

Article

The Fuel Handling Index (FHI): A Telemetry 4.0-Based Indicator for Hybrid Transition and Idle Management in Marble Quarries

Sara Innocenzi *  and Dario Lippiello

Department of Industrial, Electronic, and Mechanical Engineering Roma Tre, Via Vito Volterra 62,
00146 Rome, Italy; dario.lippiello@uniroma3.it

* Correspondence: sara.innocenzi@uniroma3.it

Abstract

The marble extractive industry heavily depends on diesel-powered equipment, particularly wheel loaders and excavators used for block handling, resulting in high energy consumption and operating costs. In this study, the potential for fuel reduction through managerial and technological transitions was evaluated using the example of the marble quarry located in the Carrara basin. The energy demand of excavators, wheel loaders, and dumpers was characterized using telemetry data gathered through an Industry 4.0 methodology. A standard elementary cycle was modeled via the program evaluation and review technique (PERT) to map productive tasks and idling periods. To ensure comparability, a specific consumption coefficient (SCC) was defined. Subsequently, a novel fuel handling index (FHI) is proposed to prioritize investments by accounting for the uncertainties and production variables typical of quarry projects. Results demonstrate that while idle management offers a 4% fuel reduction, transitioning to hybrid wheel loaders represents a more significant strategy, achieving a 12% saving among the scenarios analyzed. The full-hybrid scenario leads to a cumulative 17% reduction. This framework supports decision-making for energy efficiency in high-yield extraction sectors, mitigating the economic risk associated with technological transitions.

Keywords: sustainable mining; marble quarry; hybrid wheel loader; hybrid excavator; PERT; mining electrification; KPI; quarry 4.0

1. Introduction

Heavy-duty vehicles used in the mining sector represent one of the major sources of atmospheric pollution, contributing significantly to greenhouse gas emissions [1]. According to a report by the Southwest Research Institute [2], approximately 28,000 diesel mining trucks worldwide consume over 6 billion gallons of diesel fuel each year, generating around 68 million tons of carbon dioxide. These figures highlight the urgent need to transition toward cleaner and more efficient technologies, in line with both European and national decarbonization policies [3]. In this context, several studies have demonstrated the potential of vehicle electrification and hybridization as effective solutions to reduce both fuel consumption and emissions [4].

However, the actual efficiency of these vehicles in a quarry environment is strictly dictated by their operating conditions, primarily defined by the load factors (LFs) and the specific duty cycles of the extraction process. As emphasized by Klanfar et al. [5], determining duty cycle-specific fuel consumption coefficients is fundamental for accurate energy estimation in quarrying activities, as generic values often fail to capture the variability



Academic Editors: Fangwei Xie and
Nikita Babyr

Received: 27 January 2026

Revised: 16 February 2026

Accepted: 18 February 2026

Published: 20 February 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

of real-world mining cycles. Within the natural stone industry, economic sustainability is strictly linked to production efficiency. As noted by Buyuksagis and Goktan [6], determining optimum operational conditions is of paramount importance. This is particularly true in marble machining, where cutting and handling operations represent a significant cost item.

Life-cycle analyses [7] and studies on the electrification of mining trucks [8,9] further demonstrate that replacing conventional diesel vehicles with fully electric or hybrid alternatives can drastically reduce both energy costs and emissions.

The growing interest in these technologies is not limited to the mining sector but extends to agriculture and construction [10–12]. A detailed energy flow analysis of hybrid compact wheel loaders has shown up to a 30% reduction in fuel consumption per cycle [13]. These improvements in the efficiency of the powertrain system are achieved through both hardware and software enhancements. In this regard, Prinz et al. [14] demonstrate that modifying technical settings through the machine's own software package can significantly reduce fuel consumption and CO₂ emissions per unit of product, highlighting that operational optimization is as critical as the choice of powertrain.

In parallel, the adoption of electro-hydraulic hybrid powertrains and regenerative braking has shown reductions in peak power demand [15–17]. Comparable benefits have been reported for excavators and bulldozers [18]; specifically, Liu et al. [19] synthesize the main hybrid powertrain architectures (series, parallel, and electro-hydraulic). The integration of these advanced systems requires sophisticated monitoring and predictive tools. Recent research has emphasized the growing role of data analytics; for instance, Saim et al. [20] have demonstrated the effectiveness of machine learning techniques in predicting the fuel consumption of mining excavators, providing a baseline for data-driven energy management. Building on this, Brennan and Nojabeai [21] showed how real-time data collected from loaders and haul trucks can optimize maintenance and production efficiency.

Within this framework, the present study defines a systematic procedure to fully exploit the extensive availability of Industry 4.0 telemetry datasets, directly linking accurate data acquisition to informed operational decision-making. A new key performance indicator (KPI), the fuel handling index (FHI), is proposed using the results of a case study conducted in the Carrara marble basin. By integrating real-time telemetry data (Industry 4.0) with technical and economic analyses, this study decouples the impact of managerial interventions (idle management) from technological gains (hybridization). The objective is to identify investment priorities for the transition from diesel to hybrid solutions in the specific context of marble block handling.

To this end, this study seeks to provide answers to the following fundamental questions: First, how can Industry 4.0 telemetry data be effectively synthesized into a single indicator to prioritize energy-saving investments? Second, to what extent can managerial interventions, such as idle management, reduce fuel consumption compared to technological transitions like hybridization? Finally, can the proposed FHI serve as a scalable diagnostic tool for identifying logistical bottlenecks and guiding decarbonization strategies?

