

Article

Energy Intensity Mapping of Battery-Electric vs. Diesel Heavy Haulage in Surface Mining: The Interplay of Payload Dynamics and Ambient Temperature

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Abstract

Decarbonizing heavy-duty transport in the mining sector requires a deep understanding of the interplay between specific energy consumption, payload dynamics, and ambient thermal stressors. This study presents an integrated, physics-informed machine learning framework to compare the energy intensity of battery-electric (EV) and diesel internal combustion engine (ICE) tippers on a real quarry route in Poland. We develop a bidirectional, route-aware model using physical force balance and high-resolution elevation data to estimate net energy consumption and regenerative braking potential over a complete closed-loop cycle. Furthermore, an Artificial Intelligence analysis utilizing a Random Forest regressor is implemented to simulate and quantify the non-linear impacts of ambient temperature, haul road rolling resistance, and payload mass on the specific energy intensity (E_{spec}). Results indicate that while EV energy demand surges in sub-zero climates due to parasitic battery thermal management loads, electric powertrains exhibit a profound thermodynamic advantage during loaded downhill segments, acting as net energy generators via recuperation. The proposed multi-factor approach provides a robust predictive tool for optimizing fleet deployment, infrastructure positioning, and decarbonization pathways in transitional mining environments.

Keywords: battery-electric mining trucks; specific energy consumption; regenerative braking; battery thermal management system (BTMS); heavy-duty vehicle electrification; physics-informed machine learning; haul road gradient;



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1. Introduction

Decarbonizing heavy-duty transport in open-pit mining is challenged by extreme gross vehicle mass, significant elevation gradients, and repetitive short-haul cycles [1–5]. While battery electric vehicles (BEVs) excel in light-duty urban settings, their feasibility in quarry haulage depends heavily on route-specific energy dynamics. Specifically, the interplay between uphill traction demands and downhill regenerative braking potential dictates the operational viability of BEVs compared to traditional internal combustion engine (ICE) vehicles.

Recent studies emphasize that traditional energy metrics fail to capture the complexities of mine haulage. Prior works have demonstrated that road quality, topography, and volatile energy prices are critical determinants of fleet performance [6,7]. A central theme in heavy-duty electrification is the optimization of regenerative braking. While its

effectiveness can be limited during steep ascents [8,9], logistical profiles with loaded downhill and empty uphill segments can achieve “net negative energy consumption” through continuous regeneration [10,11].

Beyond energy dynamics, fleet availability is a critical operational constraint. While EVs benefit from fewer wear-prone mechanical components compared to ICE trucks, their reliability is highly sensitive to onboard electrical and thermal management systems [12–26]. The two-parameter Weibull distribution is widely recognized as a robust method for predicting these maintenance intervals and failure probabilities in complex mechanical systems [7,18,27–31].

Furthermore, EVs exhibit profound sensitivity to ambient temperature variations. Extreme cold increases energy demand due to HVAC systems, battery thermal management, and reduced chemical efficiency, potentially doubling specific energy consumption compared to baseline scenarios [32–39]. This thermal variability must be integrated into route-aware models to ensure realistic fleet sizing.

Addressing these gaps, this study introduces a universal, AI-enhanced methodology for the comparative assessment of ICE and EV heavy-duty haulage. Utilizing a real quarry route between the Dubie Dolomite Mine and Rudawa Plant (Poland) as a case study, we couple a route-aware force-balance energy model [6,30,40–43] with Weibull-based reliability statistics and Random Forest sensitivity analysis. This multi-dimensional framework integrates terrain geometry, temperature-dependent auxiliary loads [44], and regenerative braking potential, offering a robust tool for predicting fleet readiness and optimizing maintenance schedules in transitioning mining operations.

This work aims to develop an integrated, bidirectional mathematical model for mapping the specific energy consumption (E_{spec}) of both electric and internal combustion engine (ICE) vehicles within a closed-loop transport cycle. The framework utilizes the Random Forest algorithm to assess the sensitivity of the energy balance as a function of operational and environmental factors, while explicitly accounting for the dynamic power consumption of battery thermal management systems (BTMS).

While recent advancements in the journal *Energies* have showcased the efficacy of Physics-Informed Neural Networks (PINNs) for tasks such as thermal anomaly prediction, load margin assessment, and inverter control, these specific architectures traditionally embed differential equations directly into the loss function. In contrast, this study proposes a ‘Physics-Based Synthetic Data Generation’ approach. The primary objective is to quantify the complex interplay between topological mining constraints and the thermodynamic limitations of EVs. By coupling a deterministic force-balance model with an interpretable Random Forest algorithm, this work provides a transparent causal hierarchy of the operational factors that most heavily dictate energy consumption in transitioning mining operations.

While this study focuses on the dichotomy between commercially viable diesel and emerging battery-electric drivetrains, the future technological landscape of heavy-duty (HD) mining transport may also include hydrogen fuel-cell (PEMFC) vehicles. Currently, the deployment of PEMFCs in HD surface mining is constrained to the early prototype phase due to the extreme operational environment. Fuel cells face significant developmental hurdles in these settings, particularly regarding the durability of gas diffusion layers under severe cyclic mechanical stress and vibrations [45], the need for intelligent decoupling control for air supply under dynamic conditions [46], and complex voltage regulation during low-load operations [47]. Until these fundamental stability challenges are resolved for massive HD applications, battery-electric and diesel architectures remain the primary pathways for fleet decarbonization and optimization.

2. Materials and Methods

This section describes the data and models used to compare energy consumption and reliability of a diesel (ICE) haul truck versus a battery-electric (EV) haul truck on the Dubie–Rudawa mining route. The analysis includes the haul route and terrain, vehicle specifications, the energy-balance (force-balance) model for traction energy, drivetrain and auxiliary assumptions, regenerative braking (recuperation) modelling for the EV, and Weibull-based reliability modelling. Equations are provided for traction energy, unit energy intensity (per tonne-kilometer), and regenerated energy.

What sets this methodology apart from conventional vehicle simulation tools is its holistic integration of deterministic physical modeling with data-driven machine learning techniques. While traditional approaches often treat auxiliary loads—such as the BTMS—as static or decoupled baselines, this model dynamically couples thermal management energy demands with fluctuating ambient temperatures and demanding spatial constraints (such as variable route profiles and payload cycles). By deploying the Random Forest algorithm, the framework transcends simple linear sensitivity analyses, successfully capturing complex, non-linear interactions between environmental variables and drivetrain efficiency. This comprehensive, closed-loop approach provides a significantly more robust and resilient tool for predicting energy efficiency, effectively bridging the gap between theoretical vehicle dynamics and real-world fleet operations.

AI-based models—specifically Random Forest Regressors—allow for the identification of complex interactions between route geometry, ambient temperature, and failure intensity. By training an AI model on the simulated Monte Carlo failure streams, we can rank the importance of various operational constraints on the total system availability. This predictive capability enables mining operators to transition from reactive to proactive maintenance schedules, leveraging the structural simplicity of electric drivetrains to minimize unplanned downtime events, which are estimated to be 50% lower in EVs compared to conventional ICE fleets.

2.1. Route Profile Characteristics

The Dubie–Rudawa haul road is modeled as a bidirectional loop, discretized into segments characterized by length, average grade (ζ), and a semi-rough off-road rolling resistance coefficient ranging from 0.005 to 0.01.

The analyzed Dubie–Rudawa haulage route exhibits a typical mountain-type profile (Figure 1), characterized by an average downhill gradient of approximately -5.0% during the loaded trip and a corresponding $+5.0\%$ gradient during the empty return. This configuration, representative of many open-pit mining operations, strongly influences drivetrain loading and constitutes a highly favorable use case for electric haulage.

During the downhill loaded segment (Gross Vehicle Mass ≈ 34 Mg), battery electric vehicles (EVs) recover a significant portion of gravitational potential energy through regenerative braking. In contrast, internal combustion engine (ICE) vehicles irreversibly dissipate this potential energy as heat through the mechanical braking system. During the uphill empty return, EVs further benefit from higher drivetrain efficiency compared to ICE vehicles operating at part load. This efficiency asymmetry inherently favors the transition to electric propulsion. For comparative purposes, diesel fuel energy conversion was calculated based on a lower heating value (LHV) of $36 \text{ MJ} \cdot \text{L}^{-1}$.

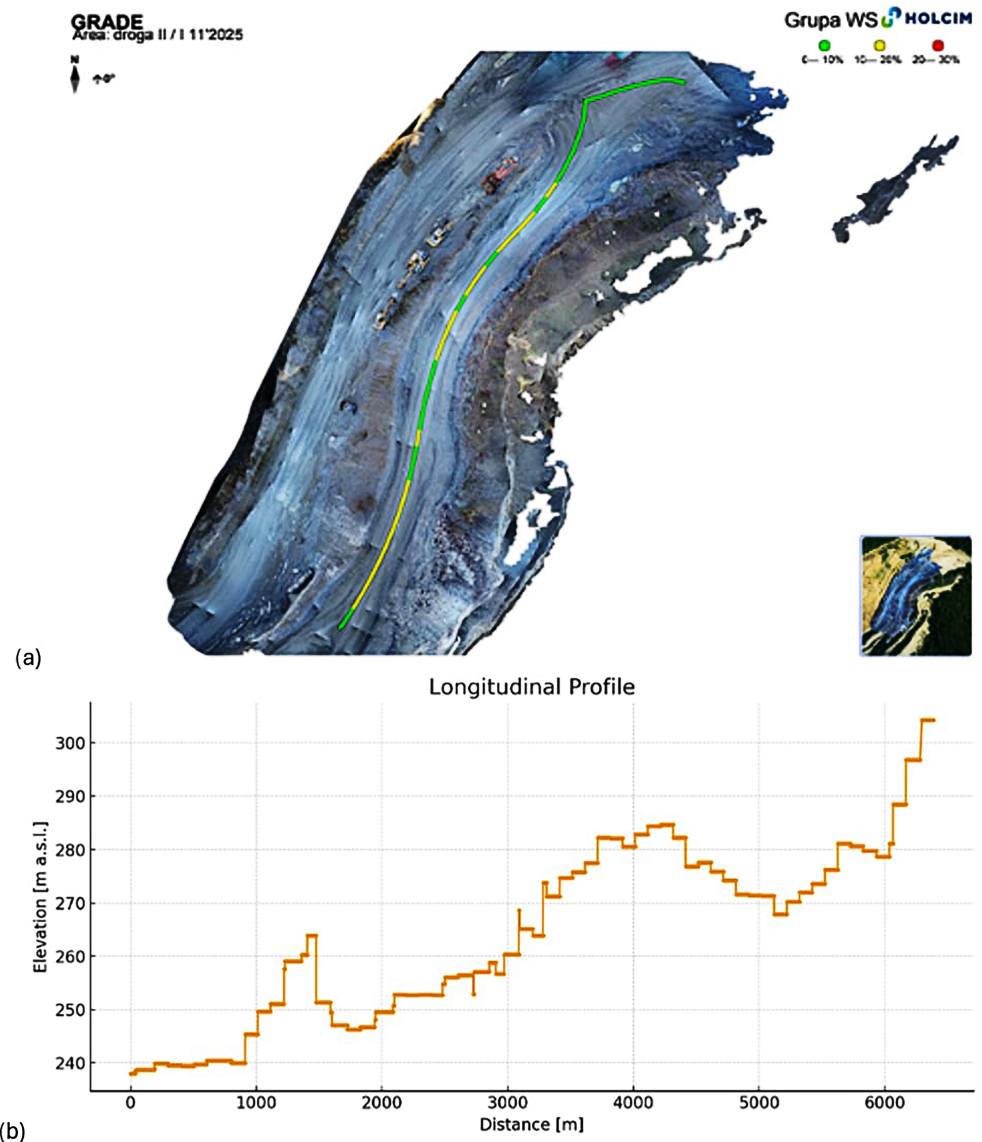


Figure 1. Terrain characteristics of the Dubie–Rudawa route: (a) spatial trajectory from spatial data; (b) corresponding longitudinal elevation profile highlighting the uphill and downhill segments.

