



# Sustainable optimization of fuel consumption and CO<sub>2</sub> emissions in mining haul trucks using machine learning: a case study in a gold mine in La Libertad, Peru

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## Abstract

This work aimed to optimize fuel consumption and CO<sub>2</sub> emissions in mining haul trucks through a sustainability focused machine learning approach in a gold mine in La Libertad, Peru. The methodology comprised three stages. First, operational data from 26 m<sup>3</sup> haul trucks (10,103 records over 12 months) were normalized using Z-score scaling. Second, a Ridge regression model was trained to predict fuel consumption based on variables such as truck utilization, trips, road gradient, material type, haul distance, and operating hours. Finally, three operational strategies were simulated: Controlled Reduction (CRS), Balanced Efficiency (BES), and Maximum Utilization (MUS), to evaluate environmental, economic, and social impacts. The results indicated that the Ridge model achieved strong predictive performance in estimating fuel consumption ( $R^2 = 0.83$ ;  $MSE = 38.16$ ). According to the simulated scenarios, environmentally, CRS reduced fuel consumption by 30% and CO<sub>2</sub> emissions by 1,481.3 tons; BES achieved 7.99% savings and 394.9 tons less CO<sub>2</sub>. Economically, CRS saved USD 664,924.6 in fuel costs and BES USD 177,276.3. Socially, the carbon cost decreased by USD 11,406.1 (CRS) and USD 3,041.0 (BES). MUS increased emissions by 864.3 tons and fuel costs by USD 387,966.4. This research proposes a novel integration of machine learning and sustainability analysis applied to haul trucks in open-pit mining material transport. It also offers a replicable, data-driven framework for mining companies to reduce emissions, optimize costs, and align their operations with sustainability goals.

## 1. Introduction

Although several material transportation systems exist in open-pit mining such as in-pit crushing and belt conveyor systems, haul trucks remain the most commonly used method, particularly in medium-scale and flexible operations, and constitute a significant portion of both capital and operational costs. It is estimated that fuel consumption by these trucks accounts for approximately 30% of the total energy usage in open pit mining operations, making them a critical factor from both economic and environmental perspectives [1]. Moreover, haul truck fleets are among the primary sources of greenhouse gas

(GHG) emissions, particularly carbon dioxide (CO<sub>2</sub>), significantly contributing to the environmental impact of the mining sector. Reducing fuel consumption in mining operations is a strategic priority due to its economic and environmental implications. Gibson [2] reported that eliminating idle time in a fleet of 20 mining trucks could result in an annual fuel savings of 145,000 gallons, equivalent to USD 577,100 (at a price of USD 3.98 per gallon), along with a reduction of 64.5 metric tons of CO<sub>2</sub> and 772 engine operating hours. These figures highlight the urgent need to implement energy efficiency



strategies in mining fleet management. From a sustainability perspective, Brundtland [3] defined sustainable development as “meeting the needs of the present without compromising the ability of future generations to meet their own needs”. In the context of this study, sustainable development implies reducing environmental impact while ensuring operational efficiency and economic viability in the mining sector. By modeling and simulating fuel consumption scenarios, this research aims to support informed decision-making that balances productivity, cost savings, and carbon emission reduction, in alignment with the three pillars of sustainability: environmental, economic, and social. However, mining operations generate significant environmental impacts, such as landscape degradation, air pollution, and acid water generation [4]. In this context, energy efficiency and emission reduction in mining haulage equipment play a crucial role in ensuring the sector’s sustainability.

Early studies utilized multiple regression models to estimate fuel consumption in light-duty vehicles, incorporating variables such as speed and acceleration [5]. Later, Rahimi-Ajdadi et al. [6] applied artificial neural networks (ANNs) to predict fuel consumption in tractors, while Kara Togun et al. [7] employed ANN models to estimate torque and specific fuel consumption in gasoline engines. Similarly, He et al. [8] analyzed fuel consumption trends in China’s road transportation sector using regression-based methods. Expanding on these approaches, Yap et al. [9] leveraged ANN models as virtual sensors for predicting and controlling emissions in gasoline engines. Mohamed et al. [10] developed an ANN-based model to forecast nine different engine shutdown responses in light-duty diesel engines. More recently, Yousefi et al. [11] introduced an optimal fuel allocation model for the mining industry, utilizing partial least squares structural equation modeling (PLS-SEM). Machine learning has emerged as an effective tool for enhancing fuel consumption prediction in mining. Alamdari et al. [12] compared multiple algorithms including multiple linear regression, random forests, artificial neural networks, and support vector machines to model fuel consumption in mining haul trucks. Several researchers have also focused on data-driven models integrating operational and simulation-based data. Hellstrom et al. [13] employed GPS data and road gradients to predict fuel consumption in diesel trucks, while Nguyen et al. [14] used daily activity logs to estimate fuel consumption in garbage trucks. Delgado et al. [15]

analyzed fuel consumption patterns based on driving cycles of heavy-duty trucks, whereas Lutsey et al. [16] evaluated the impact of auxiliary power units in reducing idling fuel consumption. Zamboni et al. [17] applied the PHEM model to estimate fuel consumption in urban heavy vehicles. Beyond empirical models, commercial simulation platforms such as EcoGest, CMEN, and ADVISOR have been widely used to assess energy consumption and emissions in the mining sector [18–20]. In recent advancements, Bao et al. [21] developed a predictive model utilizing the Random Forest (RF) algorithm to estimate gas emissions in mining operations. Similarly, Premchender et al. [22] introduced an AI-based model called FuelNet, designed to predict fuel consumption in heavy vehicles by analyzing real-time data and historical patterns. Furthermore, Golbasi et al. [23] implemented a discrete-event simulation model to analyze the fuel consumption of mining haul trucks under varying routes and operational conditions. Siami-Irdemoosa et al. [1] applied ANN models to predict fuel consumption in mining trucks based on their duty cycles. Lastly, Tadubana et al. [24] explored the use of case-based reasoning (CBR) techniques to enhance fuel consumption prediction in open-pit mining operations.

More recently, Vera-Bureau et al. [25] analyzed the impact of operational constraints and mine planning on fuel consumption and CO<sub>2</sub> emissions. Diesel-powered mining equipment significantly contributes to greenhouse gas (GHG) emissions, including CO<sub>2</sub>, CH<sub>4</sub>, N<sub>2</sub>O, ozone-depleting substances (ODS), hydrofluorocarbons (HFCs), sulfur hexafluoride (SF<sub>6</sub>), and perfluorocarbons (PFCs) [26–28]. To mitigate these environmental impacts, Biniaris et al. [29] optimized loading and hauling operations in open-pit mines using stochastic simulations, aiming to reduce fuel consumption and CO<sub>2</sub> emissions. Similarly, Nordin et al. [30] developed a spatial optimization model to assess cost-effective strategies for reducing GHG emissions in the transportation sector. In the context of underground mining, Ren et al. [31] designed a predictive model to estimate carbon emissions during the early stages of underground mining operations, before the implementation of engineering strategies. Carvalho et al. [32] introduced a methodology for calculating CO<sub>2</sub> emission factors and carbon losses in off-highway mining trucks, comparing actual combustion-based emissions with the standardized values reported by the Intergovernmental Panel on Climate Change (IPCC). Additionally, Rexis et al. [33] conducted a comparative analysis of fuel consumption and CO<sub>2</sub>

emissions from three representative types of heavy-duty vehicles in Europe. Other studies, such as those by Sun et al. and Rodriguez-Benavides et al. [34, 35], have focused on CO<sub>2</sub> emissions from residential energy consumption and cement production in China. Various strategies influence CO<sub>2</sub> emissions in transportation. Weight-specific emission models improve estimation accuracy [36], while investments in public transport reduce personal travel emissions [37]. Freight shifts from highways to rail or waterways lower emissions in the long term [38], and tax policies have demonstrated a 9% reduction in vehicle CO<sub>2</sub> emissions [39]. Additionally, the built environment plays a key role in shaping commuting emissions [40]. Urban planning significantly impacts transport efficiency and CO<sub>2</sub> emissions. Studies show that optimizing the spatial distribution of key destinations and housing can reduce intra-urban CO<sub>2</sub> emissions by up to 40% [41]. Additionally, while high-speed rail (HSR) is considered a green transport mode, it can unexpectedly increase household CO<sub>2</sub> emissions due to higher consumption levels in cities with HSR [42]. This highlights the need for integrated policies to optimize transportation sustainability.

Mining operations are highly energy-intensive, with an estimated 61% energy savings potential through operational efficiency optimization [43]. Since mining transportation primarily relies on diesel engines, its efficiency is typically assessed in terms of fuel consumption. Norgate et al. [44] proposed methodologies to estimate energy consumption in heavy-duty diesel vehicles, while Soofastaei et al. [45] developed a model to analyze variations in specific fuel consumption based on factors such as payload, speed, and travel distance. Similarly, Sahoo et al. [46] investigated the impact of payload on fuel consumption, and Giannelli et al. [47] introduced approaches to estimate energy consumption in heavy-duty diesel vehicles by assessing diesel efficiency. Fuel consumption in mining haul trucks is influenced by multiple factors, including mass balance, vehicle dynamics, and engine characteristics [46]. Payload is a key determinant, as it directly affects both fuel consumption and emissions [48]. Additionally, fuel efficiency varies depending on technical and operational factors, such as vehicle design and operating conditions [49]. Several studies have examined the relationship between these variables and energy consumption. Soofastaei et al. [50] used statistical models to assess the influence of payload, whereas Dindarloo et al. [51] evaluated the impact of cyclic activities but did not consider

key factors such as road gradient or rolling resistance. Other approaches have leveraged statistical and simulation-based models to estimate fuel consumption. Rodvalho et al. [52] developed statistical equations for fuel estimation, while Soofastaei et al. [50] utilized discrete-event simulation to evaluate operational efficiency. Furthermore, Patterson et al. [53] applied linear programming to optimize fuel consumption, considering operational changes such as route modifications. Mining haul trucks represent the largest operational cost in open-pit mining, making fuel efficiency a critical factor for both cost reduction and environmental impact mitigation [54].

Mining operations pose significant environmental challenges, including landscape degradation, acid mine drainage, and air pollution caused by greenhouse gas (GHG) emissions, particularly CO<sub>2</sub> [4]. Studies indicate that approximately 50% of open pit mining operational costs are associated with material loading and transportation [55]. Additionally, equipment aging leads to reduced haul truck efficiency, resulting in increased energy consumption and higher CO<sub>2</sub> emissions [56]. Fuel consumption in mining trucks is influenced by several factors, including payload, speed, engine power, idling time, road gradient, fuel quality, and weather conditions [26, 27]. Previous research has demonstrated that vehicle mass is directly proportional to fuel consumption [57], while factors such as rolling resistance and terrain conditions also play a crucial role [58]. Other studies have highlighted the impact of route characteristics [59] and driving efficiency [60] on fuel usage. Although numerous studies have proposed models for predicting fuel consumption in heavy vehicles, the application of these methodologies in the mining sector remains limited, particularly in terms of operational optimization and sustainability. This study aims to address these gaps through the following three key innovations: i) Fuel consumption prediction using a machine learning model (Ridge regression), incorporating multiple operational variables from mining haul trucks. ii) Fuel consumption optimization through scenario-based simulations of operational strategies, and iii) Evaluation of results based on the three pillars of sustainable development (environmental, economic, and social aspects).