2. Materials and Methods

2.1. Site Description and Data Acquisition

The present study was conducted in a marble quarry located in the Carrara basin (Italy), characterized by an annual production of approximately 15,000 m³ and a yield of 55% [22]. The analysis focused on the dimensional marble block handling operation within the quarry yard, which represents a critical process suited for fuel consumption optimization.

To ensure high data fidelity, the study relied on real-world telemetry data acquired through Industry 4.0 remote monitoring systems. The data acquisition framework involved an industrial IoT gateway interfaced with each machine's CAN bus system, utilizing the SAE J1939 protocol for direct communication with the engine control unit (ECU). The data-gathering process focused on daily aggregated records.

The fleet, monitored over a 6-month period, consists of three crawler excavators (EXC), three wheel loaders (WLO), and one articulated dumper (AD) (detailed specifications are provided in Table 1).

Table 1. Technical specifications of the heavy-duty machinery fleet monitored.

Machine Model	Operating Weight [ton]	Engine Power [kW]	Displacement [L]	Max Torque [Nm @ rpm]	Loading Capacity [m ³]	EU Stage Emission Certification
EXC 01	75.1	362	15.2	2164 @1400	3.3	Stage IV
EXC 02	75.1	362	15.2	2564 @1260	3.3	Stage IV
EXC 03	48.9	332	12.5	2144 @1400	3.3	Stage IV
WLO 01	51	439	18.1	2852 @1200	6.4–7.3	Stage IV
WLO 02	51	439	18.1	2852 @1200	6.4–7.3	Stage IV
WLO 03	30.9	313	12.5	2206 @1200	4.2–12	Stage IV
AD 01	51.9	276	12.5	2120 @1200	17.5	Stage IV

Note: the symbol @ stands for “at”, referring to the engine speed [rpm] at which the maximum torque is measured.

For each unit, the following primary duty cycle parameters were extracted:

- Operational hourly consumption (L/h_{op});
- Idling hourly consumption (L/h_{idle});
- Effective working hours and inactivity periods (h).

Following the methodology suggested by Klanfar et al. [5] regarding load-specific factors, the collected data underwent statistical validation to filter out sensor noise and ensure the representativeness of the typical quarry work cycle. This data-driven approach aligns with recent research by Saim et al. [20], confirming the reliability of telemetry for predicting energy demand in heavy mining equipment.

2.2. Data Cleaning and Pre-Processing

Given the stochastic nature of quarry operations, which involve inherent uncertainties in operational and production parameters [23], the telemetry dataset was subjected to a rigorous filtering phase to eliminate outliers and non-representative events. These anomalies, which could stem from sensor sampling errors, signal loss, or non-representative operational events, were identified and removed using the interquartile range (IQR) method.

This statistical technique was applied individually to each machine's consumption distribution to respect their specific operational profiles. Following this approach, outliers were defined as any data points falling outside the following interval:

$$[Q_1 - 1.5 \cdot IQR; Q_3 - 1.5 \cdot IQR] \quad (1)$$

where Q_1 and Q_3 represent the first and third quartiles, respectively, and the interquartile range ($IQR = Q_3 - Q_1$) represents the spread of the middle 50% of the data. On average, this filtering process resulted in the exclusion of approximately 2% of the initial observations, indicating a high level of reliability in the original telemetry signal. This process ensured that the statistical analysis and scenario modeling were based on consolidated and representative machine behaviors, providing a robust baseline for energy efficiency assessment.

2.3. Energy Normalization: Specific Consumption Coefficient (SCC)

To ensure comparability between machines of different sizes and to allow the scalability of results to other extractive contexts, fuel consumption data were normalized relative to the rated engine power (kW). This process led to the definition of a specific consumption coefficient (SCC) expressed in [L/(h · kW)].

This approach is based on the load-specific fuel consumption concept proposed by Klanfar et al. [5], who identified the ratio between hourly consumption and delivered power as a fundamental parameter for estimating energy efficiency in quarries. By using the rated power as a normalization factor, it is possible to decouple the fuel performance from specific machine size, providing a universal metric for efficiency. While the authors acknowledge that engine torque and average operational load provide a more direct representation of engine effort, the rated power was selected as a consistent and easily accessible baseline for cross-fleet benchmarking.

The coefficient is calculated as follows:

$$SCC = \frac{\text{Hourly Consumption} \left[\frac{L}{h} \right]}{\text{Rated Power [kW]}} \quad (2)$$

To capture the different thermodynamic behaviors of the engines, two distinct coefficients were calculated for each machine category:

- SCC_{op} : for active operational phases;
- SCC_{idle} : for inactivity periods with the engine running.

This decomposition is supported by the findings of Saim et al. [20], who identified effective working time and idling periods as the two primary drivers of total fuel consumption in mining units. While duty cycles are highly dependent on specific site conditions and applications, this normalization approach provides a methodological framework that can be adapted to diverse mining and quarrying environments.

2.4. Definition of the Standard Elementary Cycle

The material-handling process was decomposed into a standard elementary cycle, defined as the set of operations required to move a standard unit of 20 tons (7.5 m³). The sequential logic and the interdependence between the machines were modeled using the program evaluation and review technique (PERT), Figure 1. This scheduling approach allowed for the precise mapping of both productive work and non-productive idling times arising from logistical bottlenecks and spatial constraints.

