Chapter

Improve Energy Efficiency in Surface Mines Using Artificial Intelligence

Ali Soofastaei and Milad Fouladgar

Abstract

This chapter demonstrates the practical application of artificial intelligence (AI) to improve energy efficiency in surface mines. The suggested AI approach has been applied in two different mine sites in Australia and Iran, and the achieved results have been promising. Mobile equipment in mine sites consumes a massive amount of energy, and the main part of this energy is provided by diesel. The critical diesel consumers in surface mines are haul trucks, the huge machines that move mine materials in the mine sites. There are many effective parameters on haul trucks' fuel consumption. AI models can help mine managers to predict and minimize haul truck energy consumption and consequently reduce the greenhouse gas emission generated by these trucks. This chapter presents a practical and validated AI approach to optimize three key parameters, including truck speed and payload and the total haul road resistance to minimize haul truck fuel consumption in surface mines. The results of the developed AI model for two mine sites have been presented in this chapter. The model increased the energy efficiency of mostly used trucks in surface mining, Caterpillar 793D and Komatsu HD785. The results show the trucks' fuel consumption reduction between 9 and 12%.

Keywords: artificial intelligence, energy efficiency, fuel consumption, haul trucks, prediction, optimization, mining engineering

1. Introduction

Climate change, energy security, water scarcity, land degradation, and dwindling biodiversity put pressure on communities, requiring more excellent environmental knowledge and resource-conscious economic practices. As a response to these genuine difficulties, both mining and industrial activities have adopted environmental plans.

The global accord, which 125 countries have signed, aims to reduce global glasshouse gas (GHG) emissions by 80% by 2050 to achieve a low-carbon society. Thus far, the agreement has significantly impacted energy-related laws, such as carbon taxes and energy pricing.

However, following the Paris agreement, the energy costs in the mining industry have risen substantially in respect of overall operating costs. Six years ago, energy accounted for 10% of mining companies' operational costs; now, it is pushing close to 20%. This increases the cost base of companies significantly.

Mining is critical to our national security, economy, and the lives of individual citizens. Millions of tons of resources should be mined each year for each individual to maintain his or her quality of living [1]. In addition, the mining sector is a critical component of the world economy, supplying crucial raw materials such as coal, metals, minerals, sand, and gravel to manufacturers, utilities, and other enterprises [2]. To put it another way, mining will continue to be an essential part of the global economy for many years.

Mining necessitates much energy. Mining, for example, is one of the few non-manufacturing industrial sectors recognized as energy-intensive by the U.S. Department of Energy [3]. It is also widely acknowledged that the mining industry could enhance its energy efficiency dramatically. Using the United States as an example, the U.S. Department of Energy (DOE) estimates that the U.S. mining sector consumes around 1315 PJ per year and that this annual energy consumption might be reduced to 610 PJ or about 46% of current annual energy usage [3]. According to the most recent data, energy consumption in Australia's mining sector was at 730 petajoules (P.J.) in 2019–2020, up 9% from the previous year [4]. This is slightly greater than the average rate of increase in energy use during the last decade. Mining consumes 175 PJ of energy per year in South Africa and is the largest consumer of electricity at 110.9 PJ per year, according to 2003 figures. The association between rising interest in energy efficiency and energy prices demonstrates increasing energy intensity on mining operating expenses [5, 6]. Given recent governmental moves by various governments to make industry pay for the expenses associated with carbon emissions, such high energy-intensive processes are not sustainable or cost-effective (carbon taxes and similar regulatory costs). As a result, all stakeholders have a vested interest in improving mine energy efficiency.

Since the rise in fuel prices in the 1970s, the importance of reducing energy usage has gradually grown. In addition, because the mining industry's primary energy sources are petroleum products such as electricity, coal, and natural gas, increasing margins through efficiency savings can also save millions of tons of gas emissions.

Mining companies are looking into reducing energy consumption and emissions to cut costs and emissions, especially considering any possible carbon emissions strategy. First, however, businesses must have a comprehensive understanding of their current energy usage, which involves using technology that allows employees to make decisions.

Mining businesses actively review their investment, capital expenditure, and operational plans to ensure that their operations are sustainable and ecologically beneficial. Sustainable practices and capital equipment investments must result in measurable cost savings. Mining businesses are looking to increase their energy efficiency to cut costs and lessen their environmental effect.

Sustainable investments were not thought to produce significant returns on investment in earlier years, but they are becoming more appealing with the quickly changing legislative and economic climate. When all the advantages of new technology and business practices are considered, including direct savings from increased efficiency as well as associated incentives such as carbon tax credits, investments become much more appealing. Furthermore, when considered over a longer time horizon, these same investments in energy savings, for example, become incredibly beneficial.

Data analytics represents a very appropriate approach to pulling together disparate data sources since it is the science of examining raw data to conclude that information. In addition, cost savings, faster and better decision making, and finally, new goods and services are some of the key benefits of data analytics [7].