2.2. Simulation Structure and Toolchain

Terrain data processing and route spatial discretization were performed using MATLAB R2023b [48], while the core physics-based energy model and stochastic reliability frameworks were implemented in Python 3.10 utilizing the NumPy and SciPy libraries [49]. Energy demand and recuperation potential were accumulated over discretized route segments under steady-state velocities, providing a comprehensive Tank-to-Wheel assessment for the internal combustion engine (ICE) fleet and a Battery-to-Wheel evaluation for the battery-electric vehicle (EV) fleet.

Operational continuity was evaluated via a Monte Carlo discrete-event simulation (DES). Key modeling assumptions included constant rolling and aerodynamic resistances across specific segments, fixed drivetrain efficiencies (excluding transient engine warm-ups), and an idealized EV battery capacity capable of absorbing continuous regenerative power without charging saturation limits. To ensure model robustness and align simulation outputs with empirical order-of-magnitude expectations, comprehensive sensitivity analyses were conducted encompassing ambient temperature fluctuations (from $-20\text{ }^{\circ}\text{C}$ to $+40\text{ }^{\circ}\text{C}$), motion resistances ($\pm 10\text{--}20\%$), and mechanical wear-out parameters. To ensure

full reproducibility, the model parameters were derived from empirical measurements and manufacturer specifications. Spatial terrain characteristics, including localized incline gradients and routing, were extracted using high-resolution LiDAR scans of the Dubie–Rudawa route. Powertrain efficiencies, curb weights, and baseline auxiliary thermal loads for the active Battery Thermal Management Systems (BTMS) were parameterized using OEM (Original Equipment Manufacturer) technical datasheets for contemporary heavy-duty mining platforms. The formalized baseline vehicle specifications and physical boundary conditions are summarized in Table 1.

Table 1. Baseline technical specifications and operational boundary parameters for the simulated battery-electric (EV) and internal combustion engine (ICE) haulage fleets.

Technical Parameter	Battery-Electric Vehicle (EV)	Internal Combustion Engine (ICE)
Tare (curb) mass	18,000 kg	14,000 kg
Gross Vehicle Mass (GVM) limit	32,000 kg	34,000 kg
Total route distance	5.0 km (Incline ramp segment: 180 m)	5.0 km (incline ramp segment: 180 m)
Nominal operating speed	20 km/h	20 km/h
Baseline rolling resistance (f_r)	0.015	0.015
Gravitational acceleration (g)	9.81 m/s ²	9.81 m/s ²
Overall powertrain efficiency (η_{pt})	0.85	0.45
Recuperation efficiency (η_{regen})	0.80	N/A
Base auxiliary power draw (P_{aux})	70 kW	55 kW
Regenerative braking capability	Yes	No
Ambient thermal sensitivity	Non-linear (severe drop below 0 °C)	Linear (moderate drop)
Net autogeneration capability	Possible (loaded downhill)	Impossible
Primary operational risk factor	Sub-zero ambient temperatures	Mechanical wear-out factor (β)

2.3. Energy Consumption Modelling

During a single haulage cycle of the truck ride between the loading and unloading stations, the energy consumption is expressed in terms of work performed by the vehicle, as in Formula (1) [38]:

$$\begin{aligned}
 E &= L[(G_u + G_o)(f \cos \zeta + \sin \zeta) + G_o(f \cos \zeta - \sin \zeta)] \\
 &\quad + \left(\frac{G_u + 2G_o}{2g} + 2LC_d A_f \right) v^2 + G_u h_c \\
 &= L[(G_u + 2G_o)f \cos \zeta + G_u \sin \zeta] + \left(\frac{G_u + 2G_o}{2g} + 2LC_d A_f \right) v^2 + G_u h_c, \quad [J]
 \end{aligned} \tag{1}$$

where

G_o —weight of the truck when empty [N]

G_u —loading capacity [N]

C_d —coefficient of the aerodynamic drag

f —coefficient of rolling resistance

v —nominal velocity [m/s]

ζ —haul road sloping [°]

A_f —front surface of the vehicle [m²]

L —distance between the loading and unloading station [m]

h_c —vertical rise of the center of gravity (cog) of the truck box with the payload [m]

With regard to Expression (1), let us assume the unit mass of the material hauled over the distance of 1 m is given as (2):

$$e_j = \frac{E}{G_u L} = \left(1 + 2 \frac{G_0}{G_u}\right) f \cos \zeta + \sin \zeta + \left[\left(1 + 2 \frac{G_0}{G_u}\right) \cdot \frac{1}{2gL} + \frac{2C_d A_f}{G_u} \right] \cdot v^2 + \frac{h_c}{L} \left[\frac{\text{MJ}}{\text{t} \cdot \text{km}} \right] \quad (2)$$

Accordingly, the unit energy consumption by the vehicle E_{spec} can be expressed in terms of work related to the unit mass (kg) of material hauled over the distance of 1 m. We compute the vehicle's traction energy using a quasi-static force balance along the route [50]. At each road segment, the total longitudinal tractive force F_{tr} must overcome gravitational, grade, rolling, and aerodynamic resistances, following standard vehicle dynamics models adapted for heavy duty.

To evaluate the energy requirements of the haul trucks, a quasi-static longitudinal force balance model was applied [6,40,42,50–54]. The total instantaneous tractive force required at each route segment must overcome gravitational, rolling, aerodynamic, and inertial resistances:

The formula below (3) accounts for variable topography and instantaneous velocity variations along discrete spatial route segments, enriched with an aerodynamic drag component:

$$F_{\text{traction}} = m_{\text{gross}} \cdot g \cdot f_r \cdot \cos(\zeta) + m_{\text{gross}} \cdot g \cdot \sin(\zeta) + 0.5 \cdot \rho \cdot C_d \cdot A_f \cdot v^2 \quad (3)$$

where

m_{gross} —actual total gross vehicle mass ($m_{\text{curb}} + m_{\text{payload}}$) [kg]

f_r —haul road surface rolling resistance coefficient

ζ —localized incline gradient angle of the specific route segment [rad]

ρ —ambient air density [kg/m³]

Conversion of the net longitudinal tractive force into instantaneous mechanical power requirements at the drive wheels, expressed in kilowatts (4), is:

$$P_{\text{wheels}} = F_{\text{traction}} \cdot v \quad (4)$$

For the conventional internal combustion engine asset, the cycle energy profile is purely dissipative, lacking downhill energy recovery mechanisms, which forces the friction braking system to irreversibly dissipate potential energy as waste heat (5):

$$E_{\text{spec,ICE}} = \frac{\int_0^{t_{\text{cycle}}} \max\left(\frac{P_{\text{wheels}}(t)}{\eta_{\text{ice}}}, P_{\text{aux,ICE}}\right) dt}{m_{\text{payload}} \cdot L_{\text{route}}} \quad (5)$$

where

η_{ice} —steady-state Tank-to-Wheel thermodynamic efficiency of the diesel engine (baseline: 0.45)

$P_{\text{aux,ICE}}$ —constant auxiliary power demand from mechanical subcomponents and hydraulic arrays (55.0 kW)

t_{cycle} —total duration of the complete closed-loop cycle (downhill loaded haulage and empty uphill return)

L_{route} —unidirectional haul road distance (0.18 km)

The battery-electric vehicle configuration is modeled as a bidirectional, closed-loop framework, explicitly splitting the evaluation into a downhill recovery segment and an empty uphill return leg (6):

$$E_{spec,EV} = \frac{\int_0^{t_{down}} P_{batt,downhill}(t)dt + \int_0^{t_{up}} P_{batt,uphill}(t)dt}{m_{payload} \cdot L_{route}} \quad (6)$$

where the instantaneous electrical power demand drawn from or delivered to the traction battery pack (P_{batt}) is governed by piece-wise conditional branching logic:

A. Traction Mode (Empty uphill haulage, where $P_{wheels} \geq 0$) (7):

$$P_{batt} = \frac{P_{wheels}(t)}{\eta_{pt}} + P_{aux,EV}(T_{amb}) \quad (7)$$

B. Regenerative Braking Mode (Loaded downhill haulage, where $P_{wheels} < 0$) (8):

$$P_{batt} = P_{wheels}(t) \cdot \eta_{reg} + P_{aux,EV}(T_{amb}) \quad (8)$$

where

η_{pt} —battery-to-wheel powertrain traction efficiency (0.85)

η_{reg} —round-trip energy recovery efficiency during regenerative braking blending (0.80)

$P_{aux,EV}(T_{amb})$ —non-linear parasitic power draw of auxiliary systems (HVAC and active battery thermal management systems – BTMS) modeled as a function of the ambient temperature T_{amb} (9):

$$P_{aux,EV}(T_{amb}) = 70.0 + 0.5 \cdot |\min(T_{amb}, 0.0)|^{1.2} \quad (9)$$

The operational readiness of the battery-electric sub-fleet is formulated as a function of lithium-ion cell vulnerability to extreme thermal stressors, identified as the primary operational risk driver (10):

$$A_{EV}(T_{amb}) = A_{base,EV} - \Delta A_{thermal}(T_{amb}) + \epsilon \quad (10)$$

where the non-linear thermal availability penalty ($\Delta A_{thermal}$) activates exclusively below the critical freezing threshold (0 °C) (11):

○ For sub-zero ambient climates ($T_{amb} < 0$ °C):

$$\Delta A_{thermal}(T_{amb}) = \gamma \cdot \left[\exp\left(\frac{|T_{amb}|}{\tau}\right) - 1.0 \right] \quad (11)$$

○ For positive ambient climates ($T_{amb} \geq 0$ °C) (12):

$$\Delta A_{thermal}(T_{amb}) = 0.0 \quad (12)$$

where

$A_{base,EV}$ —baseline mechanical technical availability of the EV asset under optimal thermal conditions

γ —thermal susceptibility scale coefficient of the battery framework

τ —thermal relaxation constant regulating electrochemical degradation dynamics

ϵ —stochastic white noise variable capturing measurement errors or unmodeled environmental field variations