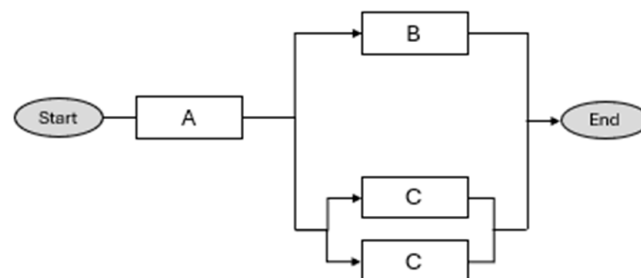


Figure 1. PERT modeling of the standard elementary cycle for marble block handling (20-ton unit). Phase designations A, B, and C refer to the activities detailed in Table 2.

Based on an observed operational yield of 55%, the total volume handled in the cycle is distributed as shown in Table 2.

Table 2. Operational phases for the elementary cycle.

Phase	Activity	Machines	Volume (m ³)	Distance (km)	Description
A	Excavation and Clearing	1 Crawler Excavator (EXC)	3.4	-	Clearing the waste material and loading debris onto the dumper to provide access to the marble block
B	Debris Transport	1 Articulated dumper (AD)	3.4	0.800	Transporting waste from the working face to the designated refuse pile
C	Block handling	2 Wheel Loaders (WLO)	4.1	0.350	Moving the commercial block from the face to the secondary handling area

The visual representation of these operational phases is provided in Figure 2, which illustrates the specific machinery involved in each task. As detailed in Table 2, phase C involves the simultaneous operation of two-wheel loaders to handle the commercial block. This cooperative handling is a logistical choice and safety requirement, dictated by the need to ensure stability during the transport of loads.



Figure 2. Phases of the standard elementary cycle: (a) Phase A—Excavator clearing waste material to provide access to the block; (b) Phase B—Articulated dumper transports waste; (c) Phase C—Wheel loaders handling and transporting the 20-ton marble block.

All the aforementioned phases are strictly governed by safety guidelines and operational best practices pertinent to the operation in the Carrara basin, which dictate recommended periods for machines not actively engaged in the concurrent task [24].

2.5. Improvement Scenarios and Sensitivity Analysis

In this study, a scenario is defined as a specific operational or technological configuration of the quarry fleet, characterized by distinct engine settings and powertrain architectures. The model compares the current state (Scenario 1) with two progressive levels of optimization to evaluate the impact of different decarbonization strategies.

- Scenario 1 (Baseline): Represents the current operational state as characterized in the 6-month monitoring campaign. It is defined by the existing machinery fleet using

conventional diesel engines and the current frequency of idling periods identified through PERT modeling.

- Scenario 2 (Managerial Optimization): Defined by the implementation of active engine-stop management to reduce idling periods while maintaining the existing technological assets. This scenario focuses on operational efficiency and behavioral changes.
- Scenario 3 (Technological Transition): Consists of the gradual replacement of conventional units equipped with diesel powertrains with comparable hybrid units featuring diesel-electric hybrid powertrains. This configuration applies to an operational consumption reduction factor ($\delta = 0.12$) derived from experimental evidence in Section 3.1.2.

To provide a contextual baseline for the annual impact, diesel fuel data from 2025 in Italy were used as a reference point [25]. Since fuel costs are subject to significant fluctuations in the international market, this parameter is utilized solely to estimate relative operational cost variations rather than as a fixed economic value.

2.6. Load Factor (LF)

The load factor (LF) represents the portion of the rated engine power effectively utilized during the machine's work cycle. This index is fundamental to understanding the operational efficiency of the fleet, as it identifies whether the engine is working within its optimal performance range. The LF is calculated as follows:

$$LF = \frac{q_h \cdot \rho}{P \cdot S_d} \quad (3)$$

where

q_h : measured hourly fuel consumption [L/h];

ρ : diesel density, assumed as 0.85 kg/L;

P : rated engine power [kW];

S_d : specific fuel consumption, assumed as 0.22 kg/kWh. This value represents an optimal efficiency benchmark for modern mining machinery equipped with advanced engine technologies, specifically validated for the power range characterizing the monitored fleet [5].

2.7. The Fuel Handling Index (FHI)

To determine the technological investment priority, the FHI is proposed. This KPI is defined as the residual fuel fraction following operational or technological modifications. Under this normalized framework, the baseline (Scenario 1) is established at a value of 1, representing the full energy demand of the current quarry cycle. Consequently, the FHI measures the residual fuel consumption fraction for each equipment category, or the entire fleet, after implementing idle management and hybridization strategies. The total fuel displacement achieved through optimization is subsequently calculated as the difference (1-FHI). By integrating machine power, phase duration, and specific consumption coefficients, the FHI provides a scalable decision-making tool for quarry operators regardless of their specific fleet size.

$$FHI = \frac{\sum_{i=1}^n (P_i \cdot T_{idle,i} \cdot SCC_{idle,i}) + ((1 - \delta) \cdot P_i \cdot T_{work,i} \cdot SCC_{op,i})}{Fuel_{cycle}} \quad (4)$$

where

P_i = rated engine power of the i -th machine [kW];

$T_{idle,i}$: total idling duration within the standard cycle [h];

$SCC_{idle,i}$: specific fuel consumption coefficient during idling [L/h/kW];

δ : hybrid reduction factor, assumed as 0.12 based on experimental evidence;

$T_{work,i}$: active operational work duration within the standard cycle [h];

$SCC_{op,i}$: specific fuel consumption coefficient during the operational phase [L/h/kW];

$Fuel_{cycle}$: total fuel consumption of the cycle [L].