This study seeks to develop a machine learning-based model to predict and reduce fuel consumption in mining haul trucks within an open-pit mining operation. The model will incorporate

operational variables and strategic simulations, with results analyzed from the perspective of the three pillars of sustainability. By adopting a sustainability-driven approach, this research provides key tools for strategic mining fleet management and carbon footprint reduction. The remainder of this article is structured as follows: Section 2 describes the methodology used in this study. Section 3 presents the results and discussion. Section 4 concludes with the key findings of the research.

## 2. Methodology

To predict fuel consumption in mining haul trucks, a Ridge regression model was developed [61, 62]. Ridge regression is an extension of multiple linear regression that incorporates regularization techniques to enhance the stability and accuracy of the model. The methodology adopted in this study was structured into five key stages, providing a systematic approach to model development and evaluation.

Figure 1 outlines the sequential methodology followed in this study. The process begins with the creation of a mining haul truck database, which includes 10,103 operational records over a 12-month period. These records are divided into training data (80%) and testing data (20%) for

model development and validation, respectively. Data preprocessing involves normalization of variables using Z-score scaling to ensure comparability between predictors of varying units. The six operational variables selected (U, NT, SR, MT, DT, OH) are those most influential in fuel consumption, as supported by the literature and the Pearson correlation analysis. A Ridge regression model is then constructed using the training dataset. The model is validated via 5-fold cross-validation, optimizing the regularization parameter ( $\alpha$ ) based on evaluation metrics:  $R^2$ , RMSE, MSE, and MAE. After training, the model is used to simulate fuel consumption under four operational scenarios: the Average Base (EB), Controlled Reduction (CRS), Balanced Efficiency (BES), and Maximum Utilization (MUS). Each scenario adjusts key variables to assess its impact on fuel consumption. The evaluation metrics allow for quantitative comparison between scenarios. These results are then interpreted through the lens of sustainable development, divided into its three pillars: environmental (fuel and  $CO_2$ ), economic (fuel cost), and social (social cost of carbon). This structured approach enables transparent and replicable analysis, allowing decision-makers to understand the trade-offs between operational performance and sustainability outcomes.

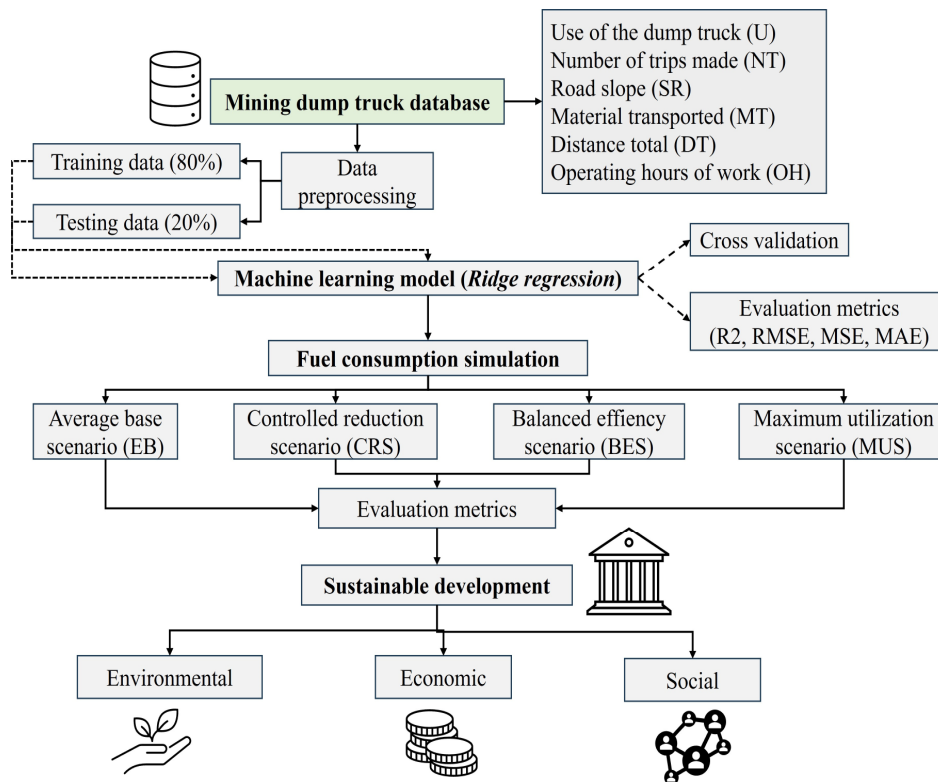


Figure 1. Research workflow

## 2.1. Operational data collection and validation

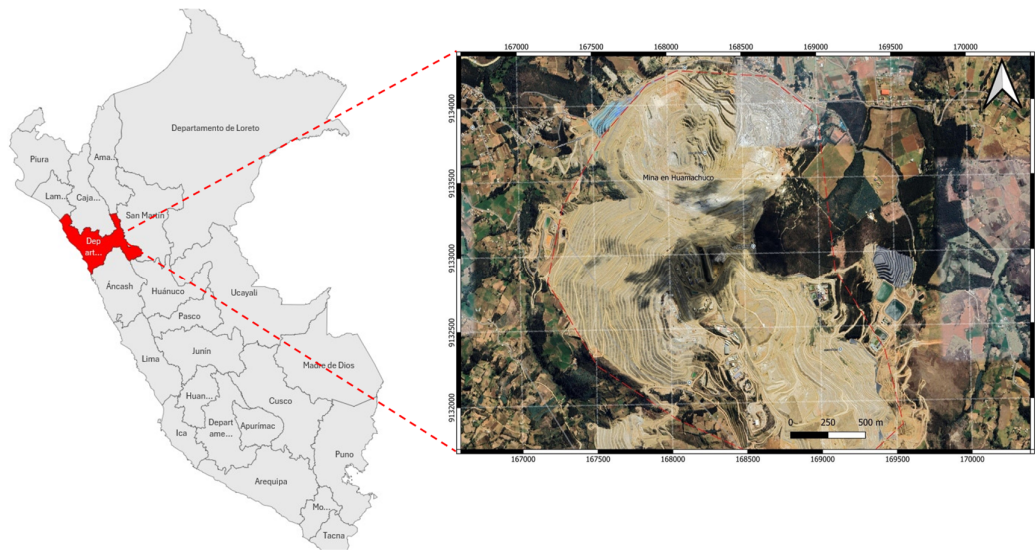
The study was conducted at large-scale open-pit gold mine located in Huamachuco, La Libertad, Peru, at an altitude of 3,341 meters above sea level. The mine has an estimated operational life until 2035, with an average annual gold production of 81,000 ounces of pure gold. The hauling fleet comprises 30 heavy-duty dump trucks, each with a 26 m<sup>3</sup> capacity, manufactured by Fameca. The fleet includes units FMX\_1500 to FMX\_1540. Loading operations are carried out using two hydraulic shovels, modeled after the Caterpillar 6020B, with a 12 m<sup>3</sup> bucket capacity.

Operational data were recorded over a 12-month period (January to December 2024), resulting in a total of 10,103 operational records. These records contain detailed measurements of key operational variables relevant to mining

activities. Figure 2 shows the location map of the open pit mine, situated in La Libertad region in Peru. In Figure 3 shows the haul trucks used in the mining operations in open pit mine in La Libertad, Peru.

Based on previous literature and their documented impact on fuel consumption in mining equipment [46, 48], six predictor variables were selected:

1. Haul truck utilization (U)
2. Number of trips (NT)
3. Road gradient (SR)
4. Transported material (MT)
5. Haul distance (DT)
6. Operating hours (OH)



**Figure 2. Geographic location of the open pit mining operation in La Libertad, Peru**



**Figure 3. Haul trucks with 26 m<sup>3</sup> capacity used in the mining operations**

Unlike telemetry-based approaches, the data used in this study were collected through structured field recording protocols. Field engineers completed standardized forms at the end of each shift, documenting key operational variables. All reports were consolidated daily and validated by shift supervisors. To ensure data consistency and accuracy, the information was cross-checked weekly against internal dispatch and fuel supply records. Although this procedure was manual, it ensured a high level of traceability, reliability, and alignment with real-world operating conditions. Table 1 summarizes the quality control procedures implemented during the data collection process.

To enhance data traceability and standardization, Table 2 presents the structured field form used to record haul truck operational variables during each shift.

**Table 1. Summary of quality control procedures applied data collection**

Component	Description	Validation variable	Frequency
Fiel reports	Daily records completed by field engineers	Reviewed and signed by shift supervisors	Daily
Fuel consumption	Logged in refueling forms and operational reports	Compared with internal supply records	Weekly
Operational variables	U, UN, SR, MT, DT, OH documented in standardized formats	Verified by the operations control department	Daily
Data consolidation	Centralized integration into a single database	Supervised by the data manager	Monthly

**Table 2. Standardized form for collecting field data collected during mining operations**

Variable code	Description	Unit	Data type
Data	Record date	DD/MM/YYYY	Date
Trucks ID	Truck identification code	-	String
Shift	Working shift (Day/Night)	-	Categorical
U	Utilization	%	Float
NT	Number of trips	Trips	Integer
SR	Road gradient	%	Float
MT	Material transported	Tons	Float
DT	Haul distance	Km	Float
OH	Operating hours	h	Float
FH	Fuel consumption	Gallons	Float
Operator code	Operator identification	-	String
Supervisor	Signature for validation	-	Boolean

## 2.2. Data preprocessing

Data preprocessing was a critical step to ensure the quality and generalizability of the model. Two key processes were applied: data partitioning into training and test sets and variable normalization to optimize model performance. To ensure a reliable evaluation, the dataset was split into 80% training and 20% testing. This ratio is widely used in machine learning applications [63, 64] as it provides a balanced trade-off between the model's ability to learn patterns and its generalization capacity on unseen data. Since the predictor variables have different scales of magnitude (e.g., haul distance in kilometers, transported material in tons, and the number of trips as integer values), Z-score normalization (StandardScaler) was applied. The objectives of this normalization were: i) Preventing variables with larger magnitudes from dominating the model's optimization process. ii) Improving the numerical stability of the model. iii) Enhancing training efficiency, accelerating model convergence, and improving accuracy. Mathematically, the Z-score transformation is expressed in Equation (1):

$$X_{norm} = \frac{X - \mu}{\sigma} \quad (1)$$

Where are:

$X$  – represents the original variable value,

$\mu$  – is the variable's mean, and  $\sigma$  is the standard deviation.

This normalization method was chosen over other scaling techniques due to its robustness against extreme values [65, 66], as it preserves data variability without distorting its distribution.

