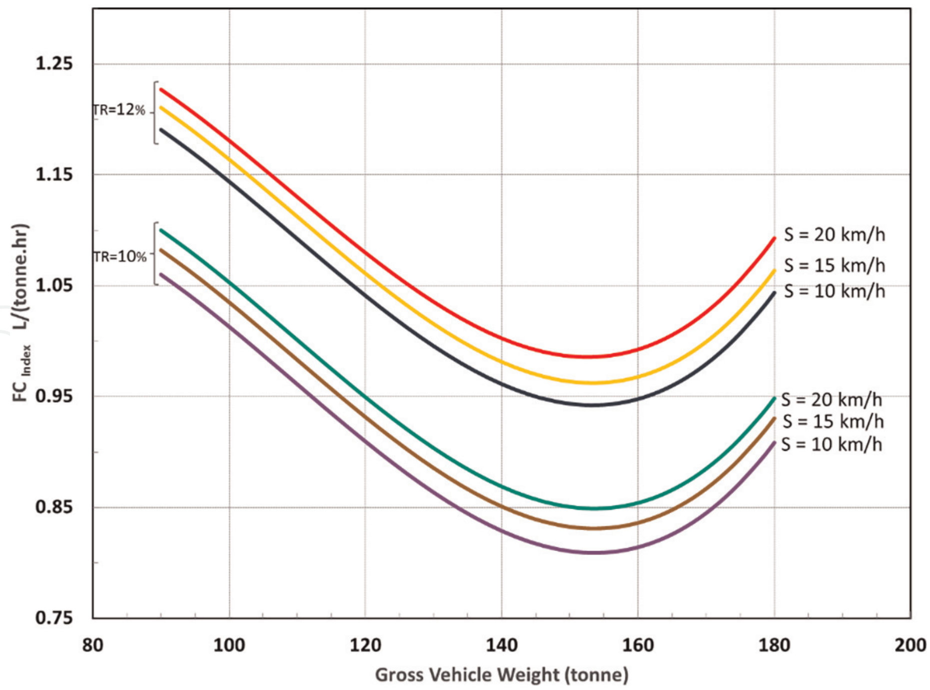

Figure 10.
Correlation between gross vehicle weight, S, T.R., and FC_{Index} based on the developed ANN model for Komatsu HD785.

The developed application also tested for a Komatsu truck (HD785) to validate the model for different truck's specifications. **Figure 10** shows the results of model testing for the Komatsu truck.

The minimum areas highlighted by the presented graphs in **Figures 9** and **10** illustrate the potential of deploying optimization algorithms aimed to improve energy efficiency in surface mines. This concept can be a title for further investigations and studies in the future.

7. Conclusion

As old industry mining uses traditional approaches to solve the business problem, energy efficiency improvement is one of the most critical challenges in the mining industry. Mine managers and researchers can benefit from digital transformation and data access by utilizing innovative data-driven solutions such as machine learning and artificial intelligence. This chapter presented a practical framework and developed an artificial neural network algorithm to predict the consumed fuel by haul trucks in surface mines. The successful results of deploying this application in different mines sites have opened a new window for researchers to use the sophisticated AI models to tackle the mining operation challenges. This chapter showed the prediction results for diesel consumption, and it is clear that the prediction is the starting point of advanced analytics. The developed model was used in a large surface mine in Australia and tested on two different trucks (CAT 793D and Komatsu HD785). For both tested trucks, the accuracy of developed mold was reported more than 85%, an acceptable result for a sophisticated AI model that unstructured and noisy datasets have fed. There are more opportunities to use AI to optimize and make decisions to increase energy efficiency in mining engineering.

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