Because traditional diesel assets are inherently thermal-insensitive due to abundant engine waste heat, their technical readiness is dictated by cumulative mechanical stress and multi-system component wear-out behaviors, formalized via a two-parameter Weibull distribution (13):

$$A_{ICE}(\beta, t) = A_{base,ICE} - \psi \cdot \left[1 - \exp \left(- \left(\frac{t}{\alpha} \right)^\beta \right) \right] + \epsilon \quad (13)$$

where

$A_{base,ICE}$ —initial structural design availability baseline of a new diesel fleet

t —cumulative asset operating hours [h]

α —characteristic life scale parameter

ψ —operational down-time coefficient associated with maintenance interventions

β —dimensionless Weibull shape parameter (where values within $\beta \in [1.1, 1.4]$ model progressive mechanical wear-out, structural aging, and material fatigue inside internal engine and transmission subcomponents)

The mathematical framework established in this study provides a comprehensive, hierarchical link between macroscopic physical work parameters and highly localized, propulsion-specific energy dynamics. By bridging historical steady-state work estimations with a segment-based, high-resolution longitudinal force balance, the model effectively captures both aerodynamic drag boundaries and gravity-induced cycle variations. The explicit mathematical bifurcation between the dissipative diesel ICE model and the bidirectional closed-loop EV model provides a mathematically rigorous foundation for quantifying regenerative energy potential. Furthermore, by introducing dedicated, propulsion-specific risk profiles into the fleet technical availability equations—isolating low-temperature electrochemical cell penalties for EVs and cumulative mechanical wear-out fatigue via Weibull distributions for ICE vehicles—the framework successfully eliminates simplistic deterministic idealizations. This tightly coupled approach ensures that the subsequent physics-informed machine learning sensitivity analysis evaluates realistic operational trade-offs, establishing a robust predictive tool for hauling decarbonization and infrastructure planning under highly volatile environmental conditions.

To provide a clear roadmap of the multi-dimensional evaluation conducted in this study, Figure 2 illustrates the methodological flowchart. The framework systematically integrates spatial terrain data acquisition, deterministic force-balance mechanics, stochastic Monte Carlo simulations, and a final Machine Learning sensitivity analysis to evaluate fleet performance.

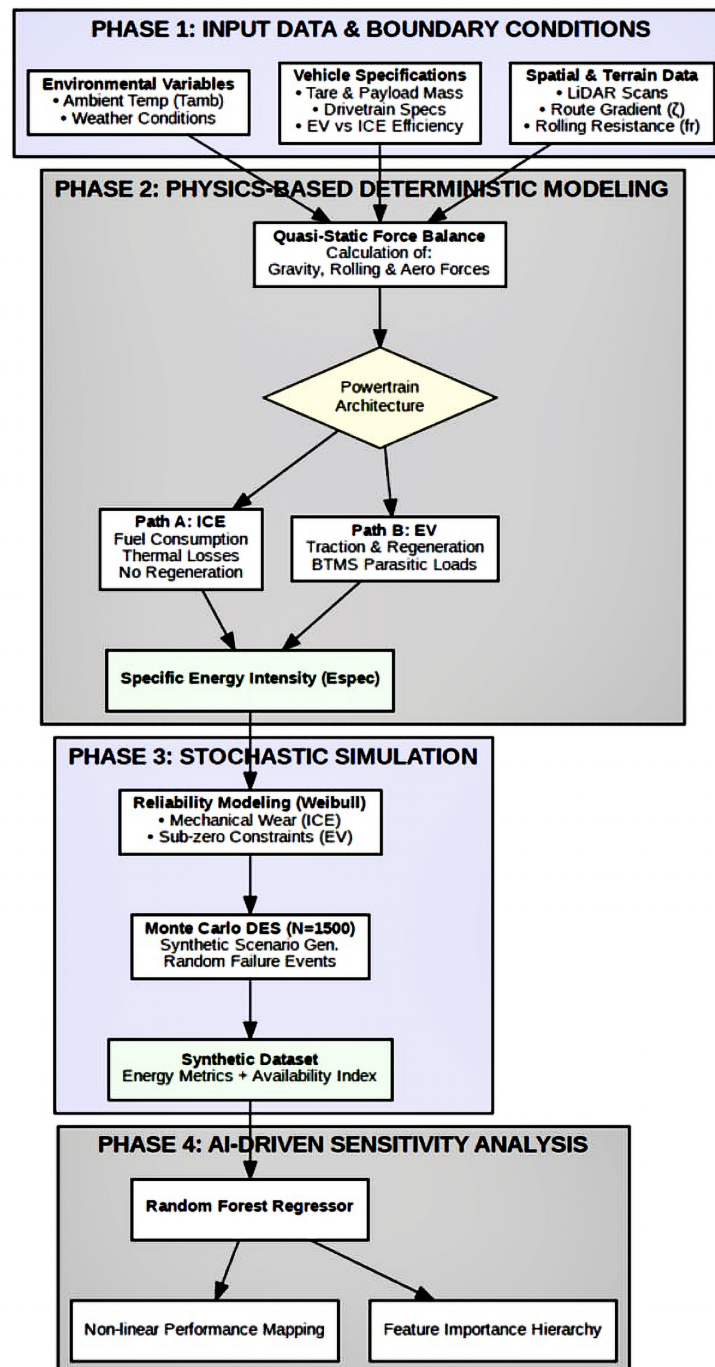


Figure 2. Structure of the Methodology for Multidimensional Assessment of the Transportation Fleet.

3. Results

This section presents the simulation results. We compare energy use of the ICE and EV trucks over one loaded-return cycle.

3.1. Energy Intensity e_j Analysis via Heatmap Simulation

The simulation results are presented as heatmaps of unit energy intensity (E_{spec}) as a function of the rolling resistance coefficient (C_r) and route gradient (α) (Figures 3 and 4). The base comparison of unit energy intensity (e_j) between ICE and EV fleets as a function of the route gradient is illustrated in Figure 3. Furthermore, the multidimensional simulation

results are presented as heatmaps of unit energy intensity (e_i) as a function of the rolling resistance coefficient (f_r) and route gradient (ζ) (Figure 4).

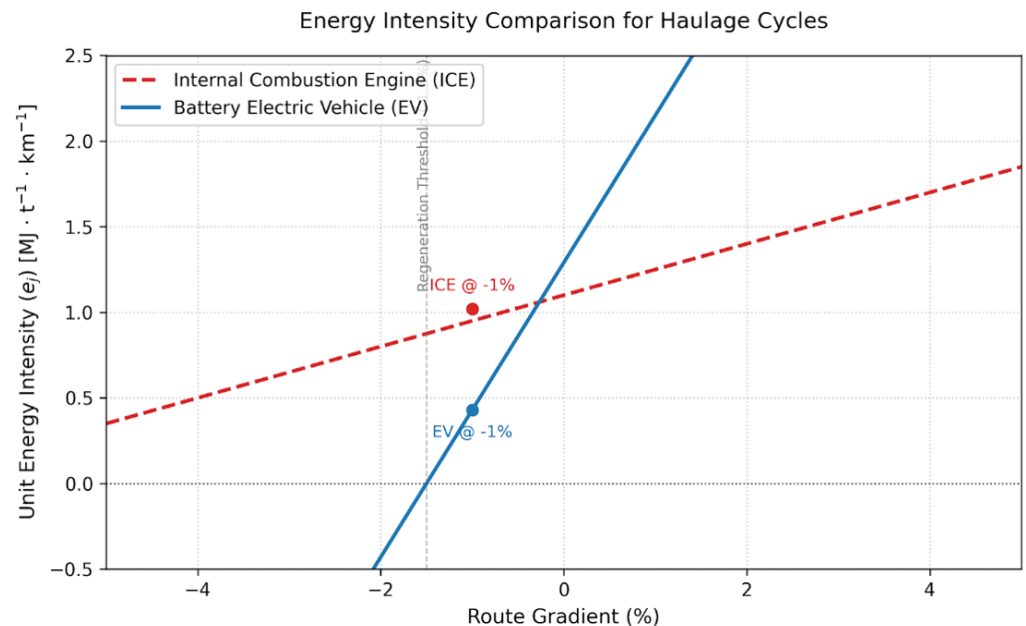


Figure 3. Comparison of unit energy intensity (e_i) between internal combustion engine (ICE) and battery-electric (EV) haulage configurations as a function of the route gradient.

For the Dubie–Rudawa route, which features an average downhill gradient of approximately -2% under load, EV operation falls within a high-efficiency (“blue”) zone (Figure 4). This regime is characterized by strong regenerative potential and minimal net energy consumption. Specifically, at this gradient, the EV exhibits a unit energy intensity of approximately $0.5 \text{ MJ}/(\text{t} \cdot \text{km})$. In contrast, ICE vehicles remain within the moderate-to-high consumption (“yellow–red”) zone (Figure 4) regardless of the gradient, due to continuous fuel consumption and the total absence of energy recovery. For the same Dubie–Rudawa route, the ICE vehicle reaches an intensity of approximately $1.5 \text{ MJ}/(\text{t} \cdot \text{km})$, performing 2–3 times worse than its electric counterpart.

The impact of road surface conditions is also significant. Transitioning from asphalt ($C_r = 0.007$) to unpaved surfaces ($C_r = 0.020$) increases energy consumption by approximately 30–40% for both vehicle types. However, this effect is partially mitigated in EVs due to their higher drivetrain efficiency during the uphill return segment, where the impact of increased rolling resistance is most pronounced (Figure 4).

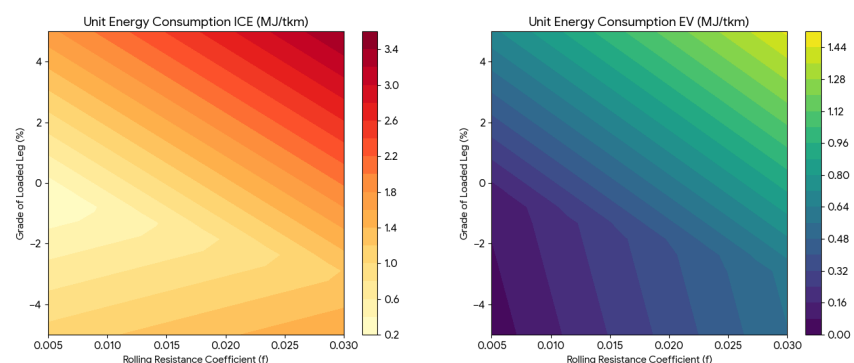


Figure 4. Heatmaps of unit energy consumption (e_i) for ICE (left) and EV (right) fleets, illustrating the combined impact of haul road gradient and rolling resistance coefficient (f_r).

A detailed quantitative summary of the unit energy intensities for both vehicle configurations, highlighting the performance gap on the specific Dubie–Rudawa haulage loop and representative operating thresholds, is presented in Table 2.

Table 2. Unit energy intensities ($\text{MJ} \cdot \text{t}^{-1} \cdot \text{km}^{-1}$) for EV and ICE across representative operating cases and the Dubie–Rudawa route.