## 2.3. Machine learning model construction

To model fuel consumption in mining haul trucks, a Ridge regression approach was adopted. Ridge regression is a variant of multiple linear regression that incorporates L2 regularization, making it suitable for handling multicollinearity [67, 68], a common characteristic in operational environments where multiple variables are intercorrelated. The Ridge regression model was selected for the following reasons: i) Multicollinearity management to prevent unstable coefficient estimates. ii) Improved model stability, reducing sensitivity to correlated predictors. iii) Enhanced interpretability, making it easier to analyze the influence of operational variables on fuel consumption. Although Ridge regression is a well-established technique in statistical learning, its application in this study is novel due to its integration with a simulation of operational scenarios guided by sustainability principles in the context of open-pit mining. This study positions Ridge regression within a multivariable assessment framework grounded in the environmental, economic, and social pillars of sustainable development. This approach transcends the conventional applications of the model by not

merely focusing on fuel consumption prediction, but by enabling decision-makers to simulate and quantify the impact of operational changes. Thus, the contribution lies not in the algorithm itself, but in its strategic deployment to align predictive analytics with the fundamental principles of sustainability.

Mathematically, Ridge regression minimizes the following cost function, shown in Equation (2):

$$J(\beta) = \sum_{i=1}^n (y_i - X_i\beta)^2 + \alpha \sum_{j=1}^p \beta_j^2 \quad (2)$$

Where:

- $J(\beta)$  - represents the total cost function,
- $y_i$  - is the actual fuel consumption value,
- $X_i\beta$  - denotes the model's prediction,
- $\alpha$  - is the regularization hyperparameter,
- $\beta_j$  - are the regression coefficients.

The parameter  $\alpha$  controls the penalty applied to the regression coefficients: Higher values of  $\alpha$  reduce model variance but may affect predictive performance. Lower values of  $\alpha$  provide minimal regularization, increasing the risk of overfitting [69–71].

To determine the optimal value of  $\alpha$ , grid search cross-validation was employed, evaluating its impact on model performance. The following values were tested (Equation 3):

$$\alpha \in \{0.01, 0.1, 1, 10, 100\} \quad (3)$$

The Ridge regression model was optimized using a cross-validation approach to determine the most suitable regularization parameter ( $\alpha$ ). The procedure followed these steps:

**Step 1:** The dataset was split into five subsets (k-fold cross-validation with ( $k = 5$ )).

**Step 2:** For each candidate  $\alpha$  value, the model was trained on four subsets and tested on the remaining subsets.

**Step 3:** The model's predictive performance was assessed based on: i) Mean Squared Error (MSE): Measures the average squared difference between actual and predicted values. ii) Coefficient of determination ( $R^2$ ): Quantifies the proportion of variance in the dependent variable (fuel consumption) explained by the model.

The results indicated that the optimal regularization parameter was (Equation 4):

$$\alpha^* = 10 \quad (4)$$

This value balanced variance reduction and information retention from the predictor variables. Higher values ( $\alpha \geq 100$ ) excessively shrank the regression coefficients, decreasing the model's predictive capacity, while lower values ( $\alpha \leq 1$ ) provided insufficient regularization, leading to potential overfitting.

Following hyperparameter tuning and model training, the final Ridge regression equation for fuel consumption (FC) was obtained (Equation 5):

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$$FC = 48.12 + 4.32 * U + 3.31 * NT + 0.03 * SR + 3.26 * MT + 2.86 * DT + 3.94 * OH \quad (5)$$


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Where:

$U$  and  $MT$  - have the highest coefficients, indicating that these variables exert the strongest influence on fuel consumption,

$NT$  and  $OH$  - also impact fuel consumption, but to a lesser extent,

$SR$  - exhibits an insignificant coefficient, suggesting that its variability within the analyzed range does not significantly affect fuel consumption.

The model's performance was assessed using the following metrics:  $R^2$  (coefficient of determination): Ranges between 0 and 1, with values closer to 1 indicating high explanatory power of the model. Mean Squared Error ( $MSE$ ): Measures the average squared difference between actual and predicted values. Root Mean Squared Error ( $RMSE$ ): Represents the square root of MSE,

expressed in the same units as the target variable, making it easier to interpret [72–75].

## 2.4. Operational scenario simulation

To analyse the impact of different operational strategies on fuel consumption in mining haul trucks, four operational scenarios were designed, adjusting key variables that influence transportation efficiency. These scenarios include: Baseline scenario (EB), represents current operational conditions, serving as a reference for comparison. Controlled reduction scenario (CRS) focuses on significant reductions in truck utilization, number of trips, and haul distance to minimize fuel consumption. Balanced efficiency scenario (BES) applies moderate adjustments to optimize fuel consumption while maintaining productivity. Maximum utilization scenario (MUS)

evaluates the impact of increased truck utilization, load capacity, and trip distance on fuel consumption.

The Balanced Efficiency Scenario was designed as a hybrid operational strategy that balances fuel efficiency and productivity. Unlike the Controlled Reduction Scenario, which imposes aggressive cuts, and the Maximum Utilization Scenario, which intensifies operations, BES applies moderate reductions (5%) across all key variables.

To formalize this logic, a weighted interpolation model was used to derive each BES variable based on the following expression, shown Equation (6).

$$BES_v = (1 - \lambda) * CRS_v + \lambda * MUS_v \quad (6)$$

Where:

$BES_v$  - is the BES value for a given variable  $v$ ,

$CRS_v$  and  $MUS_v$  – are the values from the CRS and MUS scenarios respectively,

$\lambda \in [0,1]$  - is a blending coefficient that controls the relative contribution of each extreme.

In this study, we used  $\lambda = 0.2$ . corresponding to a configuration that prioritizes fuel saving (80% CRS influence) while retaining some productivity (20% MUS).

Although switching rules were not implemented in real time, this formulation enables future development of adaptive hybrid strategies, where the  $\lambda$  value could vary dynamically based on real-world constraints such as haulage demand, queue length, fuel prices, or equipment availability. This approach enhances the replicability, interpretability, and operational realism of the proposed hybrid scenario.

The scenarios were designed to explore strategies for improving fuel efficiency, reducing operational costs and CO<sub>2</sub> emissions, while maintaining productivity levels. To assess the accuracy of the simulations in estimating fuel consumption under different conditions, two key evaluation metrics were employed:

1. Absolute error analysis in simulations: This metric quantifies the difference between predicted fuel consumption and actual values in each scenario.
2. Relative impact on fuel consumption: Measures the percentage variation in fuel consumption compared to the EB. Provides insight into the fuel savings or increases resulting from changes in operational conditions.

## 2.5. Impact assessment on the pillars of sustainable development

The results obtained were analyzed based on four key indicators, classified within the three pillars of sustainable development: environmental, economic, and social [76, 77].

In the environmental pillar, two fundamental metrics were evaluated: fuel consumption and CO<sub>2</sub> emissions. The economic pillar focused on assessing the cost of fuel consumption, while the social pillar quantified the social cost of carbon (SCC), which represents the economic impact of CO<sub>2</sub> emissions on society (see Figure 4).

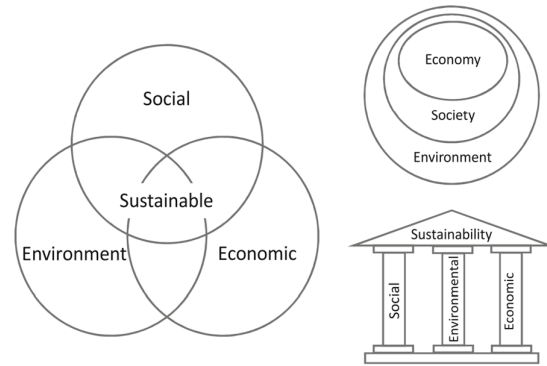


Figure 4. Sustainability pillars [78]

To ensure a comprehensive and practical evaluation of the operational strategies, this study adopts a multi-criteria decision framework that aligns with the principles of sustainable development. Rather than focusing solely on productivity or emissions, the scenarios were assessed using a combination of technical, economic, and environmental indicators, allowing for a more balanced trade-off analysis. Specifically, the framework includes:

- Environmental metrics: total CO<sub>2</sub> emissions derived from estimated fuel consumption using standard emission factors.
- Economic metrics: total cost of diesel consumption (USD), as well as estimated operational savings relative to the baseline.
- Social metrics: Social Cost of Carbon (SCC), reflecting the societal impact of emissions, calculated using a standardized carbon pricing reference.

This approach enhances the decision-making relevance of the proposed simulation strategies by integrating operational realism with sustainability objectives, following best practices in recent studies on energy efficiency and emissions reduction in the mining and transport sectors.

## 2.6. Simulation logic and dispatch model structure

The simulation model was not implemented in Arena but was entirely developed in Python using a structured logic based on discrete event simulation principles. The model uses empirical data collected from hauling operations to simulate fuel consumption under different operational scenarios (CRS, BES, MUS). Each truck is modeled as an entity that moves through a logical sequence of states: dispatch – loading – hauling – unloading – return.

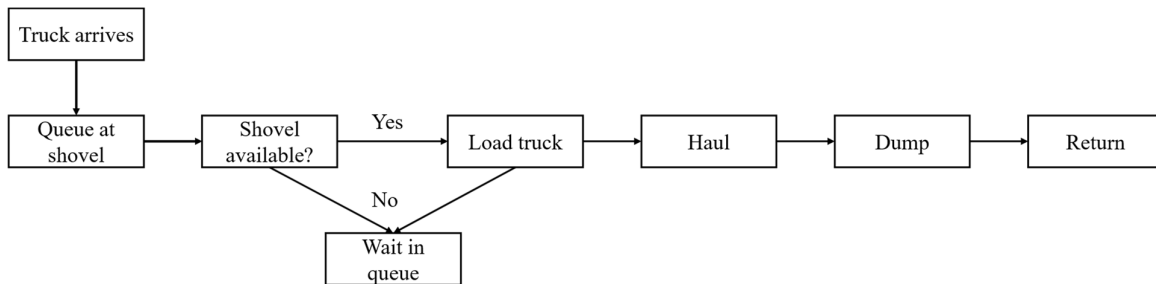


Figure 5. Simplified process logic diagram of the truck-shovel simulation model

## 3. Results and discussions

### 3.1. Descriptive data analysis

Since the dependent variable was fuel consumption (FC), representing the total diesel consumption (in gallons) per haul truck based on operational conditions, Table 3 presents the descriptive statistics of all variables used in this study.

For each simulated shift, operational parameters (number of trips, hauling distance, payload) are adjusted according to the scenario definitions. The simulation iteratively calculates the fuel consumption of each truck per shift using the Ridge regression model trained in Section 2.3. No external simulation engine was used; the entire model was custom-coded to ensure flexibility and consistency with the available data. Figure 5 presents a simplified diagram of the truck–shovel interaction flow and the sequence of implemented events.

To better understand the relationship between operational variables and fuel consumption, the Pearson correlation matrix was computed. The resulting correlation coefficients are presented in Figure 6. The variables U (haul truck utilization), NT (number of trips), MT (material transported), DT (haul distance), and OH (operating hours) exhibited the strongest correlation with fuel consumption (FC) in mining haul trucks.