Data analytics represents a very appropriate approach to pulling together these disparate data sources since it is the science of examining raw data to conclude that information. Cost savings, faster and better decision making, and finally, new goods and services are some of the most significant advantages of data analytics [7]. Data analytics is widely used and can be used in areas many might not have thought about before. One area that sees much potential in data analytics is the mining industry. Data analytics should be considered a necessity, not a luxury, for an industry that does trillions of dollars in business every year.

One of the advanced data analytic techniques discussed in this chapter aims to enhance the crucial issue of mining energy efficiency. The focus will be on open-pit mine haulage activities. This study aims to create a sophisticated data analytics model for assessing the complex connections that affect haul truck energy efficiency in surface mining. The application of Artificial Neural Networks for predictive simulation and Genetic Algorithms (GAs) for optimization in the investigation of energy efficiency is the focus of this study.

2. Mining energy efficiency—Using artificial intelligence

Global resource firms are currently struggling in challenging economic and regulatory environments. However, most companies in the mining business are now disclosing their performance in this area in response to growing social concern about the industry's numerous consequences and the birth of the idea of sustainable development. Many firm sustainability reports include total energy consumption and associated glasshouse gas (GHG) emissions in absolute and relative terms, indicating that energy consumption and its impact on climate change are priorities.

Mining companies are setting goals to improve these metrics, but there is also a global trend towards more complicated and lower-grade orebodies, which require more energy to process. As a result, mining businesses must be more innovative to improve their environmental sustainability and efficiency operations. In addition, companies must consider the specific energy usage of their processes to limit glasshouse gas emissions.

According to Australian government research, the most significant energy use industries in 2013–2014 were transportation, metal manufacturing, oil and gas, and mining. Transportation consumes a quarter of Australia's annual energy. The manufacturing of metal products such as aluminum, steel, nickel, lead, iron, zinc, copper, silver, and gold accounted for over 16% of total energy consumption. The mining industry consumes 10% of all energy used by participants. **Figure** 1 shows the other industries that used the most energy in 2019–2020.

Grinding (40%) and materials handling by diesel equipment are the most energy-intensive equipment types in the mining industry (17%) [8].

According to the Australian Energy Statistics, Australian energy consumption has increased by an average of 0.6% a year for the past decade and reached 6171 PJ in 2019–2020.

Energy efficiency can significantly cut energy demand while also assisting in reducing GHG emissions at a low cost to industry and the larger economy. Therefore, it makes commercial and environmental sense to be aware of opportunities to maximize energy efficiency. The glasshouse gas emissions produced by mining companies were calculated using various fuels, including electricity, natural gas, and diesel. The mining companies' energy savings translated to a possible reduction in glasshouse gas emissions.

Data analytics is the science of examining raw data to discover useful information, reach conclusions about the meaning of the data, and support decision-

