

Energy-Efficiency Improvement in Mine-Railway Operation Using AI

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Abstract: The mining industry consumes an enormous amount of energy globally, the main part of which is conservable. Diesel is a key source of energy in mining operations, and mine locomotives have significant diesel consumption. Train speed has been recognized as the primary parameter affecting locomotive fuel consumption. In this study, an artificial intelligence (AI) look-forward control is developed as an online method for energy-efficiency improvement in mine-railway operation. An AI controller will modify the desired train-speed profile by accounting for the grade resistance and speed limits of the route ahead. Travel-time increment is applied as an improvement constraint. Recent models for mine-train-movement simulation have estimated locomotive fuel burn using an indirect index. An AI-developed algorithm for mine-train-movement simulation can correctly predict locomotive diesel consumption based on the considered values of the transfer parameters in this paper. This algorithm finds the mine-locomotive subsystems, and satisfies the practical diesel-consumption data specified in the locomotive's manufacturer catalog. The model developed in this study has two main sections designed to estimate locomotive fuel consumption in different situations by using an artificial neural network (ANN), and an optimization section that applies a genetic algorithm (GA) to optimize train speed for the purpose of minimizing locomotive diesel consumption. The AI model proposed in this paper is learned and validated using real datasets collected from a mine-railway route in Western Australia. The simulation of a mine train with a commonly used locomotive in Australia General Motors SD40-2 (GM SD40-2) on a local railway track illustrates a significant reduction in diesel consumption along with a satisfactory travel-time increment. The simulation results also demonstrate that the AI look-forward controller has faster calculations than control systems based that use dynamic programming.

Key words: Fuel consumption, energy efficiency, locomotive, mining, railway, simulation, optimization, artificial intelligence, neural network, genetic algorithm, look-forward control.

1. Introduction

Locomotive and railway-transportation systems are generally considered an energy efficient method for transferring mining material [1]. However, this type of transportation system is one of the principal consumers of fuel in the mining industry. Therefore, decreasing locomotive diesel consumption and improving energy efficiency in the mine-railway-transportation system would have substantial economic and environmental benefits. Research in the field of energy-efficiency improvement in railway transportation has evolved during the past 16 years [1-3]. An optimized train-speed profile on a route lacking a gradient was found using the maximum principle and practical

analysis [3]. The effect of train speed limits on locomotive fuel consumption was also investigated by Howlett et al. [2]. Improved train-speed profile was explained by Pachl et al. [4] in relation to train movement between two stations on a flat route. This improved train-speed profile has four stages: (1) accelerating to reach maximum velocity; (2) maintaining constant velocity; (3) coasting exclusively of traction forces; (4) decelerating.

There is an opportunity to reduce fuel consumption by up to 15% using advanced data-analytics models to optimize energy efficiency in locomotives and railways [5]. Cheng and Howlett [1] applied an innovative model to solve a typical optimization problem for a route with a constant gradient. In 2009, Howlett et al. [5] created a set of specific equations based on the Kuhn equations. In their project, the problem of

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locomotive fuel-burn optimization was resolved for each segment of a given route by a local minimization of fuel burned by the locomotive [6]. The best point at which to increase train speed before an upward hill was attained by the developed optimization model. Khmelnitsky applied the maximum-value method to decrease the locomotive diesel consumption in underground routes [7]. In 2011, Kang [6] proposed a genetic algorithm (GA) optimization model to improve train speed. In this research, the primary parameter was the coasting point, and a fitness function was introduced for a situation in which the locomotive could pass through the distance between two positions in fixed travel time. In 2013, Li and colleagues [8] proposed a stochastic operation algorithm for locomotive fuel efficiency; in their suggested model, the coasting stage was replaced by a quasi-coasting stage. In other research, train transportation in a subway network was examined [7, 8]. In this research, the comprehensive evaluation index (CEI) was developed to investigate combined optimization models of railway transportation by estimating energy costs and the practical process time.

In all the studies discussed, the researchers used a simple model for locomotive traction force, and train energy consumption was calculated indirectly. Locomotive fuel burn is a function of an engine's operation torque and speed. Therefore, considering the working points and function limitations of locomotive subsystems has the potential to provide more correct simulation outcomes.

The numerical models reviewed in the present study deliver reputable results. However, these models use offline calculations [2-4, 6, 7, 9, 10] because they consider the static condition of the problem. Thus, if any changes occur in the railway route ahead, the models must be run again. This disadvantage highlights the importance of developing online optimization models that consider dynamic conditions in the locomotive cabin or in the train control room.

The look-forward control method proposed by Ganji

and Kouzani [9] in 2010 is an innovative method for optimizing vehicles' fuel consumption on normal roads. This method was developed based on applying future road information to make deceleration and acceleration control signals. The look-forward control method has been used as an effective instrument for reducing fuel burn by applying dynamic programming to tackle the optimization control problem [10]. In research projects completed in 2010, the results illustrated significant proficiency in road transportation [11, 12]. In research conducted in 2011, the look-forward control method was used as an effective approach for optimizing fuel consumption in hybrid electric cars [13]. This approach was also applied by Khayyam et al. [14] in 2011 to optimize ventilation systems.

The research reviewed in this study demonstrates that look-forward control algorithms do not consider vehicle speed limits in segments of the route ahead. In some cases, the developed algorithms suggested increasing vehicle speed before reaching an uphill segment, but technically, it is not correct to increase velocity when approaching a curved route or other speed limits in a segment. Moreover, the look-forward control method has not been applied practically in the field of mine-railway transportation. The aim of the present study is to use the look-forward control approach to increase energy efficiency in mine-railway transportation. The proposed artificial-intelligence (AI) prediction and optimization algorithms can be applied to reducing mine-locomotive fuel consumption.

An integrated AI look-forward algorithm as a dynamic method with online calculations is applied in this study by considering the route grade and velocity limits of the route ahead. The developed model is a combination of a prediction and optimization of AI-based algorithms. To estimate locomotive fuel consumption, an artificial neural network (ANN) is developed and explained in Section 5. The optimization problem in mine-railway operation is defined in Section 3. To reduce locomotive fuel consumption, a GA is developed and combined with

the previously developed prediction model. This algorithm will optimize train speed with the aim of decreasing the fuel burn of the locomotive engine. This optimization algorithm is explained in Section 5. The cost function is defined as travel time, and locomotive fuel burn is considered a limitation. The designed AI look-forward controller is presented in Section 4. Section 6 explains the efficiency of the proposed AI model compared with the standard speed controller based on dynamic programming using a simulation of a mine train with the GM SD40-2 locomotive on a local railway track in Western Australia. Section 7 presents the conclusion.

2. Mine-Train-Movement Simulation

Examining the algorithms developed for mine-train-movement simulation reveals that fuel burn is estimated by indirect indexes, and that no practical model has been developed to test locomotive and railway-transportation fleets in the mining industry. Therefore, the present study develops an innovative AI algorithm for mine-train-movement simulation to estimate locomotive fuel burn more accurately. This algorithm considers all the mine-locomotive subsystems that play critical roles in generating and transmitting power. The main block diagram of the proposed model is presented in Fig. 1.