Table 3. Descriptive statistics of operational variables in mining haul trucks

Statistics	U (%)	NT (trips/day)	SR (%)	MT (ton/day)	DT (km)	OH (h)	FC (gal)
Count	10,103	10,103	10,103	10,103	10,103	10,103	10,103
Mean	62	26	8.39	1,575.42	89.36	8.78	48.10
Std dev	0.12	8.62	0.6	508.96	39.27	1.24	15.39
Min	32	2	8	119.60	0.33	4.92	5.00
Q1 (25 <sup>th</sup> pct)	54	20	8	1,230.64	62.71	7.94	37.00
Q2 (Median)	62	26	8	1,561.68	89.29	8.74	48.00
Q3 (75 <sup>th</sup> pct)	70	32	9	1,907.56	115.17	9.58	58.00
Max	95	76	10	4,561.45	268.94	15.32	139.00
Variance	0.01	74.27	0.004	259,037.87	1,541.87	1.53	236.74

### 3.2. Performance of the ridge regression model

K-fold cross-validation with  $k = 5$  was applied to evaluate the performance of the Ridge regression model, testing different values of the regularization

hyperparameter  $\alpha$ . The table reports the coefficient of determination ( $R^2$ ), and the mean squared error (MSE) for both the training and testing sets (Table 4).

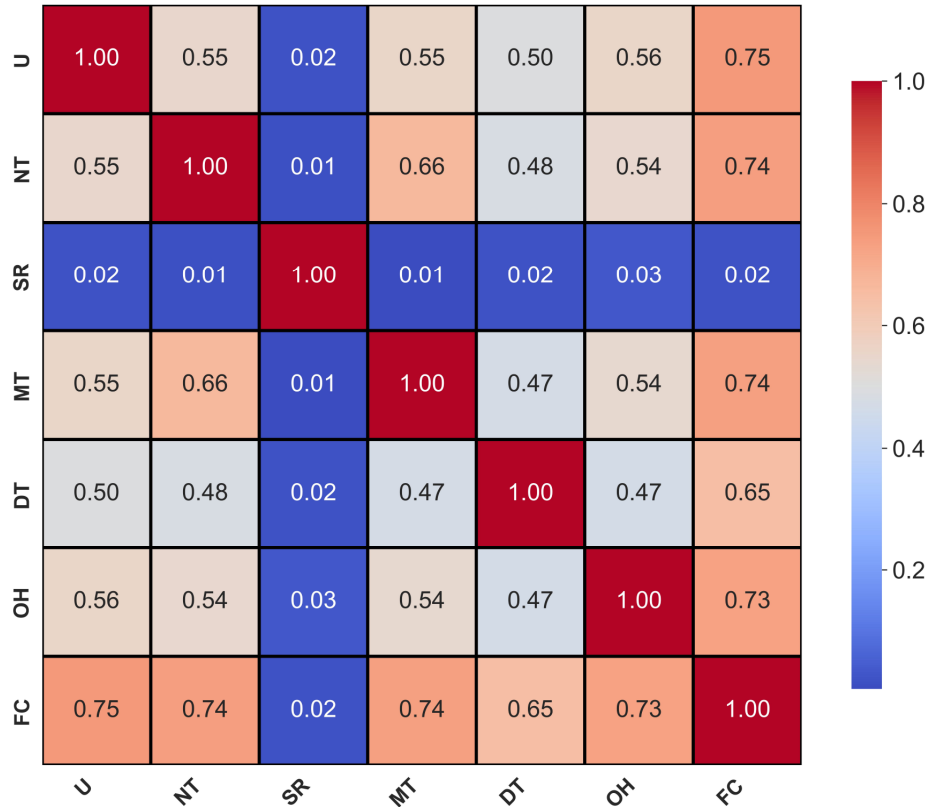


Figure 6. Pearson correlation matrix of operational variables in mining haul trucks

Table 4. Ridge regression evaluation for different  $\alpha$  values

$\alpha$	Training ( $R^2$ )	Test ( $R^2$ )	Training (MSE)	Test (MSE)
0.01	0.8313	0.8335	40.2654	38.1578
0.1	0.8313	0.8335	40.2654	38.1578
1	0.8313	0.8335	40.2654	38.1577
10	0.8313	0.8335	40.2655	38.1569
100	0.8312	0.8335	40.2688	38.1513

The Ridge regression model developed for fuel consumption prediction in mining haul trucks demonstrated strong performance, with evaluation metrics indicating its explanatory and predictive capability. Table 5 presents the model's performance on both the training and test datasets.

Table 5. Machine learning model evaluation metrics

Metrics	Training	Test
MSE	40.27	38.16
RMSE	6.35	6.18
MAE	5.03	4.84
$R^2$	0.83	0.83

The  $R^2$  of 0.83 in both datasets indicates that the model explains 83% of the variability in fuel consumption based on the selected operational variables. Furthermore, the low values of MSE and RMSE suggest that the model achieves a strong fit and high predictive accuracy, with no significant

bias between the training and test sets. The Pearson correlation coefficient ( $r$ ) between actual and predicted values was 0.90, indicating a very strong linear relationship. This high correlation supports the consistency of the model and confirms its robustness under real-world operational conditions. This level of precision is comparable to previous machine learning models applied in mining. Siami-Irdemoosa et al. [1] successfully predicted fuel consumption using artificial neural networks (ANNs), while Alamdari et al. [12] evaluated random forests, neural networks, and support vector machines (SVMs) for the same task. Figure 7 illustrates the comparison between actual and predicted fuel consumption values. The close alignment with the reference diagonal (red line) confirms the model's ability to accurately estimate fuel consumption based on the operational conditions of mining haul trucks

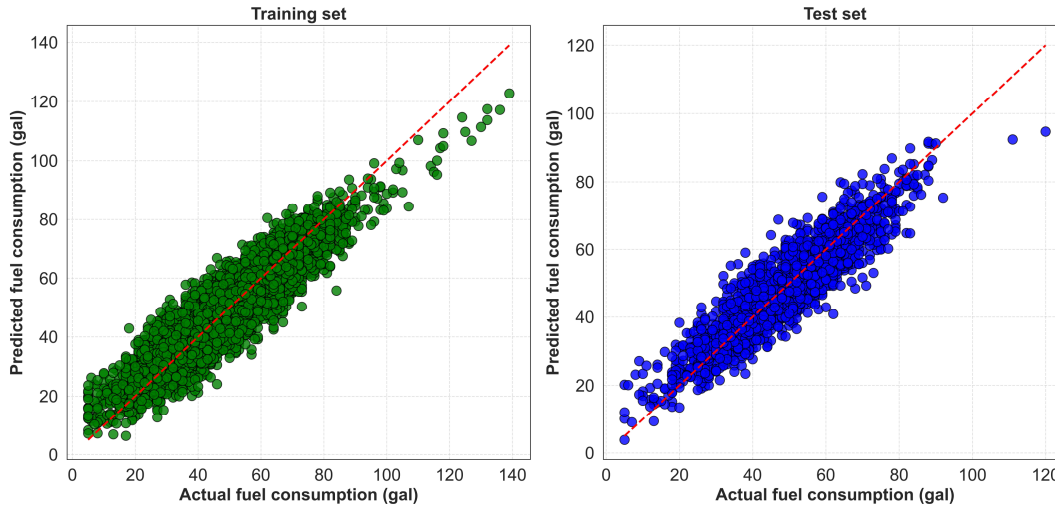


Figure 7. Comparison between actual and predicted fuel consumption

**3.3. Simulation of fuel consumption in mining haul trucks**

Table 6 shows how five key operational variables change under different scenarios

compared to the base scenario (EB). Each scenario simulates a different strategy with potential implications for energy efficiency, productivity, and emissions. An interpretative analysis by scenario is presented below:

**Table 6. Operational scenarios for fuel consumption prediction in mining haul trucks**

Parameter	EB	CRS	BES	MUS
U (%)	62.00	40.00 (-35%)	59.00 (-5%)	68.00 (+10%)
NT (Trips)	26.00	18.00 (-30%)	24.00 (-5%)	29.00 (+10%)
Mt (ton/day)	1575.42	1102.79 (-30%)	1496.65 (-5%)	1811.73 (+15%)
DT (km)	89.36	62.55 (-30%)	84.89 (-5%)	102.76 (+15%)
OH (h)	8.78	6.58 (-25%)	8.34 (-5%)	9.66 (+10%)

Fuel consumption simulations were conducted across the previously defined operational scenarios. To evaluate their accuracy, absolute error analysis was performed, as illustrated in Figure 8. The results revealed significant differences between the scenarios. CRS exhibited the greatest dispersion in error, indicating lower precision in fuel consumption estimation under reduced operational conditions. BES demonstrated the lowest variability and the smallest absolute error, suggesting that it is the most stable and accurate scenario for fuel consumption prediction. MUS, although less dispersed than CRS, showed higher errors compared to BES.

In terms of relative impact (Figure 9), the CRS scenario resulted in a 30% reduction in fuel consumption compared to the Baseline Scenario (EB), confirming that controlled reductions in operations can lead to significant fuel savings. The

BES scenario showed a more moderate reduction of 7.99%, while the MUS scenario increased fuel consumption by 17.51%, indicating that higher utilization and workload lead to increased energy expenditure. Previous studies have identified payload and vehicle speed as the primary determinants of energy consumption [26, 27]. Additionally, Soofastaei et al. [50] demonstrated that variations in rolling resistance and road gradients significantly impact fuel consumption.

To determine whether differences between scenarios were statistically significant, a one-way analysis of variance (ANOVA) was conducted [79], which is appropriate for comparing group means under multiple conditions (Table 7). The results indicated that the differences between groups were highly significant ( $p < 0.01$ ), with an F-statistic value of 4,122.69.