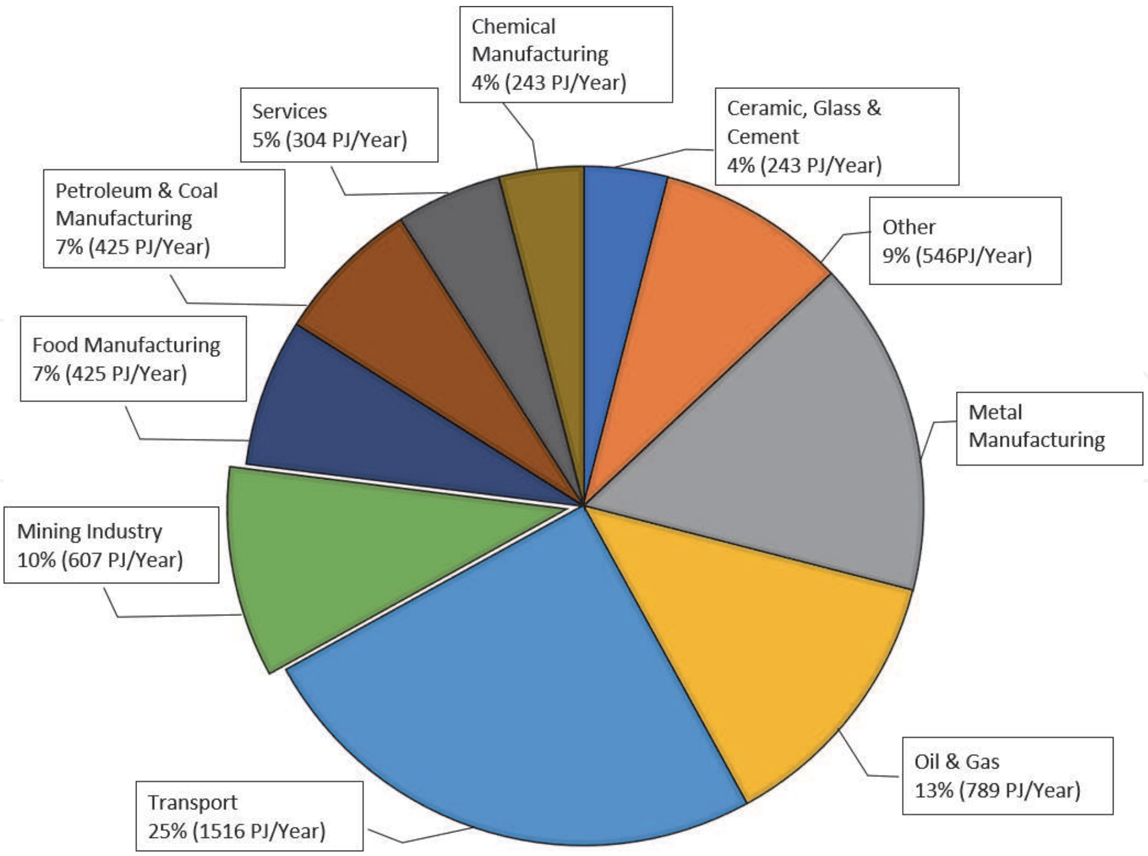

Figure 1.
Top energy users by industry sector 2019–2020 (Total 6069 PJ) [8].

making. The foremost opportunity that data analytics presents for mining is its potential to identify, understand, and then guide the correction of complex root causes of high costs, poor process performance, and adverse maintenance practices. Therefore, data analytics can reduce costs and accelerate better decision-making, which ultimately enables new products and services to be developed and delivered, creating added value for all [7].

Figure 2 illustrates the two dimensions of maturity: a time dimension (over which capability and insights are developed) and a competitive advantage dimension (the value of insights generated). At the lowest levels, analytics are routinely used to produce reports and alerts. These use simple, retrospective processing and reporting tools, such as pie graphs, top-ten histograms, and trend plots. They typically answer the fundamental question: 'what happened and why?' Increasingly, sophisticated analytical tools, capable of working at or near real-time and providing rapid insights for process improvement, can show the user "what just happened" and assist them in understanding "why" as well as the following best action to take. Towards the top end of the comparative advantage scale are predictive models and ultimately optimization tools, with the capability to evaluate 'what will happen and the ability to identify the best available responses—'what is the best that could happen?'

The mining sector and governments have been pushed to perform research on energy consumption reduction due to the potential for energy (and financial) savings. As a result, a significant number of research studies and industrial projects have been conducted worldwide to achieve this in mining operations [8]. As a result, the mining industry might save roughly 37% of its current energy use by fully implementing state-of-the-art technology and installing new technology through research and development expenditure [9]. Furthermore, energy usage is

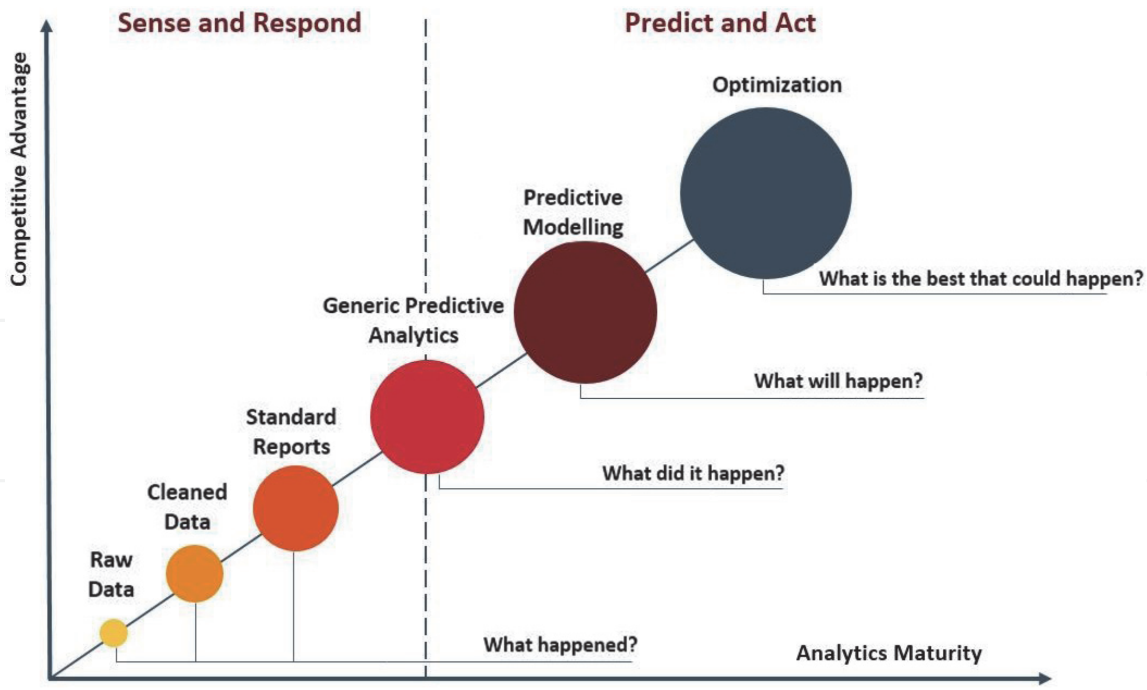

Figure 2.
Data analytics maturity levels [7].

significantly reduced when mining technologies and energy management systems improve. To put it another way, there are substantial further chances to minimize energy use in the mining business.