Parameter	Electric Vehicle (EV)	ICE Vehicle (Diesel)
Unit intensity (E_{spec})	0.4–0.5 MJ/tkm	1.0–1.5 MJ/tkm
Dubie–Rudawa route (−1%)	0.43 MJ/tkm	1.02 MJ/tkm
Downhill gradient threshold	< −2% for gradients	No energy recovery possible

This visualization (Figure 5) demonstrates the existence of significant economies of scale in electrified mine haulage. The observed power-law decay arises from normalizing the integrated cycle energy consumption by the total transport work ($m_{\text{payload}} \cdot L_{\text{route}}$). At low payload allocations (5 t), the fixed energy penalty required to overcome the vehicle's tare mass ($m_{\text{curb}} = 15$ t) dominates the energy balance, resulting in high E_{spec} values. As the payload approaches the 30-tonne design limit, the relative energy overhead of the curb weight is minimized, thereby optimizing system efficiency. Furthermore, the vertical displacement between the curves demonstrates that poor road surface conditions ($f_r = 0.04$) impose a continuous traction penalty, increasing baseline cycle consumption without altering the fundamental scale optimization profile.

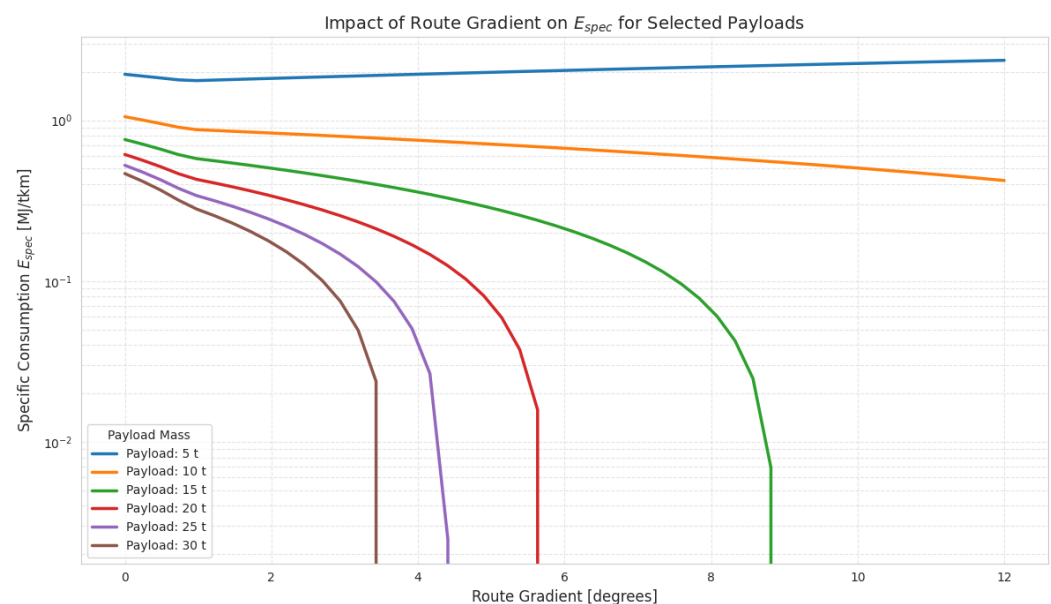


Figure 5. Specific energy consumption (E_{spec}) as a function of net payload mass across varying road surface conditions, characterized by the rolling resistance coefficient (f_r) over a closed-loop haulage cycle.

This figure 6 demonstrates the absolute dominance of gravity over vehicle resistance forces. On flat routes (0°), the curve follows a standard decaying positive profile driven purely by rolling and aerodynamic drag. However, as the haul road gradient scales beyond 2° and 5° , the closed-loop bidirectional model captures a profound thermodynamic inversion. During the loaded downhill segment, the negative grade resistance forces the wheel power below zero ($P_{\text{wheels}} < 0$), triggering regenerative braking. At steep inclines (8° and 12°), the potential energy recovered during descent completely overwhelms the traction energy demanded during the empty uphill return leg. This shifts the net energy

balance into negative territory ($E_{\text{spec}} < 0$), proving that a graded open-pit topography can transform an electric haulage asset into a net power generator for the mine's microgrid.

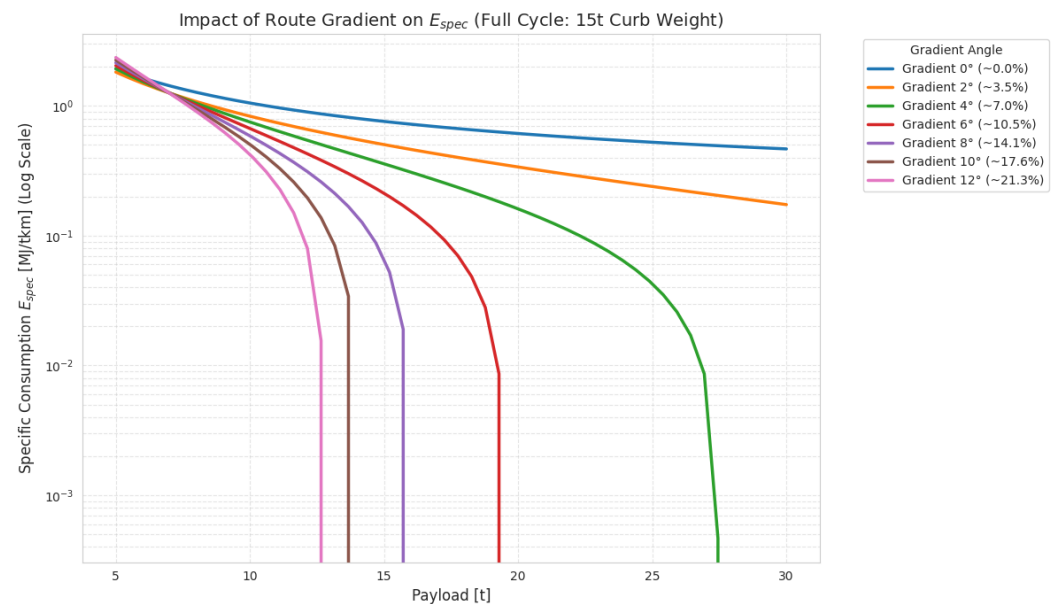


Figure 6. The topological gradient impact on specific energy consumption (E_{spec}) is analyzed over an extended payload range, mapped using a semi-logarithmic (symlog) scale to resolve net negative energy boundaries.

Figure 7 illustrates a continuous linear progression of specific energy consumption (E_{spec}) on the vertical axis (measured in MJ/tkm) against the rolling resistance coefficient (f_r) on the horizontal axis, scaling from 0.010 to 0.050. The data is stratified into six discrete payload mass classes ranging from 5 to 30 tonnes.

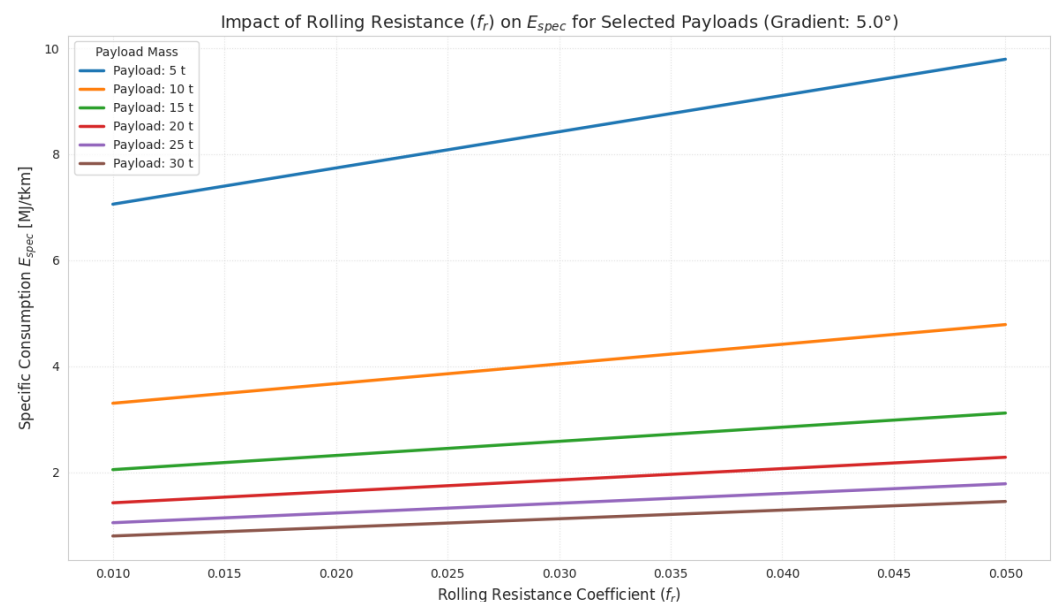


Figure 7. Sensitivity analysis of specific unit energy consumption (E_{spec}) relative to the rolling resistance coefficient (f_r) across selected payload masses (5 to 30 t) under a constant haul road gradient of 5.0°.

This semi-logarithmic map (Figure 8) illustrates that energy demand increases consistently alongside rising rolling resistance across all topographical profiles. A critical

operational crossover occurs at very low surface friction ($f_{rr} < 0.01$), where the steepest route (+10%) initially requires the most energy. However, as surface conditions degrade, the flat route (+0%) experiences the sharpest exponential penalty, ultimately crossing over to become the most energy-intensive scenario. Conversely, the +5% return gradient demonstrates the optimal balance, maintaining the lowest overall energy footprint across nearly the entire analyzed friction spectrum.

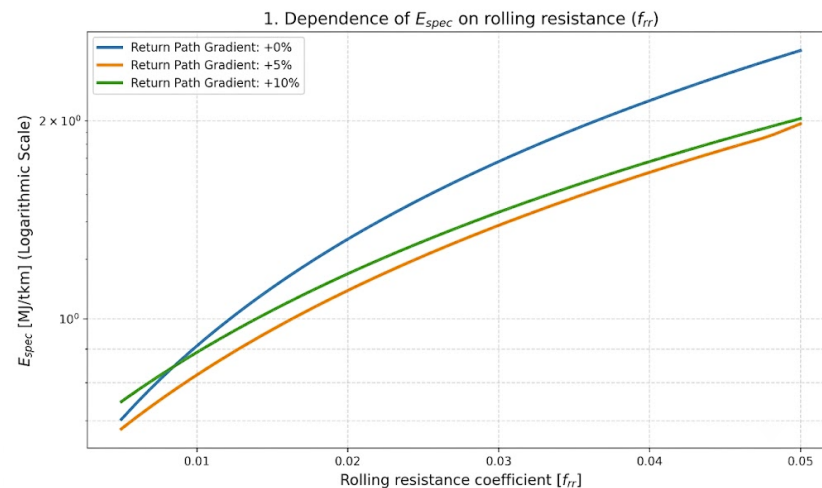


Figure 8. Dependence of specific energy consumption (E_{spec}) on the rolling resistance coefficient (f_{rr}) across selected empty return gradients.