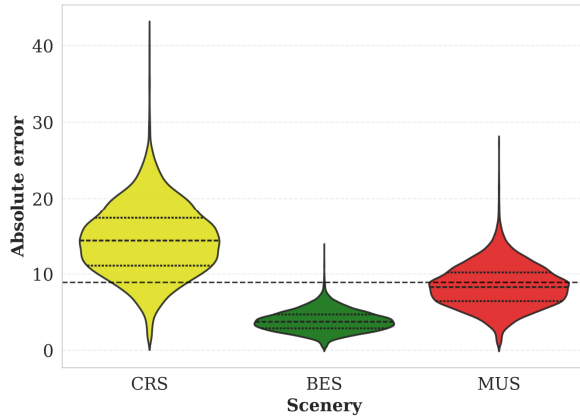


Figure 8. Distribution of absolute errors in simulations

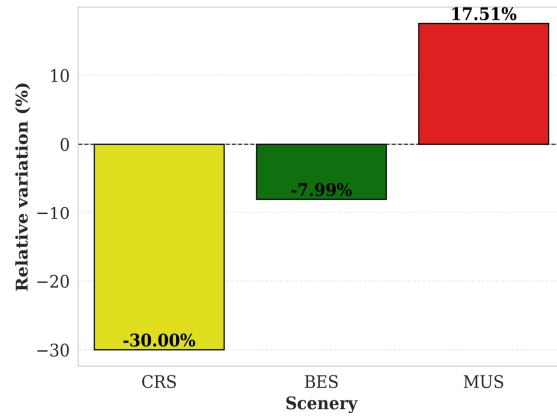


Figure 9. Relative impact of fuel consumption in simulated scenarios

Table 7. ANOVA for fuel consumption

Compared scenarios	Source of variation	Sum of squares	Degrees of freedom	Mean square	F-static	p-value
Base, CRS, BES, MUS	Between groups	2,969,936.19	3	989,978.73	4,122.69	<0.01
	Whitin groups	5,931,229.39	40,408	146.78		
	Total	8,901,165.59	40,411			

**3.4. Verification and validation of the simulation model**

To ensure scientific transparency and the reliability of the simulation results, both verification (implementation correctness) and validation (accuracy against real-world behavior) processes were conducted. The model was verified through logical tracing and modular testing in Python. Each main function (dispatch, queuing

logic, loading, hauling, unloading, and return) was individually tested to ensure appropriate responses under different operational conditions. Edge cases (such as maximum hauling distances or shifts with no trips) were also tested to validate the model’s stability under atypical inputs.

The model’s results in the base scenario (EB) were compared against 12 months of real historical data from the Huamachuco mine. Table 8 presents comparative results for two key indicators:

Table 8. Validation of simulated results against real mine data (base scenario)

Metric	Real average	Simulated average	Absolute error	Relative error (%)
Fuel consumption	48.10	49.65	1.55	3.22%
Number of trips	26.00	27.06	1.06	4.08%

The difference between simulated results and actual data remains within an acceptable margin of 3–4%, which supports the structural and operational validity of the model and provides a solid basis for sustainability analyses.

**3.5. Evaluation of sustainable development pillars**

The total fuel consumption for the analyzed period showed a significant reduction in the optimized scenarios (Table 9). In particular, the CRS resulted in total fuel consumption of 340,195.8 gallons, while the BES led to 447,122.2 gallons and the MUS recorded the highest consumption at 571,065.3 gallons. Previous studies

have highlighted key factors influencing fuel consumption and emissions. Zhang et al. [48] found that payload and driving conditions play a crucial role in determining emissions, while Sahoo et al. [46] identified that increasing payload proportionally raises fuel consumption and greenhouse gas (GHG) emissions.

The distribution of fuel consumption per shift (Figure 10) further illustrates the differences between scenarios. The CRS scenario exhibits lower fuel consumption values with a higher concentration in the lower range, indicating improved efficiency. Conversely, the MUS scenario shifts toward higher consumption values, confirming its higher energy demand.

A similar trend was observed in CO<sub>2</sub> emissions (Table 10), where optimized scenarios led to a substantial reduction in emissions. The CRS (resulted in 1,481.3 fewer tons of CO<sub>2</sub> emissions compared to the EB. The BES achieved a 7.99% reduction in emissions, while the MUS led to a 17.51% increase in CO<sub>2</sub> emissions. The distribution of emissions per shift (Figure 11)

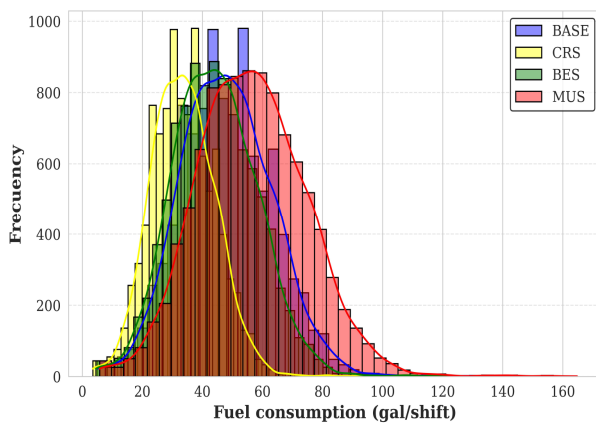
confirms these findings, with CRS exhibiting lower values and MUS demonstrating a concentration of higher emissions, reflecting its higher energy demand. Previous studies support these results, with Vera-Burau et al. [25] analyzing the impact of operational constraints on fuel consumption and CO<sub>2</sub> emissions in mining operations.

**Table 9. Total fuel consumption in mining haul trucks under different scenarios**

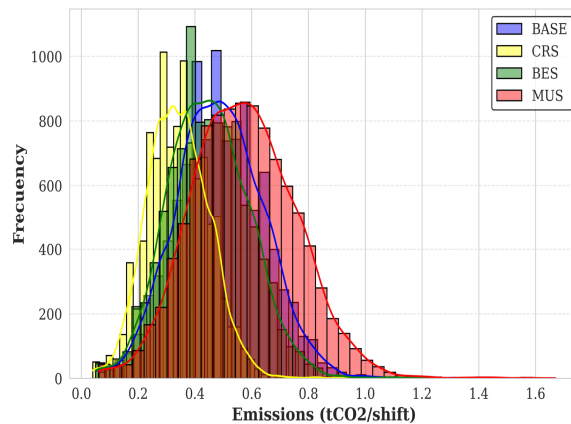
Month	Initial consumption (gal)	CRS scenario (gal)	BES scenario (gal)	MUS scenario (gal)
January	40,003.0	28,002.1	36,779.3	46,964.7
February	36,464.0	25,524.8	33,537.1	42,842.5
March	40,464.0	28,324.8	37,211.8	47,535.5
April	37,724.0	26,406.8	34,706.3	44,342.2
May	38,928.0	27,249.6	35,804.6	45,768.2
June	36,493.0	25,545.1	33,569.1	42,898.3
July	44,880.0	31,416.0	41,291.5	52,760.8
August	46,948.0	32,863.6	43,215.6	55,148.1
September	40,159.0	28,111.3	36,968.0	47,191.0
October	36,944.0	25,860.8	33,964.1	43,425.1
November	42,833.0	29,983.1	39,431.9	50,313.6
December	44,154.0	30,907.8	40,643.0	51,875.3
Total	485,994.0	340,195.8	447,122.2	571,065.3

**Table 10. Total CO<sub>2</sub> emissions in mining haul trucks under different scenarios**

Month	Initial CO <sub>2</sub> emissions (ton)	CRS scenario (ton)	BES scenario (ton)	MUS scenario (ton)
January	406.4	284.5	373.7	477.2
February	370.5	259.3	340.7	435.3
March	411.1	287.8	378.1	483.0
April	383.3	268.3	352.6	450.5
May	395.5	276.9	363.8	465.0
June	370.8	259.5	341.1	435.8
July	456.0	319.2	419.5	536.0
August	477.0	333.9	439.1	560.3
September	408.0	285.6	375.6	479.5
October	375.4	262.7	345.1	441.2
November	435.2	304.6	400.6	511.2
December	448.6	314.0	412.9	527.1
Total	4,937.7	3,456.4	4,542.8	5,802.0



**Figure 10. Distribution of fuel consumption from mining haul trucks per shift across different scenarios**



**Figure 11. Distribution of CO<sub>2</sub> emissions from mining haul trucks per shift across different scenarios**

The economic analysis assessed the fuel consumption cost under different operational scenarios (Table 11). Implementing the CRS resulted in total savings of 664,924.6 USD compared to EB. The BES achieved a cost reduction of 178,276.3 USD, whereas the MUS led to an increased fuel expenditure of 387,966.4 USD. The distribution of fuel costs per shift (Figure 12) supports these findings, showing that CRS maintains lower cost values, while MUS

demonstrates a trend towards higher costs. These results align with previous studies, such as Gibson [2], who reported that eliminating idle time in a mining fleet could reduce annual costs by 511,100 USD. Similarly, Norgate et al. [44] proposed optimization strategies capable of reducing fuel consumption by over 20%, while Topal et al. [55] estimated that 50% of mining operational costs are directly linked to material transportation.

**Table 11. Total fuel consumption cost in mining haul trucks under different scenarios**

Month	Initial fuel cost (USD)	CRS scenario (USD)	BES scenario (USD)	MUS scenario (USD)
January	179,130.9	125,391.7	164,695.2	210,305.2
February	171,862.1	120,303.5	158,066.8	201,925.0
March	187,931.0	131,551.7	172,826.4	220,774.0
April	172,138.8	120,497.2	158,368.5	202,338.4
May	171,771.3	120,239.9	157,989.1	201,953.8
June	161,026.5	112,718.6	148,124.9	189,290.1
July	196,707.1	137,695.0	180,978.9	231,248.4
August	220,162.7	154,113.9	202,659.5	258,616.9
September	185,736.0	130,015.2	170,977.8	218,258.9
October	172,573.6	120,801.5	158,653.8	202,848.2
November	187,248.2	131,073.7	172,379.9	219,950.3
December	210,126.8	147,088.8	193,418.0	246,872.3
Total	2,216,415	1,551,490	2,039,138	2,604,381

From a social perspective, the SCC was analyzed (Table 12) using a reference value of 7.7 USD per ton of CO<sub>2</sub>. The CRS resulted in cost savings of 11,406.1 USD associated with CO<sub>2</sub> pollution-related social costs. Similarly, the BES achieved a reduction of 3,041.0 USD, while the MUS led to an increase of 6,655.3 USD in social costs. The distribution of the social cost of carbon per shift (Figure 13) reinforces these findings, with

CRS showing lower costs and MUS registering higher values. These results align with previous studies, such as Correa et al. [60], who found that enhanced driving efficiency not only reduces fuel consumption but also mitigates the social impact of pollution. Likewise, Tolouei et al. [57] demonstrated that reducing vehicle mass and rolling resistance can effectively lower social carbon costs.