The four main phases of the mining process that data analytics can use are (1) extraction of ore, (2) materials handling, (3) ore comminution and separation, and (4) mineral processing. The focus of many companies is efficiency improvements in the materials handling phase. For example, the hauling activity at an open-pit mine consumes a significant amount of energy and can be more energy-efficient [10]. The case study presented here- haulage equipment- is one of these potential areas for improving the mining energy efficiency as well as reducing greenhouse gas emissions.

3. Improve haul trucks energy efficiency

In a surface mining operation, truck haulage accounts for most costs. In surface mines, diesel fuel is used as an energy source for haul trucks, which is expensive and has a significant environmental effect. Energy efficiency is widely acknowledged as the easiest and most cost-effective strategy to manage rising energy bills and lower glasshouse gas emissions.

Depending on the production capacity and site layout, haul trucks are utilized in conjunction with other equipment such as excavators, shovels, and loaders. They collaborate to dig ore or waste material out of the pit and carry it to a disposal site, stockpile, or the next step in the mining operation [11].

The pace of energy consumption is determined by various factors that can be evaluated and tweaked to achieve optimal performance levels [12]. The energy efficiency of the mine fleet is affected by a variety of factors, including site production rate, vehicle age and maintenance, payload, speed, cycle time, mine layout, mine plan, idle time, tire wear, rolling resistance, dumpsite design, engine operating parameters, and transmission shift patterns. To improve energy efficiency, this knowledge can be incorporated into mining plan costing and design methods [8].

To assess the prospects for strengthening truck energy efficiency, a comprehensive analytical framework can be built.

We can not only save money each year by improving the energy efficiency of mine haulage systems, but we can also save considerable emissions of glasshouse gases and other air pollutants.

4. Data analytics models

A novel integrated model was proposed to improve haul truck energy usage's three most significant and critical effective characteristics. Payload (P), truck speed (S), and total resistance (R) are the three parameters (T.R.). However, the relationship between energy usage and these characteristics on an actual mining site is complicated. Therefore, to predict and reduce haul truck fuel consumption in surface mines, we apply two AI technologies to develop an advanced data analytic model (**Figure** 3).

In the first step, an artificial neural network (ANN) model was developed to create a Fuel Consumption Index (FC_{Index}) as a function of P, S, and T.R. This index shows how many liters of diesel fuel are consumed to haul 1 ton of mined material in 1 h. In this model, the main parameters used to control the algorithm were R^2 and MSE. After the first step, the optimum values of P, S, and T.R. will be determined using a novel multi-objective GA model. These improved parameters can be utilized to boost haul truck energy efficiency.

The proposed model's methods are all based on actual data obtained from surface mines. Below are the results of utilizing the developed model for two genuine major surface mines in Australia and Iran. On the other hand, the finished methods can be expanded for various mines by substituting the data.

5. Prediction model—Artificial neural network

The artificial neural network (ANN) is a popular AI model and a robust computational tool based on the human brain's organizational structure [13]. ANNs are the

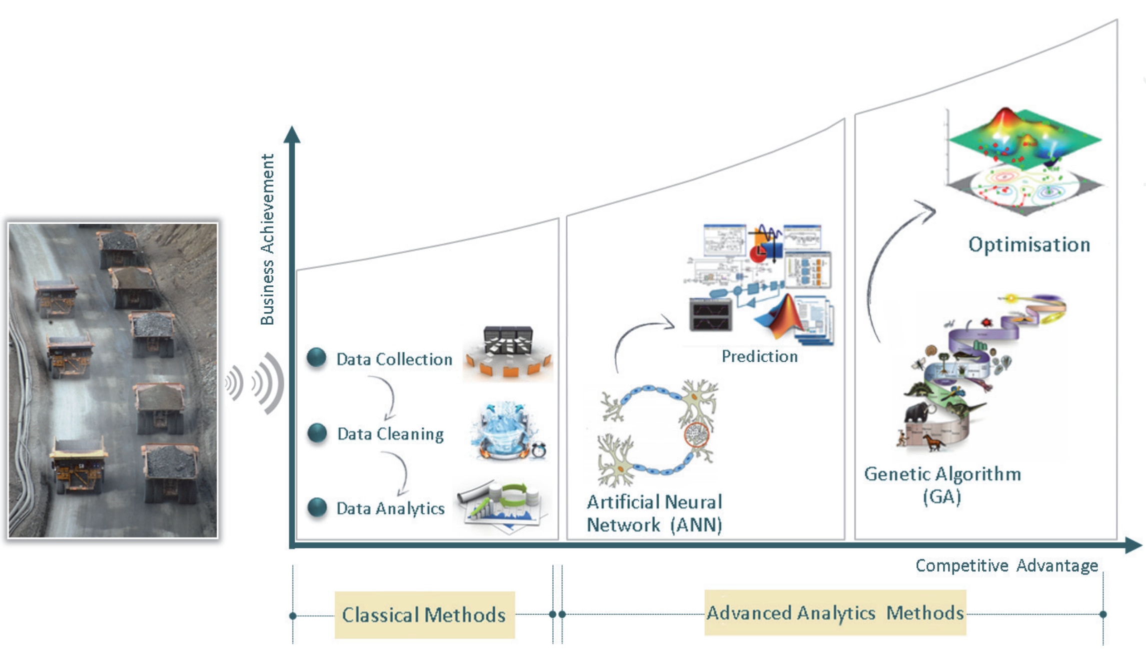

Figure 3.
A schematic of the developed model [8].

representation of methods that the brain uses for learning which are known as neural networks (NNs), simulated neural networks (SNNs), or parallel distributed processing (PDP). ANN simulates the effect of multiple variables on one significant parameter by a fitness function. Thus, ANNs are excellent solutions for complex problems as they can signify the compound relationships between the various parameters involved in a problem.