The components of the mine-train system, including the wheels, final drive, electric motor, generator, and diesel engine are illustrated in Fig. 1. In the developed

AI model, mine-locomotive fuel burn is estimated based on the specific fuel-burn graphs completed by locomotive manufacturers as a function of the diesel engine's torque and speed. Thus, the developed model can estimate locomotive fuel burn straight and more accurately than current models of mine-train-movement simulation.

Mine locomotives use an internal control loop that has a diesel-engine governor, companion equipment, and a load regulator as the principal components [15]. The real engine speed and train driver's throttle position control some external inputs of the governor. The governor controls the fuel-injector setting that regulates the load-regulator position and engine fuel rate. The load regulator is primarily a potentiometer that controls the output power of the locomotive generator by changing the loading applied to the main engine. As the load on the main engine changes, its rotational speed will also change. This is sensed by the engine governor through a change in the engine-speed feedback signal. The effect of this change is to adjust both the load-regulator position and the fuel-consumption rate. As a result, the diesel engine's torque and speed will remain constant for any given throttle position, regardless of actual mine-train speed on the route.

A mine-train driver can change the locomotive speed by using the brake handle or setting the throttle position. The mine-locomotive traction force $F_{traction}$ can be calculated by Eq. (1).

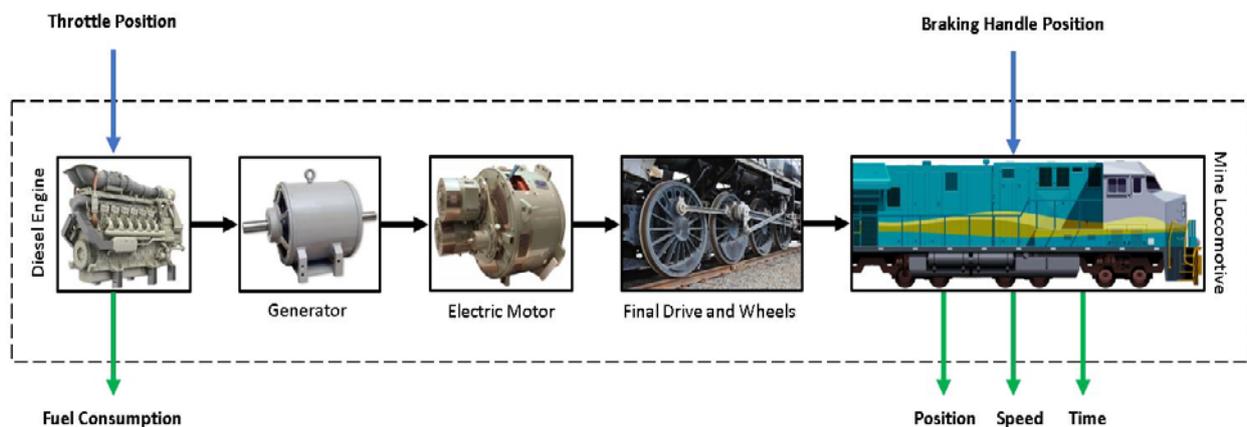


Fig. 1 Mine-train model.

$$hF_{traction} = \min(F_{motor\ traction}, F_{adhesion}) \quad (1)$$

where $F_{motor\ traction}$ is the force generated by electrical motors and $F_{adhesion}$ is the maximum adhesion force between the rail and train wheels. This constriction is measured in the axle and wheel block. The maximum adhesion force between the rail and train wheels is calculated by Eq. (2).

$$F_{adhesion} = 9.8\alpha \times W \times N \quad (2)$$

where α is the adhesion coefficient, N is the number of locomotive axles, and W is the locomotive axial load (kg). The adhesion coefficient is represented by Eqs. (3) and (4) for different weather conditions [4].

$$\alpha = 0.161 + \frac{7.5}{44 + 3.6S} \quad \text{Dry condition} \quad (3)$$

$$\alpha = \frac{3.78}{23.6 + S} \quad \text{Wet condition} \quad (4)$$

where S is the train speed (km/h).

The experimental equations of locomotive movement are applied in the mine-train longitudinal dynamics block. In this block model, resistance forces are calculated by the Davis equation where the resistance force is presented as a parabolic function of the mine-train speed [16] (see Fig. 2).

Fig. 2 shows some effective forces in mine-locomotive operation. These forces are aerodynamic resistance, Davis resistance, route resistance, curvature resistance, and traction force provided by the locomotive engine.

Davis resistance force $F_{resistance-Davis}$ is estimated

separately for the locomotive and the cars; their summation is subsequently considered. The Davis equation is written as follows:

$$F_{resistance-Davis} = 9.8 \left(A + \frac{B}{0.001W} + C \times S + \frac{E \times D \times S^2}{0.001W \times N} \right) \quad (5)$$

where N is the number of axles; W is the locomotive axial load (kg); and A , B , C , D , and E are the Davis coefficients.

In this case, additional resistance force is the route geometry resistance due to route curvature and grade. Route geometry resistance $F_{resistance-route}$ (N/kg) is calculated by Eq. (6):

$$F_{resistance-route} = 0.01(F_{resistance-grade} + 0.04F_{resistance-curvature}) \quad (6)$$

where $F_{resistance-grade}$ (N/kg) depends on elevation variations (m) per 1,000 m and $F_{resistance-curvature}$ (N/kg) is the curved-route resistance force represented by:

$$F_{resistance-curvature} = \begin{cases} \frac{650}{r-55} & r \geq 500 \\ \frac{500}{r-30} & r < 500 \end{cases} \quad (7)$$

where r is the curve radius (m) [4].

The traction force becomes zero by braking, and the braking force is replaced with the traction force. The braking force F_{brake} (N/kg) is estimated by Eq. (8).

$$F_{brake} = 5\phi_k \times \theta_b \quad (8)$$

where θ_b is the brake weight fraction, which is a function of locomotive speed and route grade [4]; and ϕ_k is the friction coefficient, expressed by Eq. (9).