**Table 12. Total social cost of carbon for mining haul trucks under different scenarios**

Month	Initial social cost (USD)	CRS scenario (USD)	BES scenario (USD)	MUS scenario (USD)
January	3,129.5	2,190.7	2,877.3	3,674.1
February	2,852.7	1,996.9	2,623.7	3,351.7
March	3,165.6	2,215.9	2,911.2	3,718.8
April	2,951.2	2,065.9	2,715.1	3,469.0
May	3,045.4	2,131.8	2,801.1	3,580.5
June	2,854.9	1,998.4	2,626.2	3,356.0
July	3,511.1	2,457.7	3,230.3	4,127.6
August	3,672.8	2,571.0	3,380.8	4,314.3
September	3,141.7	2,199.2	2,892.1	3,691.8
October	2,890.2	2,023.1	2,657.1	3,397.2
November	3,350.9	2,345.6	3,084.8	3,936.1
December	3,454.3	2,418.0	3,179.6	4,058.3
Total	38,020.3	26,614.2	34,979.3	44,675.6

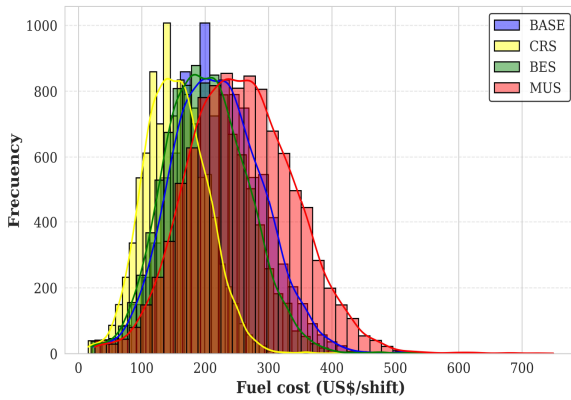


Figure 12. Distribution of fuel costs per shift across different scenarios

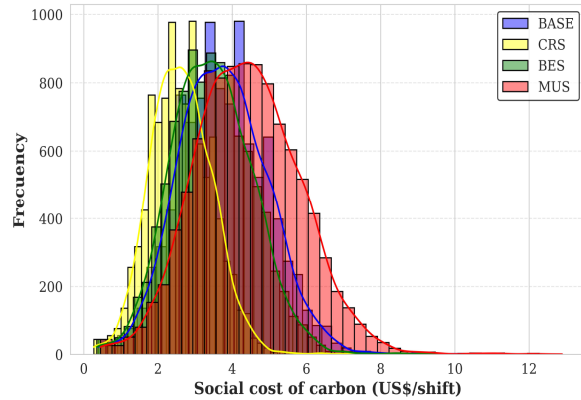


Figure 13. Distribution of social carbon cost for mining haul trucks per shift under different scenarios

### 3.6. Comparative analysis of sustainable pillars

To consolidate the findings, an integrated comparison of the three sustainability pillars environmental, economic, and social was conducted. The total values for each variable across the evaluated scenarios are presented in Table 13, 14 and 15. The sustainability analysis reveals that the CRS achieved the greatest reductions in fuel consumption (-30%), CO<sub>2</sub> emissions (-1,481.3 tons), fuel costs (-664,924.6 USD), and social carbon costs (-11,406.1 USD). In contrast, the BES achieved a moderate reduction across all variables, with 7.99% lower fuel consumption, 394.9 tons fewer CO<sub>2</sub> emissions, 177,276.3 USD in fuel cost

savings, and a 3,041.0 USD decrease in social carbon costs. Conversely, the MUS resulted in higher fuel consumption (+17.51%), increased emissions (+864.3 tons CO<sub>2</sub>), higher operational costs (387,966.4 USD), and a greater environmental impact, confirming its inefficiency. These findings align with previous research, such as Patterson et al. [53], who applied linear programming to optimize transport routes in mining, achieving cost and emissions reductions similar to the BES scenario. Similarly, Dindarloo et al. [51] emphasized the importance of considering operational factors in mining fleet management to mitigate environmental impact.

Table 13. Total values of environmental pillar variables

Pillar	Scenario	Fuel consumption (gal)	CO <sub>2</sub> emissions (ton)
Environmental	BASE	485,994.0	4,937.7
	CRS	340,195.8	3,456.4
	Savings	145,798.2	1,481.3
	BASE	485,994.0	4,937.7
	BES	447,122.2	4,542.8
	Saving	38,871.8	394.9
	BASE	485,994.0	4,937.7
	MUS	571,065.3	5,802.0
	Increase	-85,071.3	-864.3

Table 14. Total values of economic pillar variables

Pillar	Scenario	Fuel consumption cost (USD)
Economic	BASE	2,216,415.1
	CRS	1,551,490.5
	Savings	664,924.6
	BASE	2,216,415.1
	BES	2,039,138.8
	Saving	177,276.3
	BASE	2,216,415.1
	MUS	2,604,381.5
	Increase	-387,966.4

Table 15. Total values of social pillar variables

Pillar	Scenario	Social carbon cost (USD)
Social	BASE	38,020.3
	CRS	26,614.2
	Savings	11,406.1
	BASE	38,020.3
	BES	34,979.3
	Saving	3,041.0
	BASE	38,020.3
	MUS	44,675.6
	Increase	-6,655.3

To provide a normalized and comparable metric of operational cost efficiency, the total fuel expenditure was divided by the total tonnage of material transported for each scenario, as shown in Table 16. This metric expressed in USD per ton of transported material offers a standardized benchmark widely used in mining operations. The Balanced Efficiency Scenario (EEB) achieved the lowest unitary operating cost at 0.1349 USD/ton, confirming its efficiency in balancing cost and

productivity. Although the EMU transported more material overall, its higher fuel usage raised its cost to 0.1422 USD/ton, making it the least efficient. Notably, the ERC and EB scenarios had identical cost per ton (0.1393 USD/ton), but the ERC achieved this at the expense of reduced operational output. These results reinforce that the BES scenario offers the most balanced and sustainable alternative.

**Table 16. Operating cost per ton of transported material across scenarios**

Scenario	Total fuel cost (USD)	Transported material (ton)	Operating cost per ton (USD/ton)
EB	2,216,415.1	15,916,486.6	0.1393
ERC	1,551,490.5	11,141,540.6	0.1393
BES	2,039,138.8	15,120,662.3	0.1349
EMU	2,604,381.5	18,303,959.6	0.1422

The final evaluation suggests that while the CRS scenario is highly efficient in cost and emissions reduction, it may be overly optimistic, as it involves a significant operational reduction that could impact production capacity. On the other hand, the MUS scenario is clearly unfavorable, leading to higher fuel consumption, costs, and

emissions. Thus, the BES scenario is identified as the most balanced alternative. This scenario achieves a compromise between operational efficiency and environmental impact reduction, resulting in total savings of 180,317.3 USD, equivalent to an 8% reduction in operational costs compared to the EB (Table 17).

**Table 17. Total operational cost saving in mining haul trucks**

Scenario	Fuel consumption cost saving (USD)	Social carbon cost saving (USD)	Total saving (USD)	% saving compared to baseline
CRS	664,924.6	11,406.1	676,330.7	30%
BES	177,276.3	3,041.0	180,317.3	8%

### 3.7. Sensibility analysis of operational parameters

To assess the robustness of the proposed simulation model under variability in critical operational parameters, a univariate sensitivity analysis was conducted. This included adjustments to key input variables such as fleet size, shovel availability, average trips per shift, and daily payload. Three simulation scenarios were analyzed:

- ERC (Efficiency Reduction Configuration): reduced number of trucks, trips, and operating hours.
- EEB (Baseline): standard current conditions.
- EMU (Efficiency Maximization Unit): increased utilization, distance, and payload.

Table 18 presents the results of the sensitivity analysis, comparing fuel consumption and CO<sub>2</sub> emissions under each scenario. The ERC scenario reduced fuel use by 12.3%, while EMU increased it by 15.2% compared to baseline. This variability

demonstrates the model's responsiveness and provides insights into how operational configurations affect sustainability metrics.

### 3.8. Implication of sustainable transportation in mining operations

The findings of this study contribute not only to the growing body of literature on fuel consumption optimization in heavy-duty vehicle fleets but also offer an integrated perspective on sustainable transportation within extractive industries. While prior studies have primarily focused on predictive performance or technical efficiency [12, 23], this work broadens the scope in several key areas:

1. The integration of Ridge regression with scenario simulation enables the operationalization of sustainability trade-offs. This facilitates a shift from purely technical optimization toward informed decision-making that balances cost reduction with environmental impact mitigation [76]. The Balanced Efficiency Scenario (BES) exemplifies this equilibrium, achieving an 8% reduction in fuel costs without compromising

operational performance, in alignment with the principles of eco-efficiency [80].

2. In contexts where carbon taxes, GHG limits, or mining efficiency standards are in place, this modeling framework provides a quantitative foundation for planning and regulatory compliance. The potential CO<sub>2</sub> reduction under the BES scenario (394.9 tons/year) could make a meaningful contribution to Peru's nationally determined contributions (NDCs) under the Paris Agreement [81]. Furthermore, scenario analysis allows simulation of the impacts of operational adjustments within predefined boundaries.

3. The proposed methodological framework combining field-collected operational data, predictive analytics, and sustainability metrics offers high replicability potential. Similar approaches could be adapted to transportation systems in port logistics [17], construction

equipment fleets [54], or even urban distribution networks where energy efficiency and emissions are influenced by routing and equipment use [37, 38].

4. This study reinforces the role of interpretable machine learning models in operational management. Ridge regression offers a transparent structure for scenario projection and can be readily implemented in sustainability dashboards or enterprise resource planning (ERP) systems used by mining companies. As noted by Vera-Bureau et al. [25], such tools are increasingly required in operations seeking ISO 14001 certification or alignment with ESG (environmental, social, and governance) standards.

Hence, this research helps close the gap between environmental objectives and operational strategy in carbon-intensive sectors such as open-pit mining.

**Table 18. Sensitivity analysis of operational parameters affecting fuel consumption and emissions**

Description	ERC	EEB (Baseline)	EMU
Adjusted variables	Reduce fleet size, trips and OH	Standard operational conditions	Increased utilization, payload, and distance
Fleet size (trucks)	12	15	18
Shovel availability (%)	85	92	98
Avg. Trips per shift	22.1	26.0	30.5
Avg. Payload (ton/day)	1102.8	1575.4	1811.7
Fuel consumption (gal/shift)	42.7	48.7	56.1
Δ Fuel (%)	-12.3	0.0	+15.2
CO <sub>2</sub> emissions (kg/shift)	434.7	494.6	569.6
Δ CO <sub>2</sub> (%)	-12.1	0.0	+15.2

#### 4. Conclusions

This study introduced a machine learning-based approach for fuel consumption prediction and optimization in mining haul trucks, aiming to enhance operational efficiency while reducing environmental and economic impact. By applying Ridge regression, a highly predictive model was developed ( $R^2 = 0.83$ ), enabling accurate fuel consumption estimation based on key operational variables. The simulations conducted across different operational scenarios demonstrated that strategic adjustments could lead to significant reductions in fuel consumption and CO<sub>2</sub> emissions, contributing to a more sustainable mining sector.

The analysis of the three pillars of sustainable development confirmed that operational optimization not only improves energy efficiency but also reduces costs and mitigates environmental impact. Notably, the CRS resulted in the largest reductions in fuel consumption (-30%) and CO<sub>2</sub> emissions (-1,481.3 tons); however, this strategy could potentially impact mining productivity. In contrast, the BES emerged as the most viable

alternative, offering a compromise between cost reduction (180,317.3 USD in operational savings), lower social carbon costs (3,041.0 USD), and sustained operational capacity, positioning it as the optimal strategy for more sustainable mining operations.