ANN methods are established as powerful techniques to solve various real-world problems among the different machine intelligence procedures due to ANN's excellent learning capacity in recent decades. The approximate solution by ANN is found to be useful, but it depends upon the ANN model that one considers [14].

Layers are commonly used to organize neural networks. Layers are made from various interconnected "neurons/nodes," which include "activation functions." ANN processes information to solve problems through neurons/nodes in a parallel manner. First, ANN obtains knowledge through learning and is stored within interneuron connections' strength, expressed by numerical values called "weights." Then, these weights and biases are combined to calculate output signal values for a new testing input signal value. Next, patterns are provided to the network through the "input layer," which connects to one or more "hidden layers," where the actual processing is completed through a system of weighted "connections." The hidden layers then correlate to an "output layer," which generates the output through the activation functions [Eqs. (1)–(3)].

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

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

In general, the activation functions contain linear and nonlinear equations. The coefficients related to the hidden layer are grouped into matrices w_{ijk} and b_{ik}. Eq. (2) is often used as the activation function between the hidden and output layers, where f is the transfer function.

$$F_k = f(E_k) \tag{2}$$

The output layer calculates the weighted sum of the signals provided by the hidden layer, and the related coefficients are grouped into matrices W_{ok} and b_o. Thus, the network output can be determined by Eq. (3).

$$Out = \left(\sum_{k=1}^{m} w_{ok} F_k \right) + b_o \tag{3}$$

The most significant component of neural network modeling is network training, which can be done in two ways: controlled and uncontrolled. Backpropagation is the most widely used training algorithm, which was established after examining several types of algorithms. A training algorithm modifies the coefficients (weight and bias) of a network to reduce the error between the estimated and actual network outputs.

The Mean Square Error (MSE) and Coefficient of Determination (R^2) were used in this study to investigate the error and performance of the neural network output and determine the appropriate number of nodes in the hidden layer. **Figure** 4 depicts the created model's basic structure.