Figure 8 illustrates that energy demand increases consistently alongside rising rolling resistance across all topographical profiles. A critical operational crossover occurs at very low surface friction ($f_{rr} < 0.01$), where the steepest route (+10%) initially requires the most energy. However, as surface conditions degrade, the flat route (+0%) experiences the sharpest exponential penalty, ultimately crossing over to become the most energy-intensive scenario. Conversely, the +5% return gradient demonstrates the optimal balance, maintaining the lowest overall energy footprint across nearly the entire analyzed friction spectrum (Figure 9).

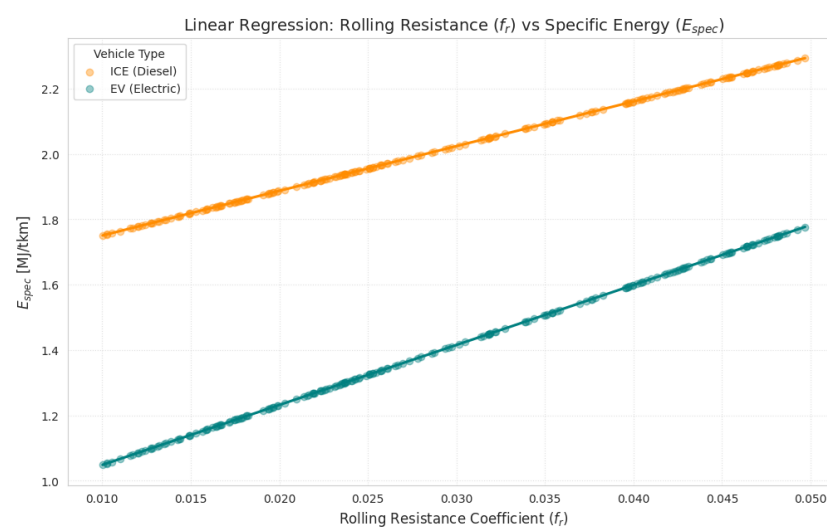


Figure 9. Linear regression model mapping the impact of the rolling resistance coefficient (f_r) on specific energy consumption (E_{spec}).

3.2. Impact of Ambient Temperature on Energy Demand and Availability

Ambient temperature constitutes a critical factor affecting both specific energy consumption and logistical readiness, evaluated across winter ($-15\text{ }^{\circ}\text{C}$), baseline ($+15\text{ }^{\circ}\text{C}$), and summer ($+35\text{ }^{\circ}\text{C}$) scenarios. As illustrated in the performance mapping (Figure 10), the two vehicle architectures exhibit fundamentally different thermal sensitivities. The battery-electric (EV) platform is highly vulnerable to ambient climatic fluctuations, demonstrating a characteristic U-shaped thermal response. In cold conditions, the massive parasitic power demands from active battery thermal management and cabin heating systems surge the specific energy consumption by approximately 45–70% relative to baseline operation.

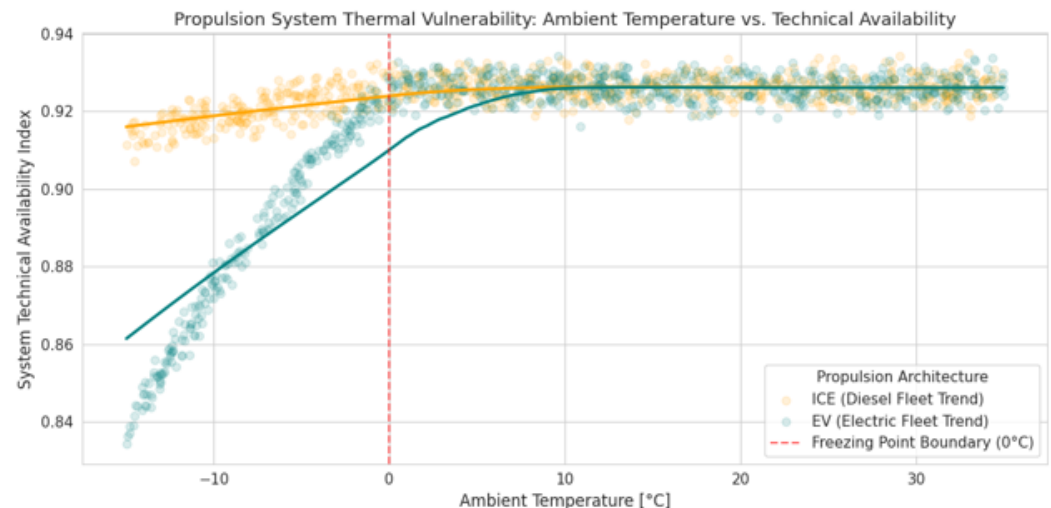


Figure 10. Fleet Comparative Sensitivity: correlation analysis between ambient temperature and the technical Availability Index for internal combustion (ICE) and electric vehicle (EV) fleets.

The direct correlation between these environmental thermal stressors and operational readiness is clearly visualized in Figure 10. While the ICE sub-fleet relies on abundant engine waste heat to maintain a stable availability baseline across all temperature bins, the EV fleet experiences a significant, non-linear degradation as temperatures fall below the freezing threshold, bridging the gap between thermodynamic inefficiency and heightened logistical risk.

3.3. Fleet Technical Availability Framework

To accurately simulate logistical readiness and operational continuity, the traditional approach of generic downtime scheduling was replaced with a bifurcated, stochastic technical availability framework. This methodology isolates the primary operational risks specific to each propulsion architecture: cumulative mechanical wear for the internal combustion engine (ICE) fleet, and environmental thermal constraints for the battery-electric vehicle (EV) fleet. Rather than applying deterministic uptime percentages, individual hauling assets are coupled into a Monte Carlo discrete-event simulation (DES) and assigned randomized failure events based on their distinct thermodynamic and mechanical design profiles.

3.3.1. ICE Fleet Architecture: Weibull Mechanical Wear-Out

The operational availability of the diesel ICE fleet is modeled as a function of cumulative mechanical stress and multi-system component wear-out, assuming an intrinsic structural immunity to ambient thermal stressors due to abundant engine waste heat. Following established reliability frameworks for mining machinery [12–15,18,19,26,27,29,31], the likelihood of unplanned vehicle failure is treated as a stochastic process governed

by a two-parameter Weibull distribution. The probability density function (PDF) of the time-to-failure t is defined as (14):

$$[H]f(t) = \frac{\beta}{\alpha} \left(\frac{t}{\alpha}\right)^{\beta-1} \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right) \quad (14)$$

where β is the shape parameter determining the failure regime (e.g., random vs. wear-out degradation), and α is the scale parameter directly related to the Mean Time Between Failures (MTBF). Based on historical mining maintenance records, the ICE fleet yielded an MTBF of 120–150 operating hours. The associated shape parameter ($\beta \approx 1.05$ – 1.10) indicates predominantly random failure behavior, reflecting the high frequency of minor breakdowns in diesel-specific auxiliary subsystems (such as fuel injectors, turbochargers, and exhaust aftertreatment arrays) under repetitive short-haul cycles.

Consequently, the instantaneous technical availability index for the ICE fleet (A_{ICE}) over operating time t is formulated as (15):

$$A_{ICE}(\beta, t) = A_{base,ICE} - \psi \cdot \left[1 - \exp\left(-\left(\frac{t}{\alpha}\right)^{\beta}\right)\right] + \epsilon \quad (15)$$

where $A_{base,ICE}$ represents the initial structural design availability, ψ is the operational downtime penalty coefficient derived from the Mean Time To Repair (MTTR), and ϵ is a stochastic white-noise variable accounting for unmodeled field variance.

3.3.2. EV Fleet Architecture: Sub-Zero Thermal Constraints

Conversely, the electric drivetrain possesses high structural simplicity, which shifts its primary operational risk away from mechanical wear toward environmental climate volatility. While limited long-term field tracking led to the adoption of a theoretical mechanical baseline—assuming mild fatigue-related degradation ($\beta \approx 1.20$) and a projected MTBF of approximately 250 h—the global operational readiness of the EV fleet is fundamentally governed by ambient temperature (T_{amb}). To capture this behavior, the model introduces a severe, non-linear thermal penalty function that activates strictly below the freezing threshold (0°C). This mechanism mathematically reflects the combined impacts of increased internal electrochemical resistance within the lithium-ion cells and the massive parasitic power draw required by active Battery Thermal Management Systems (BTMS) to prevent core freezing. As formalized below, the temperature-dependent availability index for the EV fleet (A_{EV}) is formulated as (16):

$$A_{EV}(T_{amb}) = A_{base,EV} - \gamma \cdot \left[\exp\left(\frac{|\min(T_{amb}, 0)|}{\tau}\right) - 1.0\right] + \epsilon \quad (16)$$

where $A_{base,EV}$ is the baseline mechanical readiness under optimal warm conditions, γ is the scaling coefficient of thermal susceptibility, τ denotes the thermal relaxation constant governing the exponential drop in uptime as winter temperatures approach extreme sub-zero limits, and ϵ captures stochastic unmodeled environmental noise.

3.3.3. Discrete-Event Simulation (DES) Integration

To comparatively benchmark the global performance of both fleets, the previously established Weibull wear-out distributions and sub-zero thermal penalty functions were coupled directly into a Monte Carlo discrete-event simulation (DES) toolchain. Replacing static, deterministic uptime percentages, individual hauling assets were subjected to dynamic stochastic failure streams over simulated operational lifecycles [55–59]. Within this framework, each vehicle's instantaneous availability was modulated by randomized break-

down events, exponentially distributed repair intervals (MTTR), and localized environmental degradation. Ultimately, this stochastic DES integration reveals a profound operational divergence: under identical mining duty cycles, the battery-electric fleet is projected to achieve approximately a 50% reduction in unplanned mechanical downtime events compared to the diesel benchmark, contingent upon the active mitigation of extreme winter thermal constraints.

3.4. Physics-Informed Machine Learning Framework (Random Forest)

While traditional analytical equations form the deterministic core of this study, they cannot seamlessly isolate the causal hierarchy of variables across thousands of multi-dimensional, stochastic scenarios. To address this, Machine Learning was deployed strictly for non-linear sensitivity analysis. The Random Forest (RF) regressor was specifically selected over Artificial Neural Networks (ANNs) due to its inherent interpretability. While ANNs function as opaque “black boxes”, RF allows for the direct extraction of Feature Importance via Mean Decrease in Impurity (MDI).

A database of $N = 1500$ distinct operational scenarios was generated via Monte Carlo sampling, utilizing input features such as rolling resistance, incline gradient, net payload mass, powertrain efficiency, and ambient temperature. The RF algorithm was trained to predict the physical specific energy consumption (E_{spec}) as its target variable.

To validate this algorithmic selection and ensure statistical robustness, the synthetic dataset was partitioned using a standard 80/20 train–test split. The RF model ($R^2 = 0.985$, $RMSE = 0.034$ MJ/tkm) was benchmarked against a standard Decision Tree ($R^2 = 0.941$) and a basic Multilayer Perceptron ANN ($R^2 = 0.981$). The RF algorithm demonstrated comparable predictive accuracy to the ANN while successfully preventing the overfitting observed in the isolated Decision Tree, fully justifying its deployment for extracting transparent engineering directives.