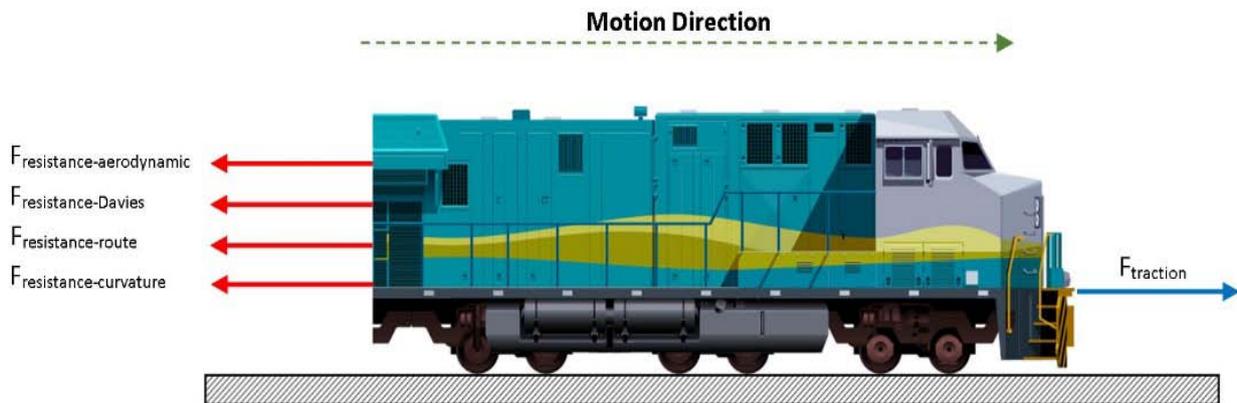


Fig. 2 Mine-locomotive and resistance forces.

$$\phi_k = 0.32 \times \frac{S + 100}{5S + 100} \quad (9)$$

where S is the mine-train speed (km/h) [4]. Therefore, the locomotive speed, acceleration, and train position, and consequently travel time, can be estimated by applying Newton's second law of motion.

3. Mine-Train Optimization

The reviewed literature demonstrates that one of the best approaches to optimize effective parameters for mine-train-movement performance is improving locomotive fuel consumption and travel time. However, these two parameters perform in an opposite way. This means that locomotive fuel-burn reduction may lead to an increase in train travel time. Thus, it is complex to find an accurate parameter that can change mine-train travel time to its corresponding in locomotive fuel burn. Defining the objective function as locomotive-engine diesel consumption and mine-train travel time as a constraint is potentially one of the most effective proposed approaches to the optimization problem of mine-train operation [6]. That is, the diesel burned by a locomotive engine must be minimized when the train travel-time increment is less than a predefined limit. In the present study, mine-train travel-time restriction is considered at most a 5% increase compared with the travel time achieved by following the initially desired speed profile. This profile is calculated by the mine-train speed-limit signs on the route. Another limitation in the optimization problem is the speed deviation from the initially desired speed profile. In this study, the speed-deviation limitation is considered 20 km/h below and above the initial desired speed.

It should be noted that the initially desired speed profile is generally below the maximum permissible speed on the railway track. Thus, 20 km/h deviation from the desired speed profile will not cause safety problems. The mine-train optimization problem is defined as follows.

Minimum locomotive fuel consumption is subject to:

$$\Delta t < 0.05t_{IDS}$$

$S_{IDS} - 20$ (km/h) $< S_d < S_{IDS} + 20$ (km/h) (10)
where Δt is the mine-train travel-time increment and t_{IDS} is the mine-train travel time reached by the initially desired speed profile estimated by the train speed-limit signs on the route. S_{IDS} is the initially desired speed profile, and S_d is the desired speed.

4. AI Controller Design

An AI controller is designed to minimize mine-train fuel burn. This controller has a wise system and changes the initially desired speed profile by using AI algorithms according to well-prepared road gradients and train speed limits of the route ahead. For example, if there is an uphill segment in the route ahead, the desired speed should be increased before the uphill segment. As a result, the train can pass through the uphill segment with less effort. A simple structure of the proposed AI controller is presented in Fig. 3.

The speed controller is the main regulator that controls the braking and throttle position based on the received speed error from the desired locomotive-speed profile. The proposed AI control system is divided into two components: the AI-designed unit and the AI controller. An AI controller block diagram is illustrated in Fig. 4.

As presented in Fig. 4, the route gradient (grade resistance), initial desired speed, and speed limits are required to use the AI control system. The locomotive speed limit, curve radius, road gradient, and start and end points should be available in provided datasets for each route in the data lake. The AI-designed unit calculates locomotive speed limit and the average gradient for a selected segment of the route ahead known as the "look-forward window". This window will be considered in the route segment ahead with a specified distance from the prompt position of the train (see Fig. 5).

In this window, previous control commands affect train speed. It is evident that the look-forward window is moving at the same speed in front of the mine train.

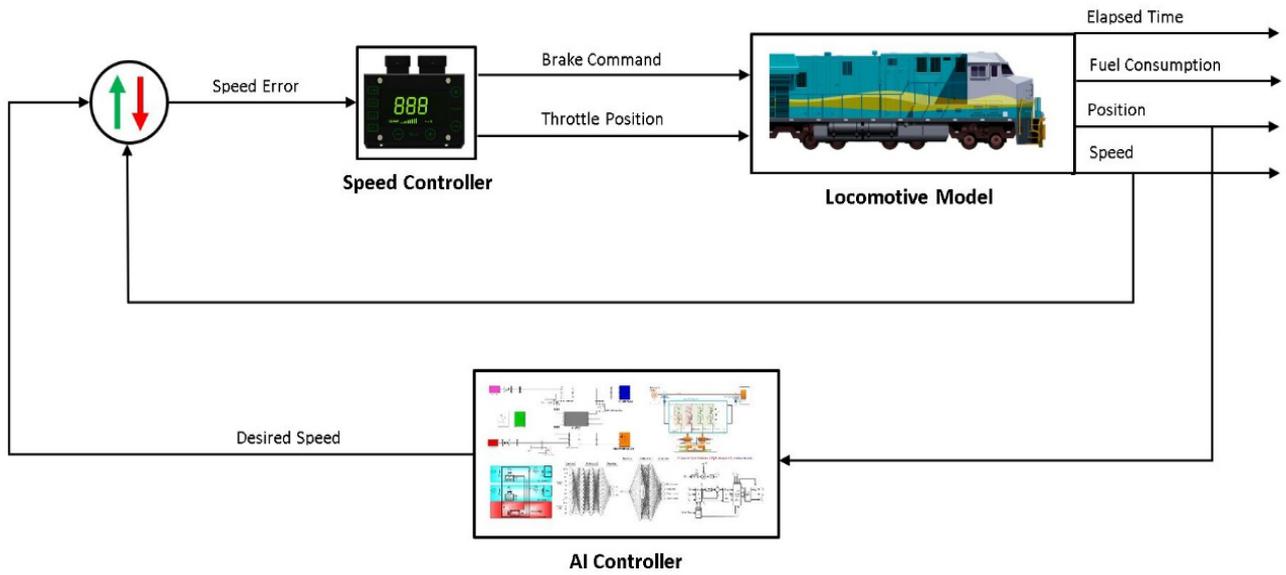


Fig. 3 Mine-train-speed AI controller.