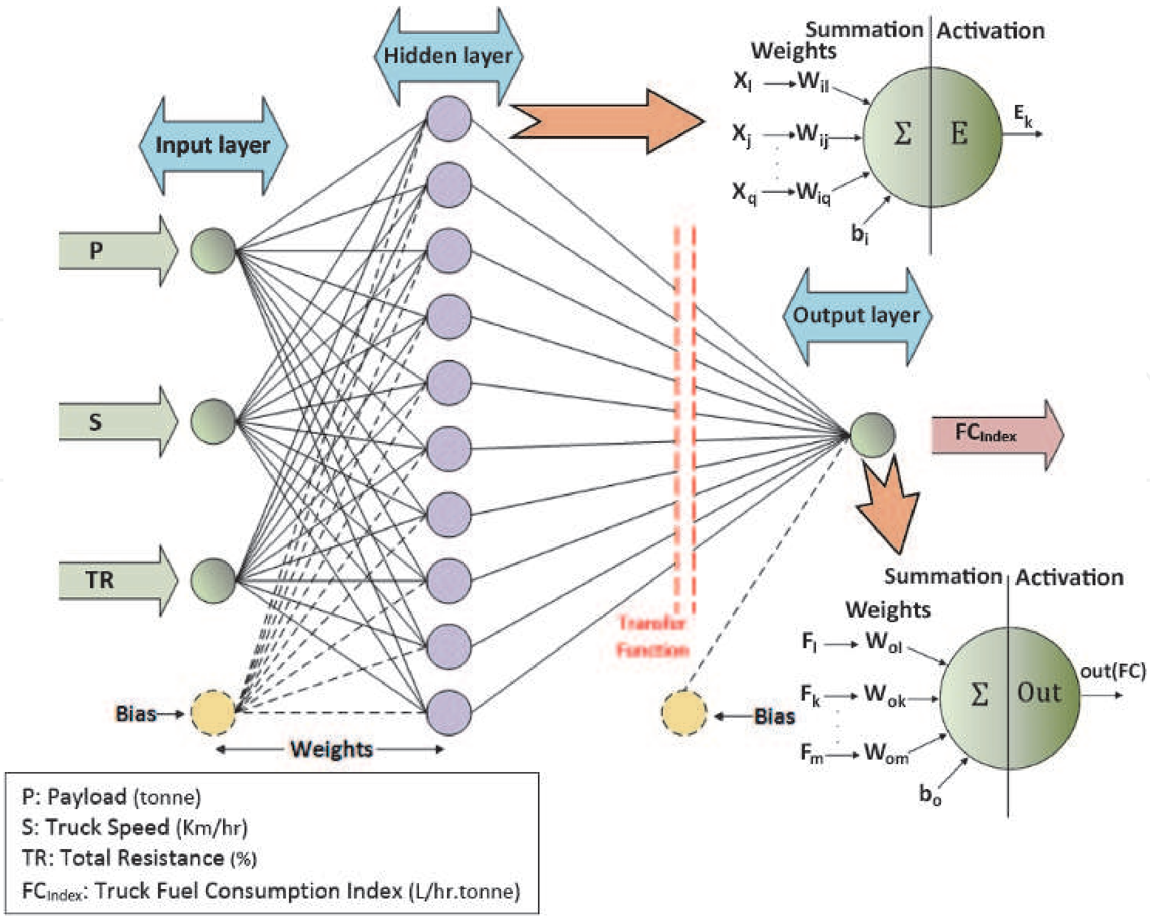

Figure 4.
Structure of artificial neural network [8].

Case study	Mine type	Mine details	Location	Investigated truck
Mine 1	Surface coal mine	The mine contains 877 million tons of coking coal reserves, making it one of Asia's and the world's most significant coal deposits. It can produce 13 million tons of coal per year.	Queensland, Australia	CAT 793D
Mine 2	Surface iron mine	There are 36 million tons of iron deposits in the mine. It has a 15-million-ton ore and waste extraction capacity per year.	Kerman, Iran	Komatsu HD785

Table 1.
Case studies information.

The developed AI model was tested against actual data taken from standard trucks in two surface mines in Australia and Iran. **Table** 1 contains some information from these case studies.

For a standard range of loads, **Figures** 5 and 6 show the correlation between P, S, T.R., and FC_{Index} created by the constructed ANN model for two types of standard trucks employed in case studies.

The presented graphs show a nonlinear relationship between FC_{Index} and P. The fuel consumption rate increases dramatically with increasing T.R. However, this rate does not change sharply with changing truck speed (S).

The results show good agreement between the estimated and actual values of fuel consumption. **Figure** 7 presents sample values for the independent (tested) and the estimated (using the ANN) fuel consumption to highlight the

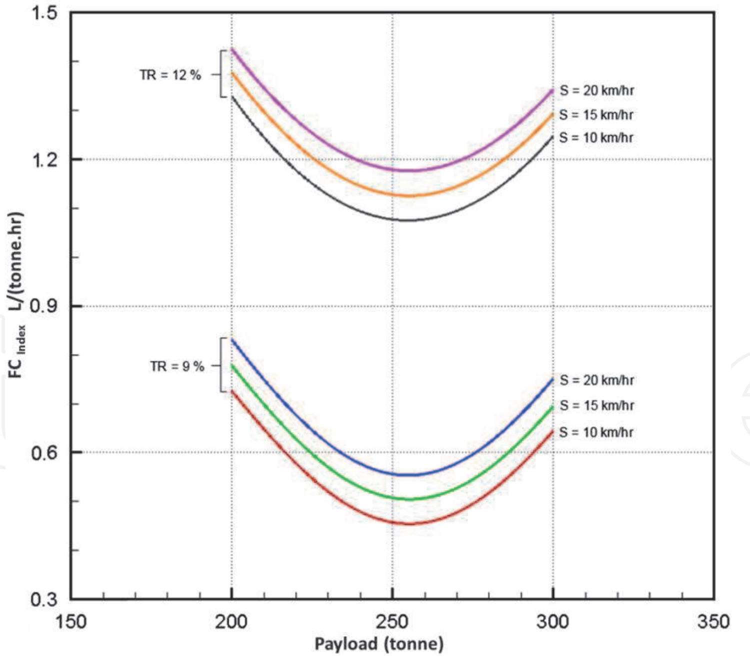

Figure 5.
Correlation between payload, S, T.R., and FC_{Index} based on the developed ANN model for CAT 793D (mine 1).

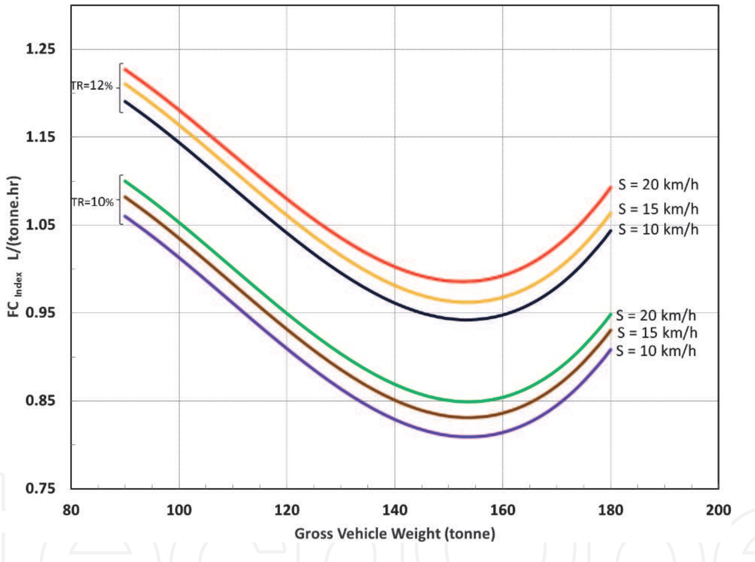

Figure 6.
Correlation between GVW, S, T.R., and FC_{Index} based on the developed ANN model for Komatsu HD785 (mine 2).

insignificance of the importance of the absolute errors in the analysis for studied mines.