The model utilizes the SCC values from the monitored diesel fleet as a reference baseline. It is assumed that the specific operational differences and duty cycle variations in the hybrid powertrains are effectively captured by the hybrid reduction factor, which accounts for the total net efficiency gain of the hybridized unit relative to its conventional counterpart.

This formulation assumes that energy contributions can be linearly aggregated across different equipment categories. This assumption is justified using machine-specific power rating (P_i) and SCC, which effectively weights each machine's contribution to the total fleet energy balance, ensuring the FHI remains a scalable and representative indicator.

FHI Efficiency Zone

The sensitivity analysis of the FHI is categorized into three efficiency zones, calibrated to reflect the fleet's progression from the current energy state toward the optimum. The thresholds for these zones are defined based on the percentage of fuel displacement achieved, linked to the LF analysis:

- Red Zone ($0.95 < FHI \leq 1$): Represents a condition where the fuel reduction is lower than 5%. This zone is assigned when the LF is lower than industrial benchmarks ($LF \ll LF_{optimum}$), placing the baseline ($FHI = 1$) in a high optimization potential area.
- Yellow Zone ($0.85 < FHI \leq 0.95$): Marks a transitional state with fuel savings between 5% and 15%. This transition represents operational improvements that move the fleet closer to its performance peak.
- Green Zone ($FHI \leq 0.85$): A value below 0.85 indicates a fuel displacement greater than 15%. This zone indicates that the optimized fleet has reached an energy performance.

3. Results

3.1. Fleet Monitoring and Parameter Validation

In this section, the technical and statistical characteristics of the monitored fleet are detailed, along with the empirical validation of the hybridization efficiency factor.

3.1.1. Statistical Characterization of Consumption

The 6-month monitoring campaign provided a dataset of fuel consumption during operational and idling phases. Table 3 presents the primary statistical descriptors for the operational hourly consumption [L/h_{op}] of each monitored unit. Similarly, Table 4 reports the statistical descriptors for the idling fuel consumption [L/h_{idle}], representing the fuel rate when the engine is running but the machine is not performing active work.

Table 3. Statistical descriptor of real-world operational fuel consumption.

Unit	Model	Mean Operational Consumption [L/h _{op}]	Std.Dev	CV [%]	Standard Error of the Mean	95% CI
Excavators	EXC 01	28.05	6.62	23.60	0.59	1.17
	EXC 02	23.69	4.82	20.38	0.45	0.89
	EXC 03	17.21	2.85	16.56	0.25	0.50
Wheel Loaders	WLO 01	21.41	4.55	21.26	0.41	0.80
	WLO 02	12.96	1.98	15.28	0.19	0.37
	WLO 03	16.67	2.83	16.95	0.24	0.47
Dumper	AD 01	11.08	0.83	7.47	0.10	0.20

Table 4. Statistical descriptor of real-world idling fuel consumption.

Unit	Model	Mean Idling Consumption [L/h _{idle}]	Std.Dev	CV [%]	Standard Error of the Mean	95% CI
Excavators	EXC 01	2.24	0.86	38.66	0.08	0.15
	EXC 02	3.54	0.65	18.39	0.06	0.11
	EXC 03	1.38	0.69	50.12	0.06	0.12
Wheel Loaders	WLO 01	1.85	0.52	28.11	0.05	0.09
	WLO 02	2.17	0.44	20.21	0.04	0.07
	WLO 03	1.02	0.44	43.34	0.04	0.08
Dumper	AD 01	1.25	0.28	22.71	0.03	0.05

Specifically, for each model, the tables report the mean consumption, the standard deviation, and the coefficient of variation (CV), which expresses the relative variability of the data. Furthermore, to account for the precision of the estimates, the standard error of the mean and 95% confidence interval (CI) are provided.

3.1.2. Field Validation of the Hybrid Efficiency Factor (δ)

To ensure the robustness of the FHI, the hybrid reduction factor ($\delta = 0.12$) was empirically validated through a dedicated two-month monitoring campaign in an auxiliary quarry. This preliminary study compared a conventional diesel unit against a hybrid unit of the same class performing identical intensity tasks.

Data acquired via Industry 4.0 telemetry revealed a consistent performance gap. As illustrated in the probabilistic analysis (Figure 3), hybrid technology achieved a mean consumption of 22.21 L/h (μ_{hybrid}), compared to the 25.17 L/h (μ_{diesel}) of the conventional diesel unit. To quantify this performance gap, the hybrid efficiency factor (δ) is defined as the percentage reduction between the two mean hourly consumptions, calculated as follows:

$$\delta = \frac{\mu_{\text{diesel}} - \mu_{\text{hybrid}}}{\mu_{\text{diesel}}} \quad (5)$$