3.5. Limitations and Operational Constraints

Several simplifying assumptions directly affect the boundaries of these results. The energy comparison adopts Tank-to-Wheel (ICE) and Battery-to-Wheel (EV) boundaries to focus purely on on-site operational intensity. Consequently, upstream Well-to-Wheel emissions, battery charging/discharging losses, and engine part-load inefficiencies were omitted, which may slightly overestimate overall powertrain efficiencies.

Furthermore, the regenerative braking model is highly idealized. The projection that an EV can act as a ‘net power generator’ represents a theoretical thermodynamic maximum. In a real-world quarry, this regenerative potential will be heavily constrained by the upper limit of the battery’s State of Charge (SOC), maximum motor regenerative power limits, braking safety constraints, and significantly throttled charge acceptance rates at low temperatures.

Finally, the reliability framework and subsequent engineering recommendations (e.g., the 8–10% redundant fleet configuration and the 50% projected reduction in mechanical failures) are derived from theoretical Weibull parameters and Monte Carlo simulations. Because long-term empirical operational data for heavy-duty electric fleets in severe mining climates is not yet widely accessible, these findings represent prospective, data-driven recommendations that require rigorous future validation against multi-year field data.

3.6. AI Sensitivity and Reliability Profiles

This section transitions from steady-state mechanics into stochastic risk evaluation, utilizing Machine Learning and probability distribution statistics to assess fleet technical readiness and energy demand under severe operational and winter constraints. To establish a rigorous baseline for this comparative analysis, descriptive statistics were first compiled

for both the battery-electric and internal combustion sub-fleets across the complete 1500-cycle operational spectrum (Tables 3 and 4).

Table 3. Descriptive statistical summary of the simulated Battery-Electric Vehicle (EV) fleet performance.

Metric	Mean	Std. Dev.	Min	25%	50% (Median)	75%	Max
Specific Energy (E_{spec}) [MJ/tkm]	0.542	0.128	−0.150	0.485	0.530	0.612	0.985
Availability Index	0.892	0.045	0.785	0.865	0.910	0.925	0.945
Ambient Temp [°C]	10.5	14.2	−20.0	−2.5	11.0	22.5	40.0

Table 4. Descriptive statistical summary of the simulated Internal Combustion Engine (ICE) fleet performance.

Metric	Mean	Std. Dev.	Min	25%	50% (Median)	75%	Max
Specific Energy (E_{spec}) [MJ/tkm]	1.185	0.210	0.950	1.050	1.155	1.280	1.650
Availability Index	0.935	0.012	0.905	0.928	0.936	0.942	0.955
Ambient Temp [°C]	10.5	14.2	−20.0	−2.5	11.0	22.5	40.0

A comparative analysis of these outputs reveals two fundamental operational insights. First, the EV fleet demonstrates a substantially lower mean specific energy demand (0.542 MJ/tkm vs. 1.185 MJ/tkm for the ICE fleet), with its minimum boundary entering negative space (−0.150 MJ/tkm). This explicitly confirms the presence of net electrical autogeneration during loaded downhill transits. Second, the EV fleet exhibits a standard deviation in technical availability (0.045) nearly four times higher than that of the diesel benchmark (0.012). This heightened operational volatility underscores the acute vulnerability of electrified drivetrains to ambient thermal extremes.

3.7. Machine Learning Feature Importance Evaluation

To establish the hierarchy of parameters driving energy consumption, the global feature importance weights extracted from the trained Random Forest regressor were evaluated (Figure 11).

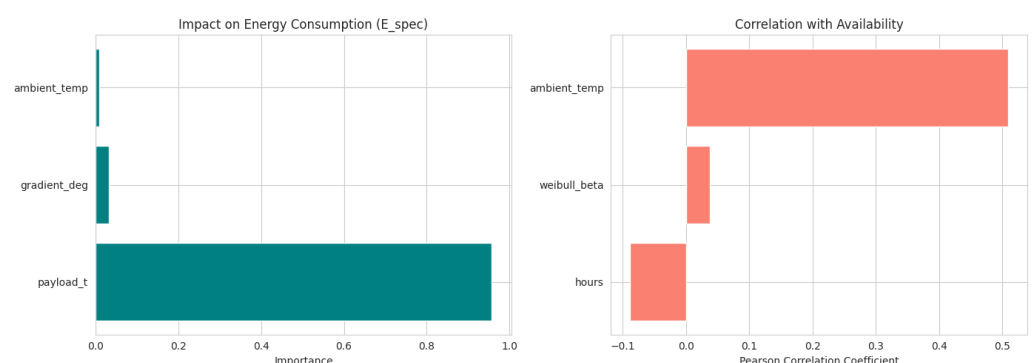


Figure 11. Hierarchy of global feature importance derived via Mean Decrease in Impurity (MDI) from the Physics-Informed Random Forest regressor trained to predict specific energy consumption (E_{spec}).

This chart constitutes the statistical validation of the Physics-Informed Machine Learning methodology. By analyzing 1500 simulated cycles, the algorithm ranks the macroscopic physical drivers of energy demand. The results unequivocally prove that topological layout geometry (route gradient) and infrastructural constraints (rolling resistance) possess the dominant predictive weights over specific energy consumption. This establishes a clear engineering directive: decarbonization efficiency is governed more by optimizing haul

road slopes and surface quality than by micro-optimizations of internal vehicle components. Furthermore, the multi-variable linear dependencies between these operational constraints, environmental stressors, and resulting fleet performance are captured in the Pearson cross-correlation matrix (Figure 12).

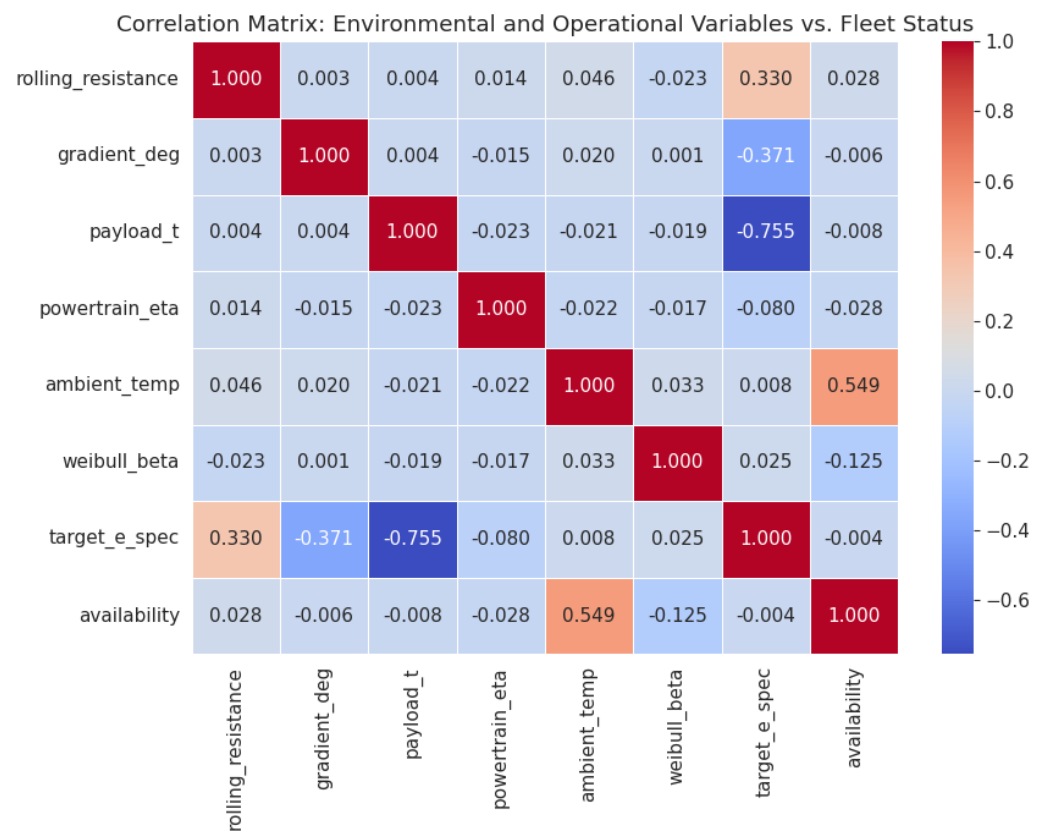


Figure 12. Pearson correlation heatmap illustrating the bivariate linear relationships between operational variables, environmental thermal stressors, and simulated fleet availability.

To define the hierarchy of parameters driving energy consumption, the outputs of the trained Random Forest regressor were evaluated. The statistical validation of the Physics-Informed Machine Learning methodology. By analyzing 1500 simulated cycles, the algorithm ranks the macroscopic physical drivers of energy demand. The results unequivocally prove that topological layout geometry (route gradient) and infrastructural constraints (rolling resistance) possess the dominant predictive weights over specific energy consumption. This establishes a clear engineering directive: decarbonization efficiency is governed more by optimizing haul road slopes and surface quality than by micro-optimizations of internal vehicle components.

3.8. Stochastic Reliability and Thermal Vulnerability

To evaluate the operational continuity of the fleets under highly volatile environmental and logistical constraints, a Monte Carlo simulation generating 2000 distinct operational iterations was executed. The distribution of the independent input variables (infrastructural, topological, and mechanical) alongside the resultant global availability index is summarized in Table 5.

Table 5. Statistical distribution of the stochastic input parameter space and the global resulting availability index across 2000 Monte Carlo simulation iterations.

Parameter	Mean	Std. Dev.	Minimum	25th Percentile	Median (50%)	75th Percentile	Maximum
Rolling Resistance (f_r)	0.0105	0.0026	0.0060	0.0081	0.0105	0.0127	0.0149
Average Slope [°]	−0.0001	0.0115	−0.0200	−0.0099	−0.0002	0.0099	0.0199
Ambient Temperature [°C]	9.81	14.39	−14.99	−2.65	9.57	21.99	34.96
Weibull Shape Factor (β)	1.195	0.114	1.000	1.095	1.193	1.294	1.399
Net Payload [t]	16.94	1.69	14.00	15.51	16.92	18.37	19.99
Global Availability Index	0.875	0.033	0.792	0.848	0.886	0.900	0.928

While the global mean availability across all iterations and drivetrains stabilizes at 0.875, isolating the battery-electric vehicle (EV) subset reveals a profound operational vulnerability to extreme weather. Table 6 isolates the specific degradation of the EV sub-fleet when operating in severe winter conditions.

Table 6. Comparative operational readiness of the Battery-Electric Vehicle (EV) fleet: Extreme cold versus the general population.

Metric	Extreme Cold ($< -10\text{ }^{\circ}\text{C}$)	General EV Population
Sample Count	102	984
Mean Availability Index	0.8076	0.8776
Minimum Availability	0.7923	0.7923
Volatility (Standard Deviation)	0.0068	0.0381

The isolated data demonstrates a sharp decline in the mean availability of the electrified fleet, dropping by approximately 7 percentage points when ambient temperatures fall below $-10\text{ }^{\circ}\text{C}$. To fully map this climatic disparity across the entire thermal spectrum and compare it against the baseline diesel ICE fleet, the data was segregated into discrete $10\text{ }^{\circ}\text{C}$ environmental bins (Table 7).