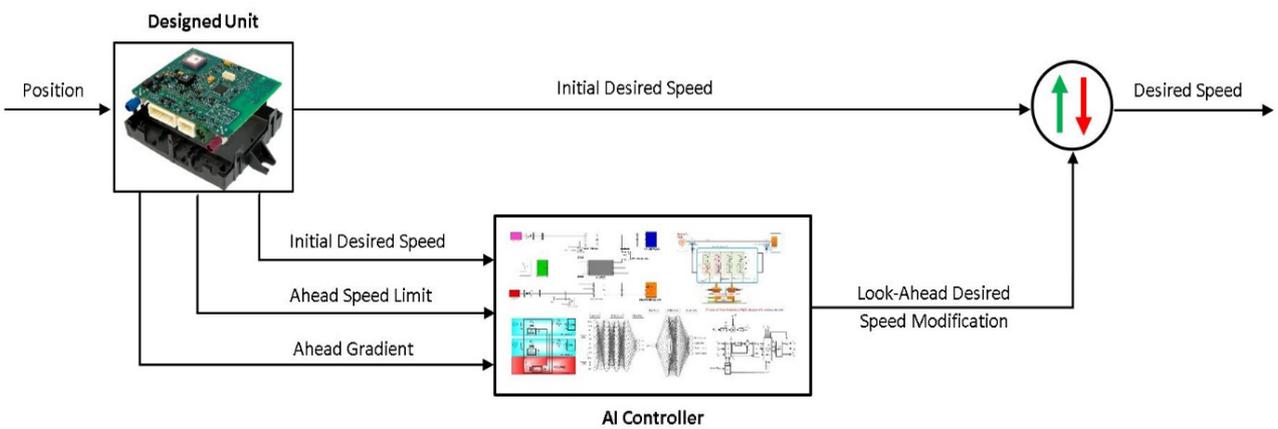


Fig. 4 AI control system's internal components.

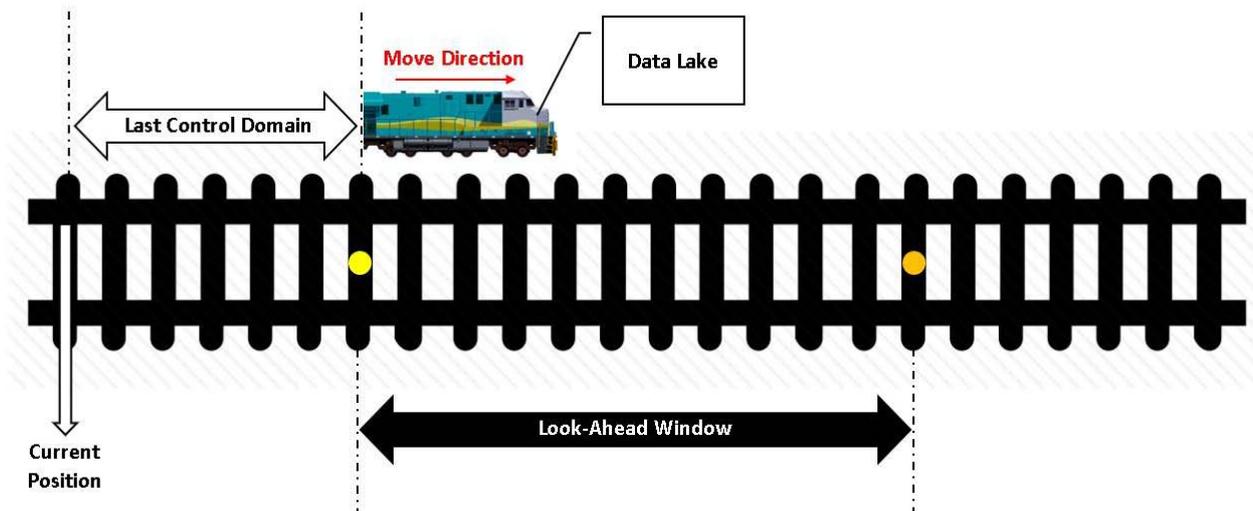


Fig. 5 Look-forward window.

The look-forward window immediately scans the route segments ahead. Therefore, the fluctuations in the route segments ahead are sensed by the opened window. The effect of each control command is anticipated to appear in the start point of its corresponding look-forward window.

To estimate the average upcoming route gradients and locomotive speed limits, the route is discretized as a set of similarly spaced repeated points where the requested information is obtainable in the data lake. If the previous control command's area and the look-forward window include m_1 and m_2 points, respectively, then the forward position (locomotive speed limit and route gradient) will be defined by Eq. (11).

Forward Situation

$$= \frac{\sum_{m_1+1}^{m_1+m_2} \text{Points Situation}}{m_2} \quad (11)$$

Therefore, the “forward position” is the average position of the points inside the look-forward window.

The second part of the AI control algorithm is the AI controller. This unit performs as a feed-forward controller and changes the initially desired speed profile (S_{IDS}) based on the train-speed limits and route gradient of the route ahead. The model of train movement is a complex model based on look-up tables and working limitations of the electric motors, generators, and diesel engines. Therefore, the development of an AI controller may be more appropriate than the other models reviewed in the present study. AI models can be trained based on the heuristically applied experiences of mine-train drivers. For example, if there is no locomotive speed limit in the route ahead and the route gradient is increasing, then the locomotive speed should be increased. However, if there is a locomotive speed limit in the route ahead and the gradient is increasing, then there is no need to increase the locomotive speed. The locomotive's energy is missed during the braking phase. As a result, using an AI controller can potentially help mine-train drivers to reduce braking

force through improved planning of the optimal speed to use in the different route segments.

5. AI Models

AI has existed since the 1950s [17]. Technologies pioneered by AI researchers that are now being used extensively by many different types of organizations include deep-learning or neural networks; natural language processes (used in conversational user interfaces); and image processing (used in products such as self-driving cars). In recent years, cheap computer processing and storage have transformed old AI techniques in practical technologies. The application of AI in the mining industry can be categorized into three main groups: development of prediction models; use of optimization applications; and use of decision-making algorithms [18]. In this study, two popular AI models (ANN and GA) have been developed to predict and minimize locomotive fuel burn (respectively) in the mining industry.

5.1 ANN (Prediction)

ANNs represent the approaches the brain uses for training [21]. They are a series of mathematical algorithms that reproduce several of the known features of natural nerve systems and sketch analogies of adaptive natural training [22]. The critical element of an ANN model is the infrequent structure of the data-processing system [23]. A typical neuronal model thus comprises weighted connectors and an activation function (see Fig. 6).

ANNs are designed for and used in numerous computer applications to solve multipart problems.

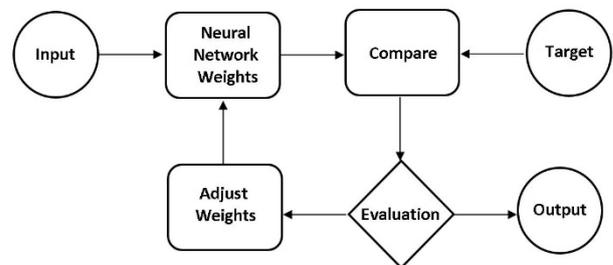


Fig. 6 Standard procedure of an ANN.