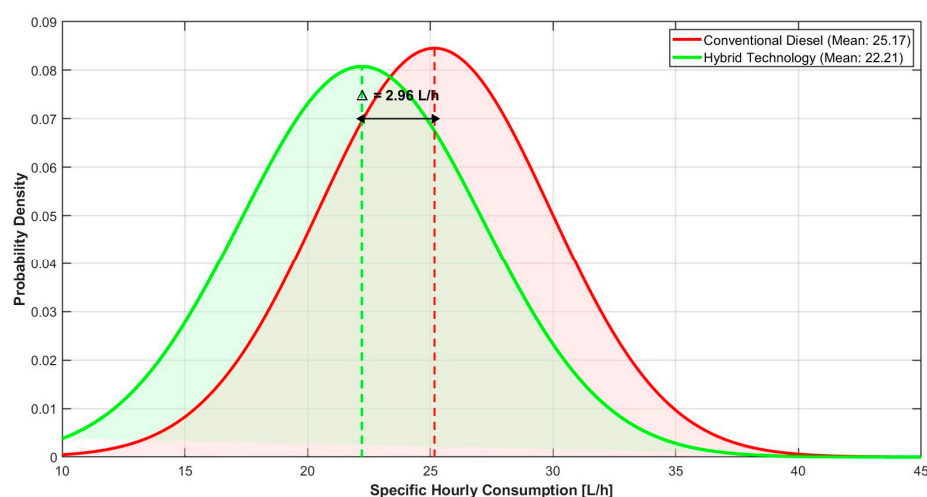


Figure 3. Probabilistic analysis of fuel displacement: comparison between conventional diesel and hybrid heavy equipment.

This result confirms a consolidated fuel reduction of 12%. It is crucial to note that this value represents a real-world field measurement, reflecting the actual operational stresses typical of heavy equipment in the quarrying sector. Consequently, $\delta = 0.12$ was adopted as the conservative empirical benchmark for the Scenario 3 modeling. While different

machinery types (EXC, WLO, AD) possess distinct hybrid architectures, the value $\delta = 0.12$ was applied uniformly as a conservative average. This simplification is justified by the study's objective to provide a scalable decision-making framework (FHI) rather than a manufacturer-specific technical assessment.

3.2. Load Factor (LF) Calculation

The results of the telemetry campaign, summarized in Table 5, reveal the current energy state of the quarry fleet compared to the benchmarks provided by Klanfar et al. [5].

Table 5. Calculated LFs vs. literature benchmarks.

Machine Category	Rated Power [kW]	Cons. (q) [L/h]	Calculated LF	Klanfar Range (LF)
Excavators	332–362	17.21–28.05	0.21–0.30	0.46–0.66
Wheel Loaders	313–439	12.96–21.41	0.21–0.22	0.25–0.31
Dumper	276	11.08	0.18	0.23–0.24

As observed, all machine categories exhibit an LF lower than the optimal range proposed by Klanfar [5]. This systematic efficiency gap justifies the positioning of the Scenario 1 baseline within the Red Zone of the FHI sensitivity charts (Figures 4 and 5).

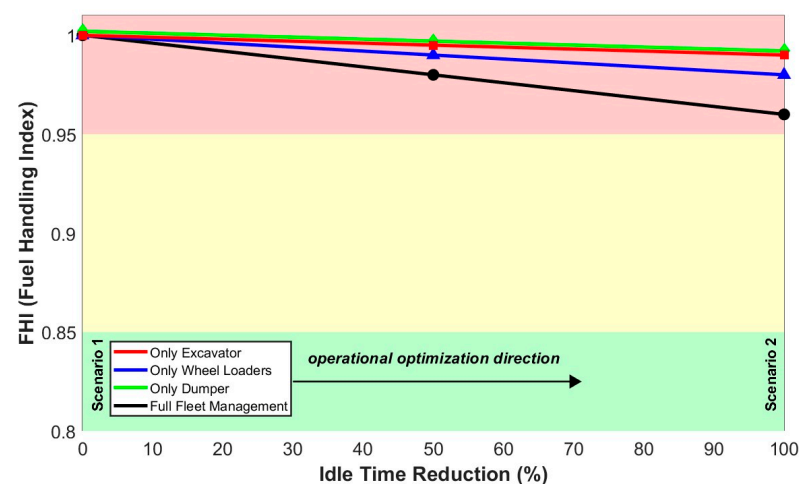


Figure 4. FHI sensitivity analysis: impact of operational idle time reduction.

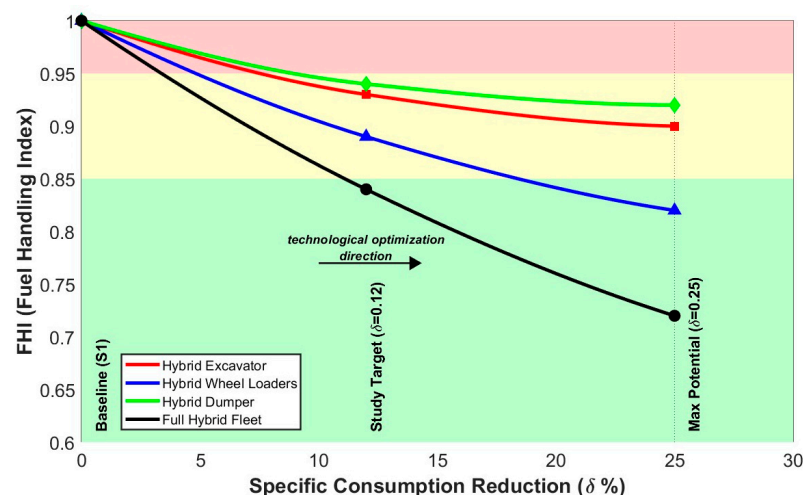


Figure 5. FHI sensitivity analysis: impact of technological hybridization.

3.3. Specific Consumption Coefficients (SCCs)

To establish a rigorous baseline for energy analysis, the telemetry data were used to calculate the average specific consumption coefficients (SCCs) for each machinery category. These coefficients, expressed in $[L/(h \cdot kW)]$, represent the fuel intensity normalized by engine power, distinguishing between active movement (operational) and static (idling) states. The calculated average values are summarized in Table 6.