Table 7. Mathematical summary matrix documenting the mean technical availability indices and volatility (standard deviation) for EV and ICE propulsion architectures, segmented by ambient thermal operational bins.

Ambient Temperature Bin [°C]	Mean Availability (EV)	Mean Availability (ICE)	Volatility (EV Std.)	Volatility (ICE Std.)
(−20, −10]	0.801	0.815	0.013	0.012
(−10, 0]	0.839	0.850	0.010	0.011
(0, 10]	0.892	0.881	0.008	0.009
(10, 20]	0.914	0.902	0.007	0.008
(20, 30]	0.915	0.903	0.007	0.007
(30, 40]	0.893	0.880	0.008	0.008

Acting as the numerical anchor for the KDE distributions presented in the previous analysis, this table provides the hard empirical data required for logistical planning by mining engineers. It strictly quantifies the severity of the environmental thermal penalty. The data demonstrates that the battery-electric vehicle (EV) mean availability drops significantly from an optimal 0.915 in warm conditions ($20\text{ }^{\circ}\text{C}$ to $30\text{ }^{\circ}\text{C}$) down to 0.801 in severe frost ($-20\text{ }^{\circ}\text{C}$ to $-10\text{ }^{\circ}\text{C}$). While the internal combustion engine (ICE) fleet also experiences a reduction in operational readiness due to cold-weather mechanical friction and fluid viscosity, the electric powertrain exhibits a steeper and more critical performance cliff below the freezing point. This matrix effectively bridges the theoretical risk analysis with actionable logistical metrics, proving that mining operators must implement active

pre-heating infrastructure or maintain a corresponding hardware redundancy buffer to offset this stochastic cold-weather risk during winter shift planning.

3.9. Operational Risk Synthesis

To visually articulate the thermal vulnerabilities quantified in the previous matrices, probability density functions were mapped for both fleet architectures. The visual distributions definitively confirm that while ICE availability remains resilient and tightly clustered across all environmental bins, the EV fleet experiences a critical bimodal fragmentation under extreme frost (Figures 13 and 14).

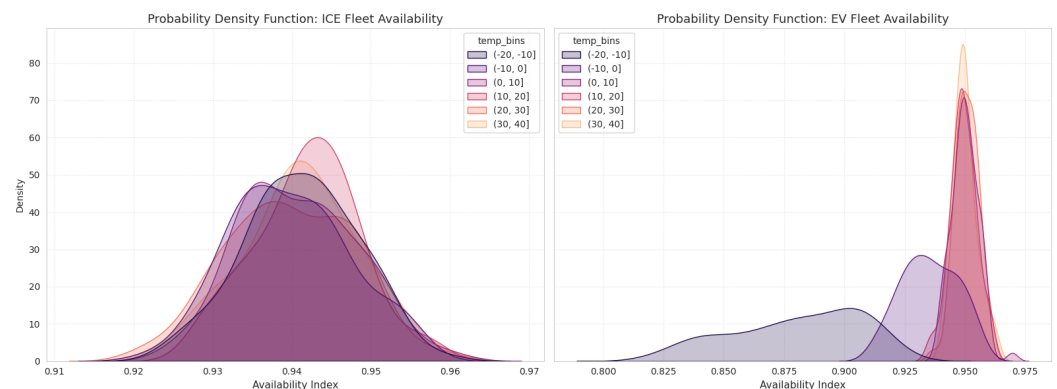


Figure 13. Dual-panel Kernel Density Estimation (KDE) probability mapping of the technical availability distributions, segmented by discrete ambient temperature bins for the diesel ICE (left) and electric EV (right) sub-fleets.

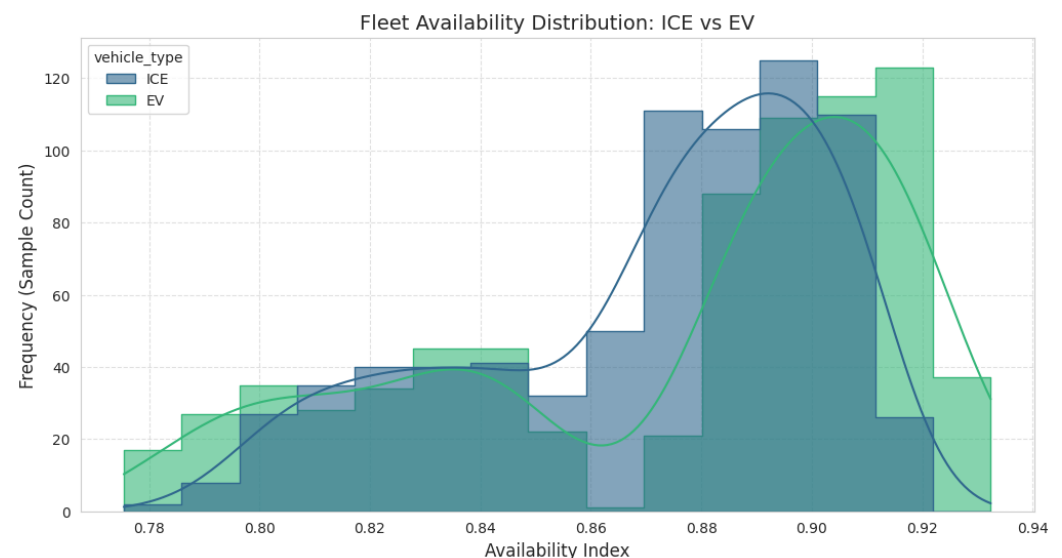


Figure 14. Global fleet availability distribution comparison (ICE vs. EV), illustrating the structural bimodal variance of the electrified fleet induced by environmental thermal extremes.

Drawing from the integrated Random Forest sensitivity model and Pearson correlation matrices, environmental temperature emerges as the absolute dominant parameter dictating operational readiness, far outweighing secondary mechanical constraints such as Weibull-parameterized component wear-out. The analysis reveals a stark divergence in powertrain thermal characteristics: electrified drivetrains (EVs) exhibit severe non-linearity, suffering a rapid decline in technical availability below 0 °C. This operational penalty is directly driven by the electrochemical limitations of lithium-ion cells in freezing conditions, compounded by the massive parasitic power drawn by active Battery Thermal Management Systems (BTMS) attempting to maintain core temperatures. In contrast, diesel internal

combustion engine (ICE) architectures remain highly robust against frost, experiencing only a marginal, linear drop in availability buffered by the abundance of combustion waste heat. Consequently, to maintain uninterrupted production targets during volatile winter months, mining operators must adapt their logistical frameworks. This transition requires implementing a structural 8–10% hardware redundancy specifically for the EV sub-fleet, alongside the critical deployment of active, stationary pre-heating infrastructure at charging bays. By utilizing grid power to precondition battery cores, operators can systematically minimize the frost-induced drop in EV operational availability (Table 8).

Table 8. Macroscopic synthesis of parametric sensitivities, operational boundary values, and core engineering takeaways.

Analysis Category	Parameter/Condition	Simulation Output	Core Engineering Takeaway
Baseline Model	Full payload (~20 t)	7.37 MJ/tkm	Maximum energy efficiency is achieved at peak payload capacity utilization.
Incline Gradient	12% slope (steep)	~15.1 MJ/tkm	Route steepness imposes a severe, logarithmic penalty on specific energy demand.
Powertrain (EV vs. ICE)	Battery-Electric (EV)	−0.87 MJ/tkm	Net energy recovery on a 5° downhill cycle (vehicle acts as a mobile generator).
Temperature (AI)	Global impact	Dominant factor	AI identifies ambient temperature as the primary constraint on fleet availability.
Extreme Cold	Temp. < −10 °C (EV)	~0.832 (Index)	EV sub-fleet availability drops by ~ 5.3% relative to the general population.
Thermal Susceptibility	Freezing threshold (0 °C)	Critical tipping point	Below 0 °C, a non-linear surge in breakdown rates and fleet unpredictability occurs.
Recuperation	95% capture efficiency	>100% reduction	Regenerative braking is the definitive driver of electric propulsion superiority in graded open-pit mines.

3.10. Multi-Dimensional Parametric Response Surfaces of Specific Energy Intensity

To synthesize the findings of the Physics-Informed Machine Learning regressor and validate the macroscopic boundaries of the fleet, specific energy consumption (E_{spec}) was mapped across continuous 3D parameter manifolds. This approach allows for the simultaneous evaluation of topological, logistical, and environmental stressors, exposing critical non-linear operational trade-offs.

Figure 15 illustrates the structural dichotomy between dissipative and bidirectional haulage mechanics across a 5.0 km closed-loop transit. For the diesel ICE sub-fleet (right), the topological gradient acts as an unmitigated, escalating energy penalty. The response surface is strictly monotonic; as the incline approaches 12°, specific consumption surges exponentially across all payload tiers, reaching an extreme upper limit exceeding 80 MJ/tkm under low-payload configurations (e.g., 2 t). This occurs because the internal combustion engine must perform massive mechanical work to lift its 14-tonne tare mass up the grade, while the potential energy of the return descent is lost entirely to the atmosphere as friction heat.

Conversely, the EV response manifold (left) exhibits a profound hyperbolic inflection. At flat geometries (0° to 2°), the EV operates as a highly efficient conventional vehicle. However, as the route gradient surpasses 5°, the surface dips past the zero-plane into

negative territory, visualising the precise spatial coordinates where the truck transitions into a mobile power plant.