6. Optimization model—Genetic algorithm

Optimization is a branch of computational science that shows how to find the best measurable solution to various issues. It is critical to consider the search area and goal function components when solving a specific problem. All the solution's possibilities are investigated in the search area. The objective function is a mathematical function that connects each point in the search area to an actual value that may be used to evaluate all search area members.

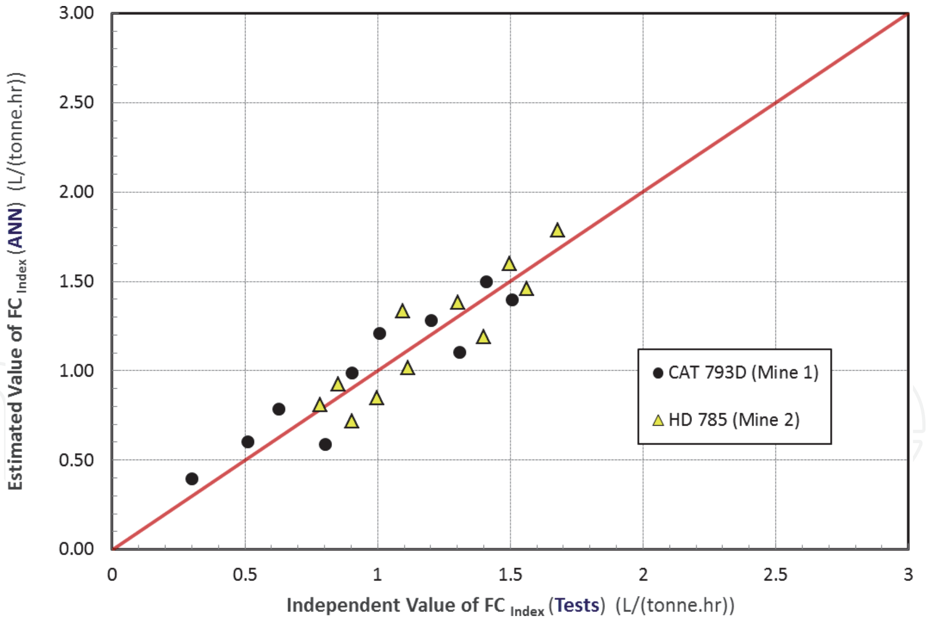

Figure 7.
Sample values for the estimated and the independent fuel consumption index.

Traditional optimization methods are described by the stiffness of their mathematical models and limit their application in presenting dynamic and complex situations of "real life." Optimization techniques based on AI, underpinned by heuristic rulings, can reduce the problem of stiffness and are suitable to solve various kinds of engineering problems.

Some heuristic algorithms were developed in the 1950s to replicate biological processes in engineering. When computers were developed in the 1980s, it became possible to employ these algorithms to optimize functions and processes, whereas older methods failed.

During the 1990s, some new heuristic methods were developed by prior algorithms, such as Swarm Algorithms, Simulated Annealing, Ant Colony Optimization, and (GA). GA is one of the most widely used evolutionary optimization algorithms.

GAs were proposed by Holland (1975) based on an abstraction of biological evolution using ideas from natural evolution and genetics to design and implement robust adaptive systems [15]. In optimization methods using the new generation of GA is relatively novel. Moreover, they have good chances to escape from local minimums because of no need for any derivative information. As a result, their application in practical engineering problems can provide more satisfactory solutions than other traditional mathematical methods [16].

GAs are similar to the evolutionary aspects of natural genetics. The individuals are randomly selected from the search area. The fitness of the solutions is determined from the fitness function, subsequently. It is the result of the variable that is to be optimized. The individual that creates the best fitness in the population (a group of possible solutions) has the highest chance to return in the next generation with the opportunity of reproduction by the crossover with another individual, thus producing decedents with both characteristics. The possible solutions will converge to an optimal solution for the proposed problem by correctly developing a GA Crossover, which contributes to the evolution based on selection, reproduction, and mutation.

Due to their potential as optimization techniques for complex functions, GAs have been used in various scientific, engineering, and economic problems [17–20]. There are four significant advantages of using GAs to optimize problems [21]:

- GAs do not have many mathematical requirements for optimization problems.
- They can use many objective functions and constraints (i.e., linear or nonlinear) defined in discrete, continuous, or mixed search spaces.
- They are very efficient at doing global searches due to the periodicity of evolution operators.
- They provide high flexibility to hybridize with domain-dependent heuristics to enable an efficient implementation for a problem.

It is crucial to investigate the impact of particular parameters on GA behavior and performance to determine their relevance to the problem requirements and available resources. Furthermore, the type of problem being addressed determines the impact of each parameter on the algorithm's performance. As a result, determining the best values for these characteristics will necessitate a significant amount of experimentation.