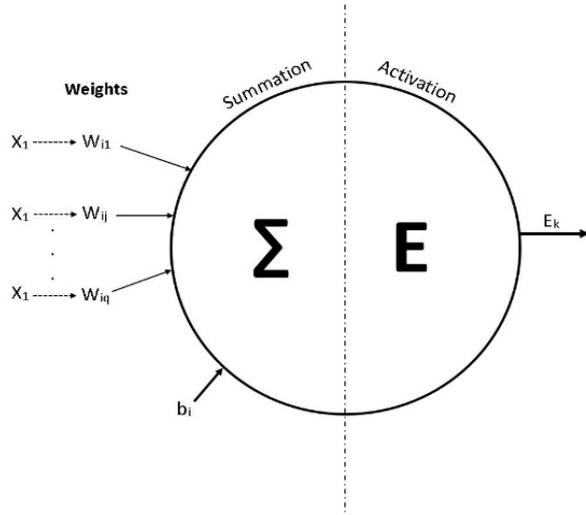


Fig. 7 Data processing in a neural-network cell [19].

They are straightforward and fault-tolerant algorithms that do not need information to recognize the associated parameters, and do not need mathematical explanations of the phenomena involved in the procedure [21].

The main part of an ANN structure is a “node”. Nodes commonly sum the signals received from many sources in different ways, and then perform a nonlinear act on the outcomes to generate the productions. Neural networks naturally have an input layer, one or more hidden layers, and an output layer. Each input is multiplied by its connected weight, and in the purest state, these quantities and biases are joints; they then pass through the activation functions to create the output (see Fig. 7 and Eqs. (12-14)).

$$E_k = \sum_{j=1}^q (w_{i,j,k} x_j + b_{i,k}) \quad k = 1, 2, \dots, m \quad (12)$$

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.

Overall, the activation functions contain both linear and nonlinear equations. The coefficients related to the hidden layer are congregated into matrices $W_{i,j,k}$ and $b_{i,k}$.

Eq. (13) can be used as the activation function

between the hidden and the output layers.

$$F_k = f(E_k) \quad (13)$$

where f is the transfer function.

The output layer calculates the weighted sum of the signals delivered by the hidden layer and the related coefficients are gathered into matrices $W_{o,k}$ and b_o . Using the matrix notation, the network output can be specified by Eq. (14).

$$Out = \left(\sum_{k=1}^m w_{o,k} F_k \right) + b_o \quad (14)$$

Learning the network is the most significant part of the neural-network demonstration, and is performed using two approaches: controllable and uncontrollable learning [24]. The most common learning algorithm is back-propagation [20]. A learning algorithm is well defined as a technique that consists of adjusting the coefficients (weights and biases) of a network to minimize the error function between the predicted network outputs and the actual outputs.

This study presents a different type of algorithm that has been examined to determine the best back-propagation learning algorithm. Unlike other back-propagation algorithms, the Levenberg-Marquardt (LM) back-propagation learning algorithm has the minimum root mean square error (RMSE), mean square error (MSE), and correlation coefficient (R^2).

Further, network learning with the LM algorithm can run efficiently with the minimum expanded memory specification (EMS) and a fast learning process. RMSE, MSE, and R^2 are the statistical criteria utilized to assess the accuracy of the results according to the following equations:

$$MSE = \frac{1}{p} \sum_{r=1}^p (y_r - z_r)^2 \quad (15)$$

$$RMSE = \left(\frac{1}{p} \sum_{r=1}^p (y_r - z_r)^2 \right)^{\frac{1}{2}} \quad (16)$$

$$R^2 = 1 - \frac{\sum_{r=1}^p (y_r - z_r)^2}{\sum_{r=1}^p (y_r - \bar{y})^2} \quad (17)$$

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.

In this study, the MSE and R^2 approaches are applied to examining the performance of the neural-network output, and the LM optimization algorithm is utilized to find the optimum weights of the network.

5.2 GA (Optimization)

The GA was first proposed by Holland to represent the concept of biological development and to illustrate ideas from natural development and genetics for enterprise and the implementation of strong adaptive structures. The new generation of GAs represents reasonably recent optimization approaches. These GAs do not apply any information on derivate, which means they have excellent opportunity for trapping local minimums. Their application in related engineering problems usually carries to the global optimal, or at least to answers that are more acceptable than those gained by traditional mathematical approaches. These GAs apply a straight analogy of the phenomena of development in nature. The individuals are randomly nominated from the research area. The fitness of the answers is the result of the variable to be optimized and is determined afterward from the fitness

function. The individual that produces the best fitness within the population has the maximum chance of returning in the following generation, and thus the opportunity to regenerate by crossover with another individual, which means creating decedents with the characteristics of both individuals. If a GA is adequately established, the population will converge to an optimal answer for the projected problem. The processes that have greater influence on the development are crossover, selection, reproduction, and mutation. Fig. 8 presents the data-processing phases in a simple GA model.

GAs have been used in a diverse range of engineering, scientific, and economic problems [20] due to their potential as optimization methods for multifaceted functions. There are four significant benefits in using GAs for optimization problems. First, GAs do not have a great deal of mathematical necessities in optimization problems. Second, GAs can handle various types of objective functions and limitations defined in continuous, discrete, or mixed search spaces. Third, the periodicity of development operators makes GAs operative during global accomplishment searches. Fourth, GAs provide extreme flexibility for hybridizing with domain-dependent heuristics to allow a well-agonized application for a specific problem.

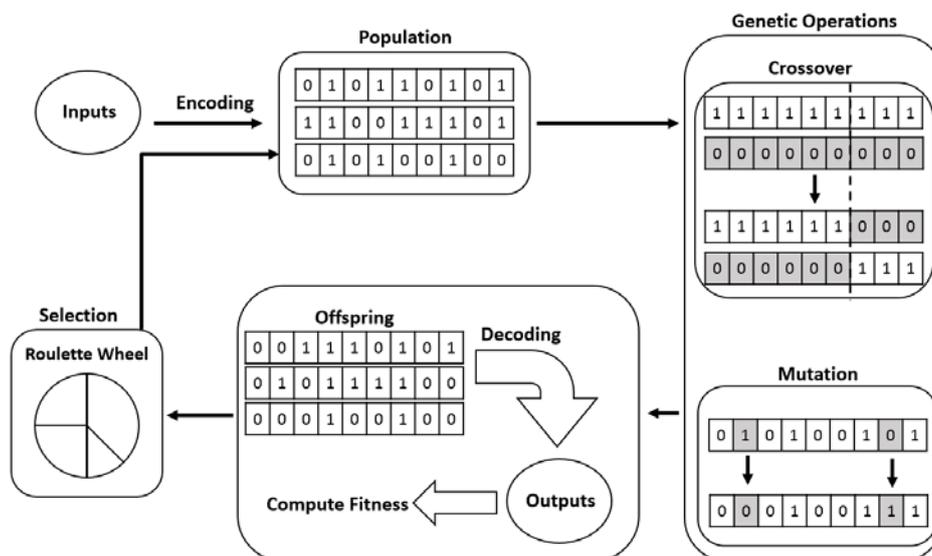


Fig. 8 Data processing in a GA model [18].

Table 1 GA parameters [18].