Table 6. Average SCCs for the monitored fleet.

Machines	Average SCC_{op} [L/(h · kW)]	Average SCC_{idle} [L/(h · kW)]
Excavators	0.065	0.007
Wheel Loaders	0.044	0.004
Dumpers	0.040	0.005

The data reveals a significant disparity in energy intensity between operational and idling states. Excavators exhibit the highest average consumption during movement ($SCC_{op} = 0.065$). In contrast, SCC_{idle} values remain consistently low across the fleet. These average coefficients serve as the fundamental inputs for the scenario modeling and the subsequent calculation of the FHI.

3.4. Calculation of the FHI

In this section, the FHI formula defined in Section 2.7 is applied to quantify investment priorities within the quarry fleet. The application of the FHI allows for the isolation of the combined saving potential—both managerial and technological—for each machine category within the standard 20-ton elementary cycle.

As shown in Figure 4, the FHI was evaluated as a function of idle time reduction (at steps of 50% and 100%). At the current state (Scenario 1), the entire fleet starts at the normalized baseline of 1.00, falling within the red zone. This position is consistent with the low LF previously discussed in Table 5. This high idling frequency is largely due to the continuous operation of HVAC and air filtration systems, which are vital for maintaining operator health and comfort against thermal stress and marble dust inhalation in the quarry environment.

Reducing the idle time by 100% (Scenario 2) results in a decrease in the FHI for all categories. However, even with a total elimination of idling, the excavators and dumper only reach an FHI of 0.99, while the wheel loaders achieve an FHI of 0.98, with all categories remaining in the red zone. Full fleet management achieves a more significant reduction to 0.96 but still fails to cross the 0.95 threshold required to enter the yellow zone.

Figure 5 (FHI sensitivity: technological impact) represents the impact of reducing the SCC_{op} through hybridization. By applying a reduction coefficient $\delta = 0.12$ (study target), the FHI for the full fleet drops to 0.84, successfully entering the green zone. According to the analysis of the impact of individual technological interventions, the standalone hybridization of the excavator would reduce the index to 0.93, while the hybridization of wheel loaders and dumpers would result in values of 0.89 and 0.94 respectively. All these individual values fall within the yellow zone.

Furthermore, the sensitivity analysis explores the maximum potential of technology. If the manufacturer's optimistic reduction of $\delta = 0.25$ were achieved, the excavator FHI across the full fleet would drop to 0.72, penetrating deeply into the green zone. These results validate the FHI as a scalable decision-making tool.

The comprehensive evolution of the FHI values across all analyzed scenarios is summarized in Table 7.

Table 7. FHI values across the three modeled scenarios.

Machines	FHI Scenario 2	FHI Scenario 3
Excavator	0.99	0.93
Wheel loader	0.98	0.89
Dumper	0.99	0.94
Fleet-wide	0.96	0.84

3.5. Scenario Analysis and Economic Impact

This section evaluates the cumulative effects of the proposed decarbonization strategies by comparing the baseline (Scenario S1) with progressive optimization levels. The transition from behavioral changes to technological replacement yields significant energy and financial benefits, as summarized in Table 8.

Table 8. Cumulative analysis of fuel consumption and savings across operational and technological scenarios.

Scenario	Description	Total Fuel [L/cycle]	Saving vs. Scenario 1 [%]
1	Current state	17.13	-
2	Fleet-wide idle management	16.42	4.1%
	Excavator idle management	16.93	1.1%
	Wheel loaders idle management	16.79	2.0%
	Dumper idle management	16.95	1.0%
3	Hybrid Fleet-wide upgrade	14.28	17%
	Excavator hybrid upgrade	15.95	7%
	Wheel loaders hybrid upgrade	15.11	12%
	Dumper hybrid upgrade	16.06	6%

The simulation results for Scenario 2 demonstrate that “Fleet-wide idle management”, a zero-cost intervention, provides a 4% reduction in fuel consumption, lowering it from 17.13 to 16.42 L per cycle. When disaggregating this impact by machine category, the wheel loaders emerge as the most sensitive unit to idling optimization, contributing to a 2% saving on the total cycle.

The impact is significantly amplified in Scenario 3, where technological hybridization is introduced. As anticipated by the FHI analysis in Section 3.4, the wheel loader hybrid upgrade yields the highest individual benefit, achieving a 12% reduction vs. Scenario 1. Interestingly, the full-hybrid fleet-wide upgrade leads to a 17% cumulative reduction.

4. Discussion

The statistical analysis reveals that the fleet’s energy consumption is characterized by moderate variability, with a coefficient of variation (CV) ranging from 7 to 23%. This variability aligns with the stochastic nature of quarry operations [23]. However, significant findings emerge from the calculated LF, with a range between 0.18 and 0.30. These values are notably lower than the benchmarks proposed by Klanfar et al. [5], who suggest ranges of 0.46–0.66 for excavators and 0.25–0.31 for wheel loaders. This discrepancy suggests that the machinery used in the Carrara site is potentially oversized for specific block-handling tasks, resulting in underutilized engine capacity. In this context, the load factor acts as a preliminary test for operational efficiency. According to the benchmark, an LF significantly lower than the literature range serves as an early warning sign of a poorly organized production cycle, characterized by excessive idling or logistical bottlenecks. This observation directly justifies the focus on Scenario 2. If the LF is below the optimal threshold, it implies that there is a substantial margin to reduce the FHI at “zero-cost” through managerial interventions alone.