#### 3.9. Limitations and future work

While this study demonstrates the potential of machine learning for optimizing fuel consumption in mining haul trucks, it is important to acknowledge several limitations. First, the model was developed using data from a single mining site over one year. As such, the findings may not be directly generalizable to other geological, operational, or regulatory contexts without further validation. Second, although Ridge regression offers interpretability and stability, more advanced models (e.g., random forests, XGBoost, or deep learning) could improve predictive performance, especially in non-linear environments. These alternatives should be explored in future research. Third, the operational strategies (CRS, BES, MUS)

were designed for simulation purposes and have not yet been implemented in a real mining environment. Practical barriers such as operator training, scheduling constraints, resistance to operational changes, and potential downtime need to be considered. Fourth, this model is not currently integrated with dispatch systems or fleet management software (e.g., Modular, MineStar, or Jigsaw). Real-time data flow and system compatibility are essential for field deployment. Implementation would require API-level integration, sensor calibration, and data security protocols. Finally, social and behavioral dimensions, such as operator compliance and safety culture, could affect real-world outcomes. These human factors are crucial for any digital transformation in mining operations.

Future work should address these constraints by developing multi-site studies, testing real-time implementation through pilot programs, incorporating user feedback, and aligning the model with existing fleet management systems and sustainability dashboards. Additionally, investigating the regulatory and economic implications of emission reductions under carbon pricing schemes may strengthen the business case for adoption.

## References

- [1]. Siami-Irdemoosa, E., & Dindarloo, S. (2015). Prediction of fuel consumption of mining dump trucks: A neural networks approach. *Applied Energy*, 151, 77–84.
- [2]. Gibson, J. (2015). Going green with mobile mining equipment. *Mining Engineering*, 67(10), 43–48.
- [3]. Brundtland, G. (1987). Our common future: Report for the World Commission on Environment and Development. *United Nations*.
- [4]. Moran, C., Lodhia, S., Kunz, N., & Husingh, D. (2014). Sustainability in mining, minerals and energy: New processes, pathways and human interactions for a cautiously optimistic future. *Journal of Cleaner Production*, 84, 1–15.
- [5]. Ahn, K., Rakha, H., Trani, A., & Van Aerde, M. (2002). Estimating vehicle fuel consumption and emissions based on instantaneous speed and acceleration levels. *Journal of Transportation Engineering*, 128(2), 182–190.
- [6]. Rahimi-Ajdadi, F., & Abbaspour-Gilandeh, Y. (2011). Artificial neural network and stepwise multiple range regression methods for prediction of tractor fuel consumption. *Measurement*, 44(10), 2104–2111.
- [7]. Kara Togun, N., & Baysec, S. (2010). Prediction of torque and specific fuel consumption of a gasoline engine by using artificial neural networks. *Applied Energy*, 87(11), 3490–3501.
- [8]. He, K., Huo, H., Zhang, Q., He, D., An, F., Wang, M., & Walsh, M. (2005). Oil consumption and CO<sub>2</sub> emissions in China's road transport: Current status, future trends, and policy implications. *Energy Policy*, 33(12), 1499–1507.
- [9]. Yap, W., & Karri, V. (2011). ANN virtual sensors for emissions prediction and control. *Applied Energy*, 88(12), 4857–4869.
- [10]. Mohamed Ismail, H., Ng, H., Queck, C. W., & Gan, S. (2012). Artificial neural networks modelling of engine-out responses for a light-duty diesel engine fuelled with biodiesel blends. *Applied Energy*, 92, 769–777.
- [11]. Yousefi Nejad Attari, M., Farrashzadeh Miandoab, T., Ejlali, B., & Torkayesh, A. (2021). Fuel consumption in mining industry using partial least squares structural equation modeling approach. *International Journal of Energy Sector Management*, 15.
- [12]. Alamdari, S., Hossein Basiri, M., Mousavi, A., & Soofastaei, A. (2022). Application of machine learning techniques to predict haul truck fuel consumption in open-pit mines. *Journal of Mining and Environment*, 13.
- [13]. Hellström, E., Ivarsson, M., Åslund, J., & Nielsen, L. (2009). Look-ahead control for heavy trucks to minimize trip time and fuel consumption. *Control Engineering Practice*, 17, 163–174.
- [14]. Nguyen, T., & Wilson, B. (2010). Fuel consumption estimation for kerbside municipal solid waste (MSW) collection activities. *Waste Management and Research*, 28(4), 289–297.
- [15]. Delgado, O., Clark, N., & Thompson, G. (2012). Heavy duty truck fuel consumption prediction based on driving cycle properties. *International Journal of Sustainable Transportation*, 6(5), 297–313.
- [16]. Lutsey, N., Brodrick, C., & Lipman, T. (2007). Analysis of potential fuel consumption and emissions reductions from fuel cell auxiliary power units (APUs) in long-haul trucks. *Energy*, 32(2), 314–327.
- [17]. Zamboni, G., Malfettani, S., André, M., Carraro, C., Marelli, S., & Capobianco, M. (2013). Assessment of heavy-duty vehicle activities, fuel consumption and exhaust emissions in port areas. *Applied Energy*, 111, 888–898.
- [18]. Silva, C., Farias, T., Frey, H., & Rouphail, N. (2006). Evaluation of numerical models for simulation of real-world hot-stabilized fuel consumption and emissions of gasoline light-duty vehicles. *Transportation Research Part D: Transport and Environment*, 11(5), 377–385.
- [19]. Silva, C., Gonçalves, G., Farias, T., & Mendes-Lopes, J. (2006). A tank-to-wheel analysis tool for

- energy and emissions studies in road vehicles. *Science of the Total Environment*, 367, 441–447.
- [20]. Ribau, J., Silva, C., & Sousa, J. (2014). Efficiency, cost and life cycle CO<sub>2</sub> optimization of fuel cell hybrid and plug-in hybrid urban buses. *Applied Energy*, 129, 320–335.
- [21]. Bao, R., Feng, Q., Lei, C. (2025) Influencing Factors Analysis and Prediction of Gas Emission in Mining Face. *Sustainability* 17:578.
- [22]. Premchender, M., Pooja, K., Rajitha, K., Prathyusha, K., & Vaishnavi, M. (2023). Fuel Net: Artificial intelligence tool for fuel consumption prediction in heavy vehicles. *Turkish Journal of Computer and Mathematical Education (TURCOMAT)*, 14.
- [23]. Golbasi, O., & Kina, E. (2022). Haul truck fuel consumption modeling under random operating conditions: A case study. *Transportation Research Part D: Transport and Environment*, 102, 103135.
- [24]. Tadubana, G., Sigweni, B., & Suglo, R. (2021). Case-based reasoning system for prediction of fuel consumption by haulage trucks in open-pit mines. *International Journal of Electrical and Computer Engineering*, 11(4), 3129–3136.
- [25]. Vera-Burau, A., Álvarez-Ramírez, D., Sanmiquel, L., & Bascompta, M. (2023). A comparison of the fuel consumption and truck models in different production scenarios. *Applied Sciences*, 13(9), 5769.
- [26]. Norgate, T., & Haque, N. (2012). Using life cycle assessment to evaluate some environmental impacts of gold production. *Journal of Cleaner Production*, 29–30, 53–63.
- [27]. Peralta, S., Sasmito, A. P., & Kumral, M. (2016). Reliability effect on energy consumption and greenhouse gas emissions of mining hauling fleet towards sustainable mining. *Journal of Sustainable Mining*, 15(3), 115–122.
- [28]. Jayanthakumaran, K., Verma, R., & Liu, Y. (2012). CO<sub>2</sub> emissions, energy consumption, trade and income: A comparative analysis of China and India. *Energy Policy*, 42, 450–460.
- [29]. Biniaris, D., Xiroudakis, G., Saratsis, G., Exadaktylos, G., & Varouchakis, E. (2025). Minimization of CO<sub>2</sub> emissions in open-pit mines by using stochastic simulations. *Circular Economy and Sustainability*.
- [30]. Nordin, I., Elofsson, K., & Jansson, T. (2024). Cost-effective reductions in greenhouse gas emissions: Reducing fuel consumption or replacing fossil fuels with biofuels. *Energy Policy*, 190, 114138.
- [31]. Ren, G., Wang, W., Wu, W., Hu, Y., & Liu, Y. (2023). Carbon emission prediction model for the underground mining stage of metal mines. *Sustainability*, 15.
- [32]. de Carvalho, J., de Castro, A., Brasil, G., de Souza, P., & Mendiburu, A. (2022). CO<sub>2</sub> emission factors and carbon losses for off-road mining trucks. *Energies*, 15.
- [33]. REXIS, M., RÖCK, M., & HAUSBERGER, S. (2018). Comparison of fuel consumption and emissions for representative heavy-duty vehicles in Europe. *The International Council on Clean Transportation, FVT-099/17*.
- [34]. Sun, X., Mi, Z., Zhang, J., & Li, J. (2024). Driving factors of carbon emissions from household energy combustion in China. *Energy Policy*, 186, 114013.
- [35]. Rodríguez-Benavides, D., Andrés-Rosales, R., Álvarez-García, J., & Bekun, F. V. (2024). Convergence of clubs between per capita carbon dioxide emissions from fossil fuels and cement production. *Energy Policy*, 186, 114007.
- [36]. Huang, Y., Song, G., & Yu, L. (2024). Development of weight-specific scaled tractive power distributions of heavy-duty trucks for emission estimation. *International Journal of Sustainable Transportation*, 1–13.
- [37]. Kim, D., Ki, H., Suh, W., Lee, S., & Ko, J. (2024). Factors driving reduction in CO<sub>2</sub> emissions from personal travel: A repeated cross-sectional analysis. *International Journal of Sustainable Transportation*, 18, 662–679.
- [38]. Yin, C., Wang, C., Wang, Q., & Ge, Y. (2024). Effects of regional freight structure and energy intensity on CO<sub>2</sub> emission of transport a case study in Yangtze River Delta. *International Journal of Sustainable Transportation*, 18, 379–392.
- [39]. O’Riordan, V., Rogan, F., Ó’Gallachóir, B., & Daly, H. (2023). Impact of an emissions-based car tax policy on CO<sub>2</sub> emissions and tax revenue from private cars in Ireland. *International Journal of Sustainable Transportation*, 17, 969–981.
- [40]. Ashik, F., Rahman, M., Antipova, A., & Zafri, N. (2023). Analyzing the impact of the built environment on commuting-related carbon dioxide emissions. *International Journal of Sustainable Transportation*, 17.
- [41]. Han, M., Håkansson, J., Svensson, T., & Zhao, X. (2025). Planning for energy-efficient transport in a small town: Influence from different urban configurations of destination points and housing establishments. *International Journal of Sustainable Transportation*, 19, 121–132.
- [42]. Wu, S., Yang, Z., & Yao, S. (2025). Impacts of high-speed rail on household carbon dioxide emissions: Evidence from China. *International Journal of Sustainable Transportation*, 19, 149–164.
- [43]. Kaarsberg, T., HuangFu, E., & Roop, J. (2007). Extreme energy efficiency in the U.S.: Industrial, economic and environmental impacts. *ACEEE Summer Study on Energy Efficiency in Industry*, 4, 24–35.