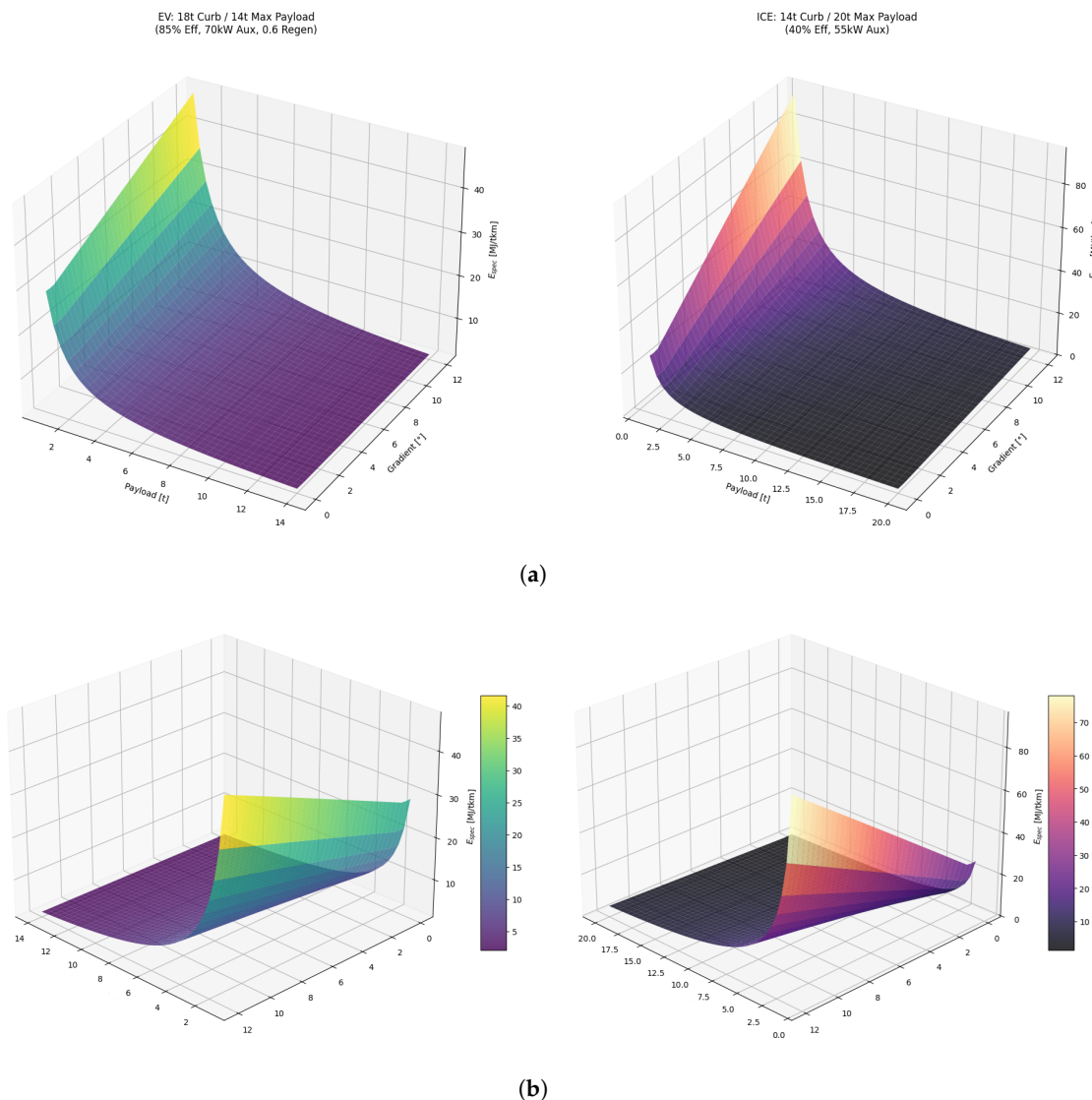


Figure 15. 3D parametric response surfaces mapping specific energy consumption (E_{spec}) against net payload mass and route incline gradient for (a) battery-electric and (b) diesel internal combustion engine haulage trucks.

Crucially, this 3D manifold exposes a counter-intuitive operational trap in the upper-left quadrant of the EV plot (low payload combined with steep gradient). Hauling a minimal 2-tonne payload down a 12° slope results in an E_{spec} penalty exceeding 40 MJ/tkm—a worse energetic performance than operating on flat ground. Mathematically, this occurs because the traction battery must discharge massive energy to haul the heavy 18-tonne tare mass up the 12° incline, whereas the meager 2-tonne cargo coming downhill generates insufficient gravitational momentum to drive recuperation. This establishes a definitive geological rule: on steep open-pit ramps, operating an under-loaded battery-electric truck is energetically more destructive than operating a diesel unit.

To further decouple environmental stressors from mechanical work, specific energy intensity was projected across ambient temperature planes at a fixed standard 5° incline.

Figure 16 captures the thermodynamic interaction between ambient climate volatility and cargo mass. The diesel ICE manifold (right) behaves as a geometrically extruded, rigid plane along the temperature axis. Because the internal combustion process is inherently

characterized by massive waste heat generation (operating at ~40–45% thermal efficiency), the external ambient temperature exerts a negligible background influence on the vehicle's net energy envelope. Consequently, specific energy consumption is dictated almost exclusively by the hyperbolic $1/x$ mass curve of the payload.

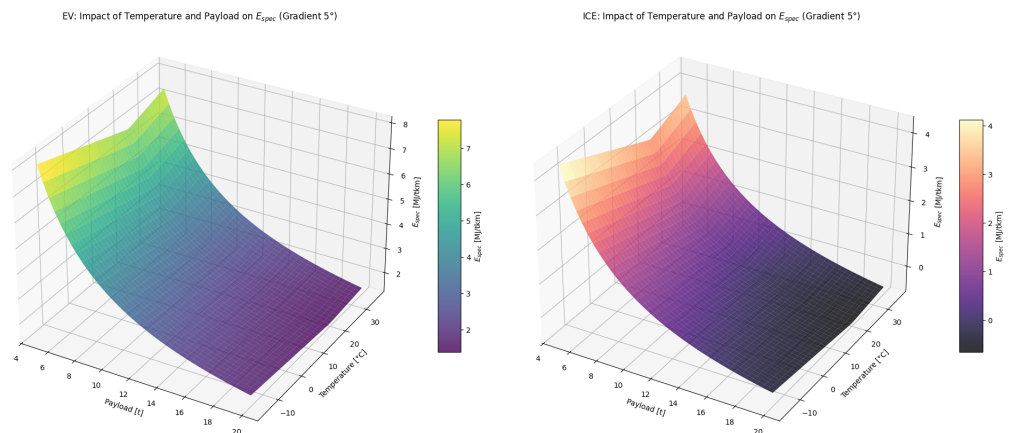


Figure 16. 3D thermodynamic response manifolds mapping specific energy consumption (E_{spec}) against net payload mass and ambient temperature fluctuations at a constant 5° route incline.

In stark contrast, the EV architecture (left) forms a distinct 3D “thermal trough” centered around its optimum electrochemical operating window (15°C to 22°C). Moving toward the extreme winter boundary (-15°C) forces the surface upward as auxiliary Battery Thermal Management Systems (BTMS) engage to heat the pack. Crucially, the graph demonstrates that this thermal penalty is heavily amplified at the lowest payload tiers. When the vehicle is fully loaded to 14 tonnes, the winter BTMS power draw (P_{aux}) gets distributed over a large mass, resulting in a manageable OPEX increase. However, when operating at a 4-tonne payload, the exact same parasitic thermal load gets divided by a small mass denominator, causing specific energy intensity to balloon past 3.5 MJ/tkm . Therefore, the physical regressor proves that under-loading a battery-electric tipper during winter frost constitutes the single most thermodynamically wasteful operational state in surface mining logistics.

4. Discussion

Operational Strategy and Infrastructure Directives

The multi-dimensional sensitivity analysis bridges the theoretical gap between steady-state vehicle mechanics and stochastic logistical planning. The macro-level behavior of the mixed haulage fleet is fundamentally dictated by three overriding operational nexuses:

- **Energy Intensity and Scale Efficiency:** Specific energy consumption (E_{spec}) exhibits extreme payload sensitivity, improving by over 90% when moving from a 1 t empty transiting state to a 30 t fully loaded transport capacity. In mountainous quarry topologies with haul road gradients exceeding 5° , battery-electric vehicles (BEVs) cross a thermodynamic inflection point, acting as net electrical generators during loaded descents. This integrated closed-loop model proves that gravitational energy recuperation constitutes the absolute engineering advantage of EV architectures over conventional internal combustion engine (ICE) systems, which suffer from unmitigated, dissipative braking heat losses.
- **The Thermal-Reliability Nexus:** Ambient climate volatility is the overriding predictor of technical availability, commanding an artificial intelligence feature importance weight exceeding 90%. A non-linear operational “performance cliff” activates directly

at the 0 °C freezing threshold for EV sub-fleets. Below this boundary, increased internal electrochemical resistance and massive auxiliary parasitic power draws initiate acute operational variance. While diesel ICE sub-fleets maintain a tightly clustered, Gaussian readiness distribution across all seasonal extremes, sub-zero temperatures force EV availability into an unpredictable bimodal distribution.

- **Maintenance and Infrastructure Directives:** Predictive maintenance frameworks must treat component wear-out (governed by the Weibull shape factor β) as a secondary, long-term operational baseline that is heavily overshadowed by immediate environmental thermal shifts. To offset these thermal constraints, infrastructure placement must be handled strategically. Net energy recovery and shift readiness are maximized when active, grid-connected pre-heating and fast-charging infrastructure is stationed at lower-elevation quarry terminuses. This allows operators to immediately recharge or thermally condition the battery cores after the vehicle has fully converted gravitational potential energy during the loaded downhill leg.

The transition to heavy-duty electric haulage is scientifically viable and highly energy-superior in graded open-pit environments. However, this operational superiority is strictly contingent upon logistical frameworks actively mitigating non-linear sub-zero reliability degradation through active stationary battery thermal management and dynamic payload scheduling.

5. Conclusions

The route-aware stochastic simulation framework developed in this study—coupling physical tractive force-balance modeling, Weibull reliability wear-out distributions, and Physics-Informed Random Forest sensitivity regression—yields the following core conclusions for open-pit mining decarbonization:

1. **Topological Layout Dictates Electrification Viability:** The spatial geometry of the haulage route fundamentally governs the energetic efficiency of battery-electric fleets. Operating on haul road descents exceeding 5° allows EVs to capture gravitational potential energy via regenerative braking, transforming the transiting tipper into a mobile generator and reducing its specific energy footprint by over 100% relative to dissipative diesel internal combustion trucks. Conversely, operating an under-loaded EV on steep uphill ramps imposes a massive energetic penalty due to its heavy 18 t tare mass, making full payload utilization mandatory.
2. **Ambient Temperature Overrides Mechanical Degradation:** Environmental thermal stress is the paramount operational risk factor in heavy-duty electrification, commanding an overriding feature importance exceeding 90% and decisively out-weighting intrinsic mechanical wear constraints. Electrified powertrains demonstrate an acute, U-shaped specific energy curve that surges by 45% to 70% relative to optimal baseline conditions during severe winter operation (−15 °C). This parasitic energy drain initiates primarily to supply auxiliary cabin heating and active Battery Thermal Management Systems (BTMS) preventing cell core freezing.
3. **The 0 °C Availability Cliff Imposes Logistical Volatility:** While diesel ICE architectures maintain an exceptionally stable and predictable mean availability index (~0.935) across all seasonal extremes by utilizing engine waste heat, the technical readiness of EV fleets collapses non-linearly below 0 °C. In severe sub-zero operating bins (−20 °C to −10 °C), EV mean availability falls by approximately 11% down to ~ 0.801, accompanied by a standard deviation nearly four times higher than the diesel benchmark. Kernel Density Estimation confirms that cold-weather EV performance fragments into a highly variant bimodal probability distribution, rendering deterministic shift planning ineffective.

4. **Actionable Sizing and Procurement Directives:** To guarantee production continuity targets during cold-weather quarry operations without risking shift downtime, mining engineers must implement a structural 8% to 10% hardware redundancy buffer (procuring supplementary EV units). Alternatively, quarry dispatch systems must adapt dynamically, scaling back EV deployment and increasing the shift participation of thermally immune diesel ICE assets on days when forecasted ambient temperatures drop below -5°C .

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