In the GA model, Fitness Function, Individuals, Populations and Generations, Fitness Value, Parents and Children are the main parameters [17]. In addition, the population size impacts global performance and GA efficiency, and the mutation rate ensure that a given position does not remain fixed in value or the search becomes essentially random. **Figure** 8 depicts the basic framework of a GA model.

A GA model was created to optimize the significant, influential factors on the energy consumption of haul trucks. **Tables 2** and 3 show the outcomes of utilizing the proposed model for actual case studies with an optimal range of variables.

Using the developed AI models in the two studied mines site shows energy efficiency improvements between 9 and 12%. Reaching the mentioned fuel consumption reduction and energy efficiency is promising when one mostly used truck in the mine site consumes around 110 L of diesel per hour. The haul trucks normally are used 24 h and 7 days per week to move mined materials in the site. Studied mine site had more than 100 trucks in their fleet, and the average price of diesel in those regions was 1.3 dollars per liter. It means that 9–12% energy efficiency improvement equals millions of dollars in saving annually.

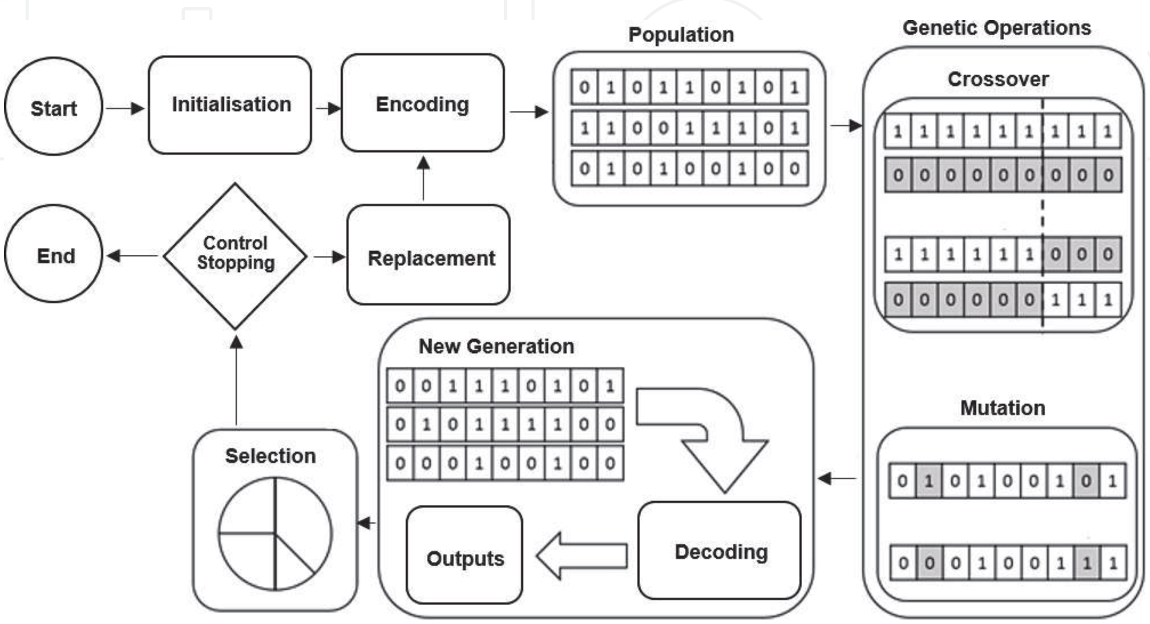

Figure 8.
GA processes (developed model) [8].

Variables	Normal values		Optimized values	
	Minimum	Maximum	Minimum	Maximum
Gross vehicle weight (ton)	150	380	330	370
Total resistance (%)	8	20	8	9
Truck speed (Km/hr.)	5	25	10	15

Table 2.
The result of the GA model for CAT 793D in mine (1).

Variables	Normal values		Optimized values	
	Minimum	Maximum	Minimum	Maximum
Gross vehicle weight (ton)	75	170	150	160
Total resistance (%)	8	15	8	10
Truck speed (Km/hr.)	5	40	10	18

Table 3.
The result of the GA model for HD 785 in mine (2).

7. Conclusion

The purpose of this chapter was to demonstrate the value of modern data analytics models in improving energy efficiency in mining sectors, particularly in haulage operations, which are one of the most energy-intensive activities. However, improving haul truck fuel consumption for actual mining operations based on the link between influential factors, such as P, S, and T.R., was difficult. Thus, two AI methods were utilized to construct a reliable model to assess the problem.

At first, an ANN model was utilized to simulate truck fuel consumption as a function of payload, truck speed, and total resistance. Then, the ANN was generated and tested using the collected accurate mine site datasets, and the results showed good agreement between the actual and estimated values of FC_{Index}.

After that, to improve the energy efficiency in haulage operations, a GA method was developed to determine the optimal value of effective parameters on fuel consumption in haulage trucks. The developed model was used to analyze data for two surface mines in Australia and Iran. This model also can be applied to improve the haul truck fuel consumption for any dataset obtained from actual mine operations.

The results of two successful case studies show plenty of opportunities to use advanced analytics and AI in the mining industry to improve energy efficiency.

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