- [44]. Norgate, T., & Haque, N. (2010). Energy and greenhouse gas impacts of mining and mineral processing operations. *Journal of Cleaner Production*, 18.
- [45]. Soofastaei, A., Aminossadati, S., Arefi, M., & Kizil, M. (2016). Development of a multi-layer perceptron artificial neural network model to determine haul trucks energy consumption. *International Journal of Mining Science and Technology*, 26.
- [46]. Sahoo, L., Bandyopadhyay, S., & Banerjee, R. (2014). Benchmarking energy consumption for dump trucks in mines. *Applied Energy*, 113, 1386–1396.
- [47]. Giannelli, R., Nam, E., Helmer, K., Younglove, T., Scora, G., & Barth, M. (2005). Heavy-duty diesel vehicle fuel consumption modeling based on road load and power train parameters. *SAE Technical Papers*.
- [48]. Zhang, K., & Frey, H. C. (2006). Road grade estimation for on-road vehicle emissions modeling using light detection and ranging data. *Journal of the Air & Waste Management Association*, 56, 777–788.
- [49]. Cloke, J., Boulter, P., & Davies, G. (1998). Traffic management and air quality research programme. *TRL Report*, 327.
- [50]. Soofastaei, A., Aminossadati, S., Kizil, M., & Knights, P. (2016). A discrete-event model to simulate the effect of truck bunching due to payload variance on cycle time, hauled mine materials and fuel consumption. *International Journal of Mining Science and Technology*, 26.
- [51]. Dindarloo, S., & Siami-Irdemoosa, E. (2016). Determinants of fuel consumption in mining trucks. *Energy*, 112.
- [52]. Rodovalho, E. da C., Lima, H., & de Tomi, G. (2016). New approach for reduction of diesel consumption by comparing different mining haulage configurations. *Journal of Environmental Management*, 172.
- [53]. Patterson, S. R., Kozan, E., & Hyland, P. (2017). Energy efficient scheduling of open-pit coal mine trucks. *European Journal of Operational Research*, 262.
- [54]. Kecojevic, V., & Komljenovic, D. (2011). Haul truck fuel consumption and CO<sub>2</sub> emission under various engine load conditions. *SME Annual Meeting and Exhibit and CMA 113th National Western Mining Conference 2011*.
- [55]. Topal, E., & Ramazan, S. (2010). A new MIP model for mine equipment scheduling by minimizing maintenance cost. *European Journal of Operational Research*, 207.
- [56]. Soofastaei, A., Aminossadati, S., & Knights, P. (2014). Payload variance plays a critical role in fuel consumption of mining haul trucks. *Australian Resources and Investment*, 8.
- [57]. Tolouei, R., & Titheridge, H. (2009). Vehicle mass as a determinant of fuel consumption and secondary safety performance. *Transportation Research Part D: Transport and Environment*, 14.
- [58]. Oh, Y., Park, J., Lee, J., Eom, M. Do, & Park, S. (2014). Modeling effects of vehicle specifications on fuel economy based on engine fuel consumption map and vehicle dynamics. *Transportation Research Part D: Transport and Environment*, 32.
- [59]. Xiao, Y., Zhao, Q., Kaku, I., & Xu, Y. (2012). Development of a fuel consumption optimization model for the capacitated vehicle routing problem. *Computers & Operations Research*, 39.
- [60]. Correa Espinal, A., Cogollo Flórez, J., & Salazar López, J. (2010). Evaluación del efecto de la conducción eficiente en el consumo de combustible en vehículos de transporte de carga pesada usando diseño de experimentos. *Producción + Limpia*, 5.
- [61]. Melkumova, L., & Shatskikh, S. (2017). Comparing Ridge and LASSO estimators for data analysis. *Procedia Engineering*.
- [62]. Lawrence, K. (1984). Robust ridge estimation methods for predicting U.S. coal mining fatalities. *Communications in Statistics - Theory and Methods*, 13.
- [63]. Cotrina, M., Marquina, J., Mamani, J., Arango, S., Gonzalez, J., Ccatamayo, J., & Noriega, E. (2024). Predictive model using machine learning to determine fuel consumption in CAT-777F mining equipment. *International Journal of Mining and Mineral Engineering*, 15, 147–160.
- [64]. Cotrina, M., Marquina, J., & Noriega, E., et al. (2024). Predicting open pit mine production using machine learning techniques: A case study in Peru. *Journal of Mining and Environment*, 15, 1345–1355.
- [65]. Marquina, J., Cotrina, M., Mamani, J., Noriega, E., Vega, J., & Cruz, J. (2024). Copper ore grade prediction using machine learning techniques in a copper deposit. *Journal of Mining and Environment*, 15(3), 1011–1027.
- [66]. Marquina, J., Cotrina, M., Mamani, J., Soto, L., Ccatamayo, J., Ortiz, S., & Cruz, J. (2023). Application of multilayer perceptron neural network in geological modeling of categorical variables: A case study in Peru. *Mathematical Modelling of Engineering Problems*, 11(6), 1463–1472.
- [67]. Carneiro, T., Rocha, P., Carvalho, P., & Fernández, L. (2022). Ridge regression ensemble of machine learning models applied to solar and wind forecasting in Brazil and Spain. *Applied Energy*, 314, 118936.
- [68]. Wang, X., Wang, X., Ma, B., Li, Q., Wang, C., & Shi, Y. (2023). High-performance reversible data hiding based on ridge regression prediction algorithm. *Signal Processing*, 204, 108818.
- [69]. Geraldo-Campos, L., Soria, J., & Pando-Ezcurra, T. (2022). Machine learning for credit risk in the

Reactive Peru Program: A comparison of the Lasso and Ridge regression models. *Economies*, 10.

[70]. Carneiro, T., Rocha, P., Carvalho, P., & Fernández-Ramírez, L. (2022). Ridge regression ensemble of machine learning models applied to solar and wind forecasting in Brazil and Spain. *Applied Energy*, 314.

[71]. Cotrina, M., Marquina, J., & Polo, J. (2025). Prediction of unit haulage cost in an underground mine using machine learning techniques. *Journal of Sustainable Mining*, 24, 250–266.

[72]. Priya Varshini, A., Anitha Kumari, K., Janani, D., & Soundariya, S. (2021). Comparative analysis of machine learning and deep learning algorithms for software effort estimation. *Journal of Physics: Conference Series*.

[73]. Yashwanth, N. (2020). Evaluation metrics & model selection in linear regression. *Towards Data Science*.

[74]. Anticona Cueva, J., Anticona Cueva, T., Cotrina Teatino, M., Noriega Vidal, E., Valdivieso Velarde, A., & Vera Encarnación, J. (2023). Optimización de la fragmentación de la voladura de rocas en open pit mediante modelos predictivos. *Proceedings of the 3rd LACCEI International Multiconference on Entrepreneurship, Innovation and Regional Development (LEIRD 2023)*.

[75]. Anticona-Cueva, J., Noriega-Vidal, E., Cotrina-Teatino, M., & Arango-Retamozo, M. (2024). Evaluation of predictive models for the optimization of the cost of unit operations in artisanal underground mining. *Mathematical Modelling of Engineering Problems*, 11, 2901–2911.

[76]. Mangukiya, R., & Sklarew, D. (2023). Analyzing three pillars of sustainable development goals at sub-national scales within the USA. *World Development Sustainability*, 2.

[77]. Mensah, J. (2019). Sustainable development: Meaning, history, principles, pillars, and implications for human action: Literature review. *Cogent Social Sciences*, 5.

[78]. Purvis, B., Mao, Y., & Robinson, D. (2019). Three pillars of sustainability: In search of conceptual origins. *Sustainability Science*, 14.

[79]. Niedoba, T., & Pieta, P. (2016). Applications of ANOVA in mineral processing. *Mining Science*, 23, 43–54.

[80]. WBCSD (2016). Contribuyendo a los Objetivos de Desarrollo Sostenible: El enfoque de Negocios Inclusivos.

[81]. Ministerio del Ambiente (2020). Perú ratifica sus compromisos asumidos en el Acuerdo de París e incrementará su ambición climática.



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انجمن مهندسی معدن ایران

## بهینه سازی پایدار مصرف سوخت و انتشار CO<sub>2</sub> در کامیون های حمل و نقل معدن با استفاده از یادگیری ماشین: مطالعه موردی در یک معدن طلا در لا لیبرتاد، پرو

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### چکیده

این کار با هدف بهینه‌سازی مصرف سوخت و انتشار CO<sub>2</sub> در کامیون‌های حمل و نقل معدنی از طریق رویکرد یادگیری ماشینی متمرکز بر پایداری در یک معدن طلا در لا لیبرتاد، پرو انجام شد. این روش شامل سه مرحله بود. اول، داده‌های عملیاتی از ۲۶ کامیون حمل و نقل متر مکعبی (۱۰۱۰۳ رکورد در طول ۱۲ ماه) با استفاده از مقیاس‌بندی Z-score نرمال‌سازی شدند. دوم، یک مدل رگرسیون ریج برای پیش‌بینی مصرف سوخت بر اساس متغیرهایی مانند استفاده از کامیون، سفرها، شیب جاده، نوع مواد، مسافت حمل و نقل و ساعات کاری آموزش داده شد. در نهایت، سه استراتژی عملیاتی شبیه‌سازی شدند: کاهش کنترل‌شده (CRS)، بهره‌وری متعادل (BES) و حداکثر استفاده (MUS)، برای ارزیابی اثرات زیست‌محیطی، اقتصادی و اجتماعی. نتایج نشان داد که مدل ریج در تخمین مصرف سوخت به عملکرد پیش‌بینی‌کننده قوی دست یافته است ( $R^2 = 0.83$ ؛  $MSE = 38.16$ ). طبق سناریوهای شبیه‌سازی شده، از نظر زیست‌محیطی، CRS مصرف سوخت را ۳۰٪ و انتشار CO<sub>2</sub> را ۱۴۸۱.۳ تن کاهش داد؛ BES به ۷.۹۹٪ صرفه‌جویی و ۳۹۴.۹ تن CO<sub>2</sub> کمتر دست یافت. از نظر اقتصادی، CRS 664,924.6 دلار آمریکا در هزینه‌های سوخت و ۱۷۷,۲۷۶.۳ دلار در هزینه‌های BES صرفه‌جویی کرد. از نظر اجتماعی، هزینه کربن ۱۱,۴۰۶.۱ دلار آمریکا (CRS) و ۳,۰۴۱.۰ دلار آمریکا (BES) کاهش یافت. MUS میزان انتشار گازهای گلخانه‌ای را ۸۶۴.۳ تن و هزینه‌های سوخت را ۲۸۷,۹۶۶.۴ دلار آمریکا افزایش داد. این تحقیق، ادغام جدیدی از یادگیری ماشین و تحلیل پایداری را که برای کامیون‌های حمل مواد معدنی روباز اعمال می‌شود، پیشنهاد می‌دهد. همچنین، یک چارچوب قابل تکرار و داده‌محور برای شرکت‌های معدنی ارائه می‌دهد تا انتشار گازهای گلخانه‌ای را کاهش دهند، هزینه‌ها را بهینه کنند و عملیات خود را با اهداف پایداری همسو کنند.

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### کلمات کلیدی

بهره‌وری انرژی  
دی‌اکسید کربن  
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