GA parameter	Details
Fitness function	Main function for optimization.
Individuals	Any parameter to affect the fitness function; the value of the fitness function for an individual is its score.
Populations and generations	An array of individuals; at each iteration, the algorithm makes a series of calculations on the existing population to create a new population; each succeeding population is referred to as a “new generation”.
Fitness value	Value of the fitness function for the individual.
Parents and children	Selected individuals in the existing population, referred to as “parents” and used to generate individuals in the next generation, referred to as “children”.

Moreover, it is significant to analyze the effect of some parameters in the behavior and the performance of GAs to create them conferring to the problem requirements and the existing resources. The effect of each parameter in the algorithm’s performance depends on the class of problems that is being treated. Therefore, the determination of an optimized collection of values for these parameters depends on an excessive number of experimentations and examinations. There are several key parameters applied in the GA technique. Details of GA main processes and parameters are presented in Table 1.

The primary genetic parameters are the dimension of the population, which affects the global performance and the effectiveness of the algorithm and the mutation rate, which avoids a specified position remaining stationary in value or the search becoming fundamentally random.

6. Implementation of Proposed Method

To test the proposed AI application, a mine locomotive was tested on a real railway track in a 100 km segment of the Goldsworthy railway in Western Australia. The Goldsworthy railway is owned and operated by a large mining company, and is a private rail network in the Pilbara district that was built to transport iron ore. The Goldsworthy heavy railway is 208 km long, joining the Yarrie mine to Finucane Island near Port Hedland (see the red line in Fig. 9).

The mine trains on the Goldsworthy railway track have 90 wagons per train. Each wagon transports up to 126 tons of iron ore. The railroad grade is in the variety of -10 to $+10$ per 1,000 m. The minimum road curve radius is 300 m. The grade profile for the 100 km of

railway (i.e. tested segment) is presented in Fig. 10. The way is discretized into a set of points with an equal distance of $dx = 10$ m between them.

The mine-locomotive model used by the study is the GM SD40-2, which is a commonly used model in the Australian railway-transportation system. The functional specifications of the train model and the locomotive are presented in Table 2.

The present study analyzed a set of real data collected over six months to estimate the amount of the diesel burned by a locomotive in the selected segment of railway track in different conditions. The results of these analyses are presented in Table 3.

The fuel burn of the mine diesel locomotive is at a constant rate in each throttle position.

6.1 Prediction Model

The construction of the planned ANN algorithm for function calculation is a feed-forward multilayer-perceptron neural network. The activation functions in the hidden layers (f) are the continuous, differentiable nonlinear tangents sigmoid (see Eq. (18)).

$$f = \text{tansig}(E) = \frac{2}{1 + \exp(-2E)} - 1 \quad (18)$$

where E can be determined by Eq. (6).

$$E_k = \sum_{j=1}^q (w_{ijk} x_j + b_{ik}) \quad k = 1, 2, \dots, m \quad (19)$$

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.



Fig. 9 Western Australia railway map.

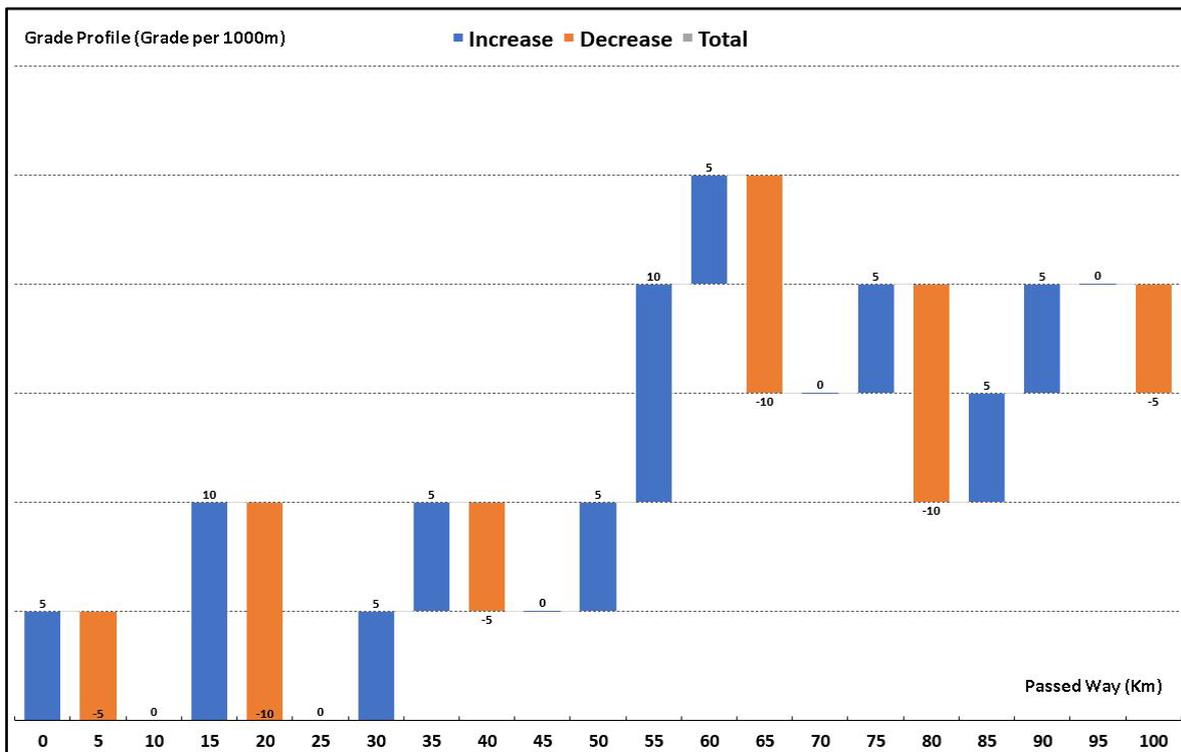


Fig. 10 Road grade profile of path for tested segment.

Table 2 Tested locomotive and train parameters.

Parameter	Value	Parameter	Value
Locomotive model	GM SD40-2	Wheel mass	7,000 kg
Initial friction coefficient	2.7	Wheel radius	0.96 m
Secondary friction coefficient	0.03 s/m	Wheel-friction coefficient	0.3
Drag coefficient	0.0024	Generator model	AR10JBA
Locomotive frontal area	11.148 m ²	Generator mass	7,200 kg
Center of mass height	2.6 m	Generator maximum current	4,200 A
Weight ratio on front bogie	0.5	Generator minimum voltage	1,250 V
Distance between two bogies	13.8 m	Generator maximum output power	5,250 kW
Locomotive mass	167,000 kg	Electric-motor model	D77
Cars' mass	300,000 kg	Electric-motor power	360 kW
Diesel-engine model	645 E3C	Electric-motor mass	2,722 kg
Diesel-engine speed range	300-1,100 rpm	Electric-motor maximum current	1,120 A
Diesel-engine maximum power	2,250 kW	Bus voltage	1,250 V
Diesel-engine mass	14,742 kg	Final-drive mass	1,200 kg
Final-drive ratio	4	Final-drive loss	0.2 input torque

Table 3 Locomotive fuel consumption.