A key contribution to this research is the introduction of the FHI as a diagnostic tool for cycle efficiency. Unlike traditional consumption metrics, the FHI integrates specific fuel coefficients with operational time management. If a high FHI is detected, quarry managers can use it as a trigger to re-examine the PERT modeling of the production cycle. By identifying which phase or machine is causing the index to spike, it becomes possible to pinpoint logistical bottlenecks or spatial constraints that were previously hidden. This allows for a targeted optimization of the scheduling logic before any capital investment is considered. Specifically, while established KPIs such as specific fuel consumption or production-based metrics provide an absolute measure of energy intensity, they often act as “black box” indicators that fail to isolate the source of inefficiency. The FHI offers incremental value by providing a normalized baseline that decouples the impact of operational behavior from powertrain technology. This allows for a direct, percentage-based comparison between managerial improvements and technological upgrades, which is not easily captured by traditional parameters.

While scenario 2 (idle management) offers a potential saving of 4% by altering operational behavior, it is crucial to recognize that a portion of the idling time is a technical necessity for maintaining HVAC and air filtration systems. Consequently, achieving the full saving potential without compromising operator health might not be entirely “zero-cost”, as it could require alternative solutions for cabin environmental systems during downtime. The FHI demonstrated that once idle times are minimized through managerial interventions, a technical ceiling is reached. To break through this limit and achieve more substantial decarbonization, the transition to hybrid technology (Scenario 3) is necessary to reach the 17% threshold. These figures are more conservative than the 30% reduction reported by Allam et al. [13] for compact loaders, reflecting the higher operational stress of 20-ton marble block handling. Additionally, while hybrid powertrains may experience efficiency fluctuations under continuous maximum load, the intermittent duty cycles typical of marble quarrying, characterized by frequent energy recovery opportunities during maneuvering and load lowering, minimize the risk of significant system degradation.

5. Conclusions

This study demonstrates that the integration of Industry 4.0 telemetry and data analytics is a fundamental prerequisite for the energy transition in the marble sector. A novel KPI, the fuel handling index (FHI), was proposed and validated as a practical tool for monitoring cycle efficiency.

The FHI serves a dual purpose: first, as an operational monitor to verify whether the production cycle is performing according to the optimal PERT logic, and second, as a strategic guide for fleet renewal. Our findings show that while “zero-cost” interventions, such as idle management, can yield immediate fuel savings of 4%, the transition to hybrid technology is essential to achieve more substantial reductions (up to 17%). However, the FHI clearly indicates that managerial optimization alone is insufficient to meet modern sustainability targets. The transition to hybrid technology, particularly for wheel loaders, is essential to achieve more substantial reductions.

In conclusion, this research provides quarry managers with a practical decision-making framework. By using the FHI to identify inefficiencies in real time, operators can first optimize their current logistical assets and then prioritize investments in hybrid equipment. This integrated approach decouples production from carbon emission, ensuring the long-term economic and environmental sustainability of the natural stone industry.

Although the proposed model could potentially be further improved through the inclusion of a wider variety of machine models and geological conditions, it establishes a solid baseline for future developments. Future research should focus on the scalability

of the proposed framework to fully electric fleets, evaluating the impact of charging infrastructure on quarry logistics and grid stability. Building on the predictive capabilities of machine learning models, further research could integrate real-time telemetry with AI-driven dispatch systems to dynamically optimize engine load factors and minimize idle times.

Author Contributions: Conceptualization, S.I. and D.L.; methodology, S.I.; software, S.I.; validation, S.I. and D.L.; formal analysis, S.I.; investigation, S.I.; resources, S.I.; data curation, S.I.; writing—original draft preparation, S.I.; writing—review and editing, D.L.; visualization, S.I.; supervision, D.L.; project administration, D.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data supporting the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments: The authors would like to express their gratitude to Studio Orlando Pandolfi for providing access to their proprietary platform and for technical support.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CV	Coefficient of Variation
FHI	Fuel Handling Index
LF	Load Factor
IQR	Interquartile Range
PERT	Program Evaluation and Review Technique