Throttle position	<i>N</i>	1	2	3	4	5	6	7	8
Average fuel burn (l/h)	6.1	9.8	23.7	45.3	62.5	78.5	104.8	135.5	167.4

Eq. (20) can be used as the activation function between the hidden and output layers. In this equation, F is the transfer function.

$$F_k = f(E_k) \quad (20)$$

The output layer computes the weighted sum of the signals provided by the hidden layer and the related coefficients. The network output is specified by Eq. (21).

$$Out = \left(\sum_{k=1}^m w_{ok} F_k \right) + b_o \quad (21)$$

To find the optimal number of nodes in the hidden layer, MSE and the coefficient of determination (R^2) were considered for different numbers of nodes in the hidden layer. The minimum MSE and the maximum R^2 (best performance) were found for ten nodes in the hidden layers. The schematic structure of the designed neural network is presented in Fig. 11.

To learn the proposed ANN model, 85,000 pairing data were randomly selected from the 175,000 values of the collected real data. To examine network accuracy and validate the model, 90,000 independent samples were used. The results show good agreement

between the actual and estimated values of locomotive fuel consumption.

The validation results of the synthesized network are presented in Fig. 12, where the vertical and horizontal axes demonstrate the real fuel-consumption values and the estimated fuel-consumption values by the developed model, respectively. The locomotive throttle position is illustrated on the right side of Fig. 12. The figure also presents the average estimated fuel consumption for each throttle position (shown in red on the left).

The achieved results demonstrate that the developed ANN model can estimate locomotive fuel burn with an acceptable error. The fitness function produced by ANN is fed to the developed AI optimization model that aimed to optimize the train speed in different segments of railway track to allow minimizing the fuel burned by the locomotive.

6.2 Optimization Model

This study has developed a GA algorithm to optimize train speed to allow locomotive diesel consumption to be minimized. In this model, the fitness

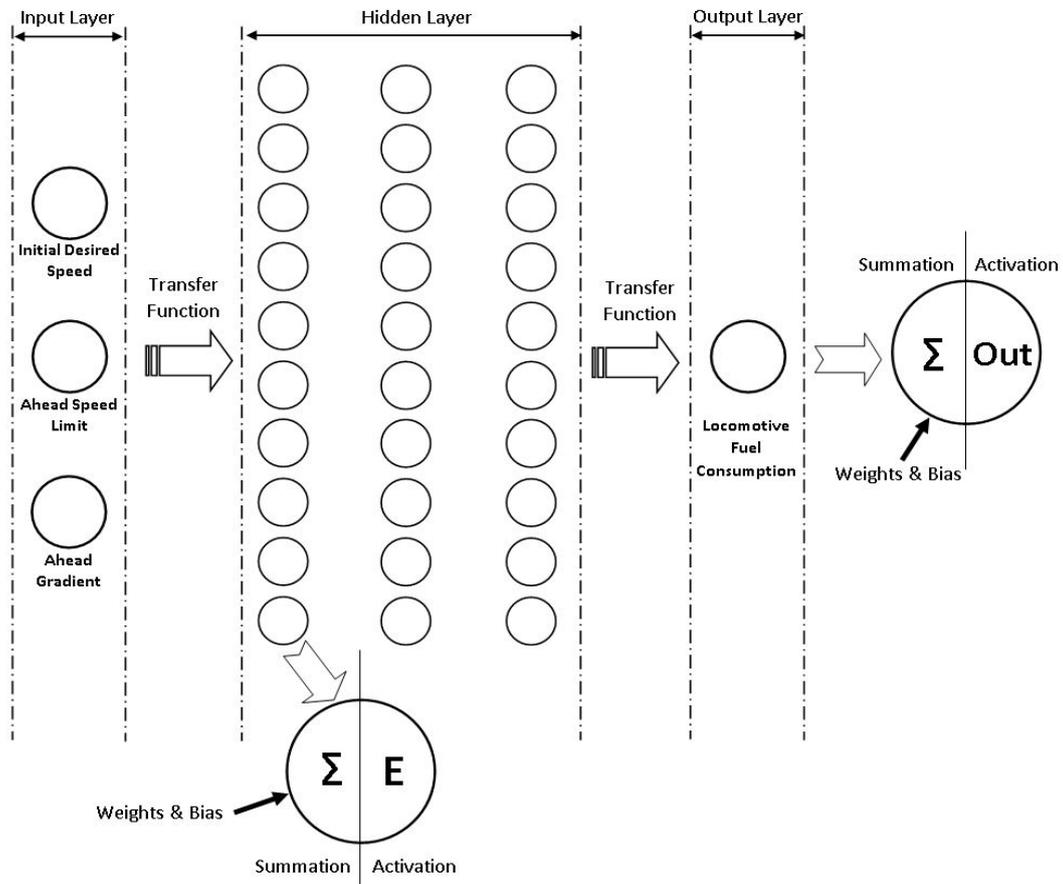


Fig. 11 Data processing in a neural-network model.