References

1. Kumar, A.; Kumar, A.; Vatsala; Singh, S. A Comparative Analysis of Emissions from Mining Sector in G20 Countries. *Anthr. Sci.* **2025**, *4*, 198–212. [CrossRef]
2. Southwest Research Institute. Decarbonizing Heavy Machinery. Available online: <https://www.swri.org/newsroom/technology-today/decarbonizing-heavy-machinery> (accessed on 4 November 2025).
3. European Parliament and Council. Regulation (EU) 2016/1628 on requirements relating to gaseous and particulate pollutant emission limits and type-approval for internal combustion engines for non-road mobile machinery. *Off. J. Eur. Union* **2016**, *L252*, 1–114.
4. Tokac, B.; Zhang, Q.; Sari, Y.A. Environmental and economic comparison of diesel and electric trucks in open-pit mining operations. *J. Clean. Prod.* **2025**, *507*, 145540. [CrossRef]
5. Klanfar, M.; Korman, T.; Kujundžić, T. Fuel consumption and engine load factors of equipment in quarrying of crushed stone. *Teh. Vjesn.* **2016**, *23*, 111–120.
6. Buyuksagis, I.S.; Goktan, R.M. Investigation of marble machining performance using an instrumented block-cutter. *J. Mater. Process. Technol.* **2005**, *169*, 258–262. [CrossRef]
7. Balboa-Espinoza, V.; Segura-Salazar, J.; Hunt, C.; Aitken, D.; Campos, L. Comparative life cycle assessment of battery-electric and diesel underground mining trucks. *J. Clean. Prod.* **2023**, *425*, 139056. [CrossRef]
8. Gao, Z.; Lin, Z.; Franzese, O. Energy Consumption and Cost Savings of Truck Electrification for Heavy-Duty Vehicle Applications. *Transp. Res. Rec.* **2017**, *2628*, 99–109. [CrossRef]
9. Baranauskas, M.; Graber, G.; Gagliardi, G.; Calderaro, V.; Galdi, V. Feasibility and benefits of off-highway mining trucks electrification for different mine profiles. *Energies* **2022**, *15*, 4628. [CrossRef]
10. Un-Noor, F.; Padmanaban, S.; Mihet-Popa, L.; Mollah, M.N.; Hossain, E. Off-Road Construction and Agricultural Equipment Electrification: Review, Challenges, and Opportunities. *Vehicles* **2022**, *4*, 780–807. [CrossRef]
11. Ali, D.; De Castro, R.; Ehsani, R.; Vougioukas, S.; Wei, P. Unlocking the potential of electric and hybrid tractors via sensitivity and techno-economic analysis. *Appl. Energy* **2025**, *377*, 124545. [CrossRef]

12. Pena, J. Case Study: Diesel-Powered Loaders Compared to Hybrid Loaders in Heavy Civil Construction. Master's thesis, California Polytechnic State University, San Luis Obispo, CA, USA, 2020.
13. Allam, M.; Fernandez, O.; Linjama, M. Fuel Efficiency Analysis and Control of a Series Electric Hybrid Compact Wheel Loader. *Commer. Veh.* **2024**, *17*, 197–211. [\[CrossRef\]](#)
14. Prinz, R.; Spinelli, R.; Magagnotti, N.; Routa, J.; Asikainen, A. Modifying the settings of CTL timber harvesting machines to reduce fuel consumption and CO2 emissions. *J. Clean. Prod.* **2018**, *197*, 208–217. [\[CrossRef\]](#)
15. Wang, X.; Ge, L.; Li, Y.; Quan, L. Research on Energy Efficiency Characteristics of Mining Shovel Hoisting and Slewing System Driven by Hydraulic-Electric Hybrid System. *Chin. J. Mech. Eng.* **2023**, *36*, 156. [\[CrossRef\]](#)
16. Fei, X.; Cheng, Z.; Wong, S.V.; Azman, M.A.; Wang, D.; Zhang, X.; Shao, Q.; Lin, Q. A Comprehensive Overview of the Development and Research of Energy Savings of Electric Wheel Loader. *World Electr. Veh. J.* **2025**, *16*, 164. [\[CrossRef\]](#)
17. Zhang, H.; Wang, F.; Xu, B.; Fiebig, W. Extending battery lifetime for electric wheel loaders with electric-hydraulic hybrid powertrain. *Energy* **2022**, *261*, 125190. [\[CrossRef\]](#)
18. Holian, M.; Pyeon, J.-H. *Analyzing the Potential of Hybrid and Electric Off-Road Equipment in Reducing Carbon Emissions from Construction Industries*; Mineta Transportation Institute: San Jose, CA, USA, 2021; Available online: <https://transweb.sjsu.edu/research/Analyzing-Potential-Hybrid-and-Electric-Road-Equipment-Reducing-Carbon-Emissions-Construction-Industries> (accessed on 11 November 2025).
19. Liu, J.; Liang, Y.; Chen, Z.; Chen, W. Energy Management Strategies for Hybrid Loaders: Classification, Comparison and Prospect. *Energies* **2023**, *16*, 3018. [\[CrossRef\]](#)
20. Saim, A.K.; Kumah, F.N.; Oppong, M.N. Predicting Mining Excavator Fuel Consumption using Machine Learning Techniques. *Adv. Eng. Des. Technol.* **2020**, *2*, 12–23.
21. George, B.; Nojabaei, B. Data Analyses of Quarry Operations and Maintenance Schedules: A Production Optimization Study. *Mining* **2023**, *3*, 347–366. [\[CrossRef\]](#)
22. Innocenzi, S.; Lippiello, D.; Alfaro Degan, G.; Antonucci, A. Operational cost analysis of an elementary extraction cycle in a marble quarry of the Apuan Alps. In *Proceedings of the 25th SGEM International Multidisciplinary Scientific GeoConference 2025*; SGEM: Albena, Bulgaria, 2025; Volume 5.1.
23. Mariz, J.L.V.; Rocha, S.S.; Souza, J.C.D.; Maior, G.R.D.S. Stochastic economic feasibility assessment and risk analysis of a quarry mine focusing on the Brazilian tax system. *REM Int. Eng. J.* **2023**, *76*, 89–100. [\[CrossRef\]](#)
24. Guidelines for Safety Analysis in the Extraction Sector in Open-Pit Quarries. Available online: <https://www.vegaengineering.com/linee-guida/linee-guida-analisi-della-sicurezza-nel-settore-estrattivo-in-cave-a-cielo-aperto/> (accessed on 11 November 2025). (In Italian)
25. Average Fuel Prices—Data by Region. Available online: https://www.mimit.gov.it/it/prezzo-medio-carburanti/regioni?utm_source#toscana (accessed on 3 January 2026). (In Italian)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.