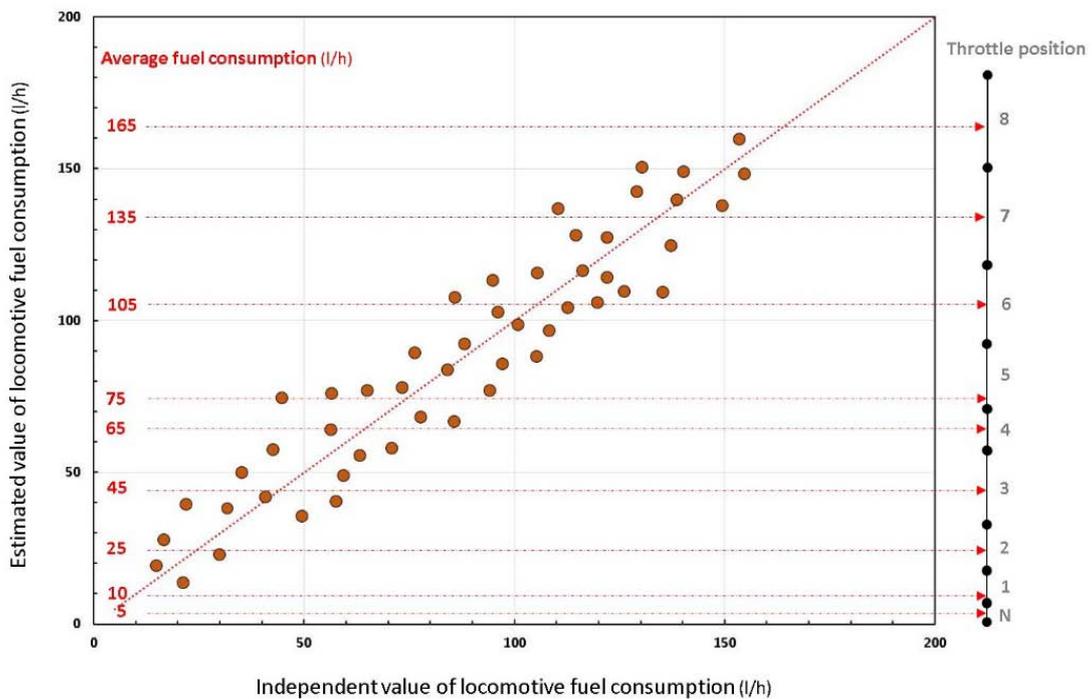
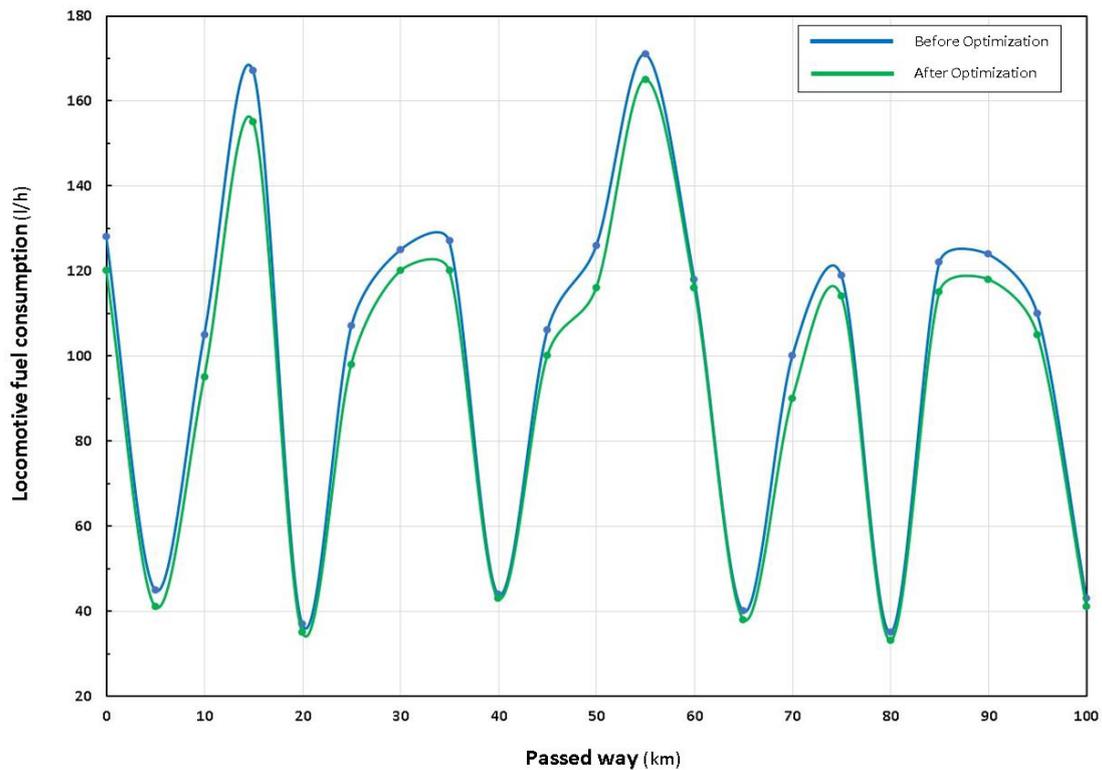


Fig. 12 Prediction-model validation.

Table 4 GA processes [18].

Process	Details
Initialization	Generate initial population of candidate solutions.
Encoding	Digitalize initial population value.
Crossover	Combine parts of two or more parental solutions to create new.
Mutation	Divergence operation; this operation is intended to occasionally break one or more members of a population out of local minimum space, and potentially discover a better answer.
Decoding	Change digitalized format of the 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.

**Fig. 13** Optimization result for selected railway path.

function is created by the developed ANN to feed to the GA algorithm. In the developed GA algorithm, the following seven main processes were defined: initialization, encoding, crossover, mutation, decoding, selection, and replacement. The details of these seven processes are presented in Table 4. In the completed model, the main factors used to control the algorithm are R^2 and MSE .

6.3 Results

The first step of running the developed optimization model is defining the minimum and maximum value of the variable (train speed). The range of possible values

for variables in the established model is based on the collected real dataset. The parameters used to control the established models are R^2 and MSE . The value of MSE was very close to 0, and the value of R^2 was approximately 0.96 after the fifty-seventh generation. These values did not change until the GA model was stopped in the sixty-third generation. In addition, the values of the control parameters were constant after the fifty-seventh generation, but the model continued all processes until the sixty-third. This is because a confidence interval was defined for the model to find reliable results. Fig. 13 presents the rate of locomotive fuel consumption before and after optimization for a

Table 5 Locomotive fuel consumption.

Real fuel consumption (l/h)		Minimized fuel consumption (l/h)		Fuel-consumption improvement (%)	
Min	Max	Min	Max	Min	Max
35	171	33	165	1.69	9.85

selected railway path. The rate of locomotive fuel consumption changes based on the road profile and grade resistance. The large range of presented fuel-consumption rates in Fig. 13 returns to the illustrated road profile in Fig. 10.

The result shows that increasing the road grade increases locomotive fuel consumption, and creates a considerable reduction in train speed. The lowest level of fuel consumption for the locomotive is predicted for the flat segments where the grade resistance is equal to zero, and in some segments of railway path that have a negative grade.

Table 5 presents the range of locomotive fuel consumption in real and optimized conditions (before and after using the developed model) in the investigated case study in Western Australia.

The results presented in Table 5 confirm that using the proposed and validated AI model can provide practical help that will allow the operation team to reach to the minimum 1.69% and maximum 9.85% energy-efficiency improvement in the studied transportation system of the mine railway.

7. Conclusion

This study developed an AI look-forward control as an online approach for energy-efficiency improvement. The AI controller modifies the desired train-speed profile by accounting for the grade resistance and speed limits of the route ahead. Travel-time increment was applied as an improvement constraint. The AI model developed for train-movement simulation was able to accurately predict locomotive fuel consumption based on the values of the transfer parameters considered in this study. The developed model considered the locomotive subsystems and satisfied the experimental fuel-consumption data specified in the locomotive's

catalog. The developed model in this study had two main sections for estimating locomotive fuel consumption in the different situations: one section applies ANN, and the other section (the optimization section) applies GA to optimize the train speed that will minimize locomotive diesel consumption. The proposed AI model in this study was trained and tested using real data collected from a mine-railway route in Western Australia. The simulation of a train with a GM SD40-2 locomotive on a local railway track presented a significant reduction in locomotive fuel burn along with a satisfactory travel-time increment. The model's achievements were also that the AI look-forward controller has faster computations than the controller based on the dynamic-encoding method. The results achieved in this study illustrate that using the developed AI model means that reaching an average of 5.77% energy-efficiency improvement is practically possible. Development of an AI look-forward controller working with a dynamic look-forward window can be suggested as an avenue for future research that could achieve even further locomotive fuel-consumption reduction.

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