Digital Twin-Enabled Real-Time Monitoring in Mineral Processing - The Skaland Graphite Case

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***Abstract*—This paper presents the development, architecture, and deployment results of a Mineral Processing Model (MPM) operating as a physics-based digital twin within the EU-funded DINAMINE project framework. Focused on the industrial operations at the Skaland Graphite facility in Norway, the MPM integrates continuous real-time data streams from multiple heterogeneous sensors to reconstruct time-aligned mass balances, resource consumption profiles, and carbon footprint indicators. Utilizing high-frequency online Laser-Induced Breakdown Spectroscopy (LIBS) for input elemental carbon tracking alongside localized empirical engine combustion models, the developed framework demonstrates automated 24/7 analytical capabilities. Baseline operations analysis reveals that thermal drying via propane represents the primary environmental driver, accounting for 73% of total site emissions, followed by diesel mining equipment (15%) and electrical power consumption (12% under national grid comparability metrics). The implemented standalone software system provides actionable operational insights, preventing flotation circuit overflows and establishing automated tools for sustainable resource management in critical raw material value chains.**

Keywords*—*Digital twins, Mineral processing model, Carbon footprint, Real-time monitoring, Graphite mining

I. Introduction

Optimizing resource usage and reducing the environmental footprint of critical raw material extraction are key challenges for the modern mining industry [1]. This work presents the engineering implementation and operational results of the Mineral Processing Model (MPM), developed under the European Union's Horizon Europe DINAMINE project. The primary scope of this module is the operational demonstration of a physics-based digital twin tailored for industrial mineral processing, along with its bi-directional integration into the unified DINAMINE Integrated Smart Mine Planning and Managing Unit (ISM-PM) platform.

Recent advances in digital twins for mineral processing emphasize hybrid modelling approaches, real-time analytics, and integration with sustainability metrics [2-4]. Unlike existing digital twins that rely on simplified, steady-state or unit-level analysis, the proposed MPM integrates heterogeneous real-time sensors, dynamic time-aligned mass balances, and carbon footprint tracking within a fully deployed industrial system, enabling continuous plant-wide monitoring and decision support in mineral processing. The MPM acts as a high-fidelity digital module focusing on the downstream processing stages of mining operations [5]. By dynamically ingesting sensor network readings, the module continuously monitors the raw ore feed entering the processing plant, the concentrated final products, the generated waste streams, and the multi-utility resources consumed throughout the processing sequence. The core objective of the MPM is to transform raw, noisy, or disconnected industrial sensor data into robust, actionable performance indicators. These outputs provide real-time visibility into ore quality, carbon grade distribution, industrial productivity, multi-stage process recovery, and the immediate greenhouse gas environmental footprint of the operation.

II. General Description of the MPM

A. MPM Inputs and Pilot Site Characterization

The MPM functions as an interactive data model designed specifically for industrial mineral processing plants (Fig. 1). Building a reliable digital twin requires defining a standard set of variables to capture the dynamics of complex material transitions and resource utilities. Within DINAMINE project framework, the monitoring boundary encompasses material input streams, recovered concentrates, and final waste flow, coupled with continuous tracking of electricity, water flow, and fossil fuel consumption.

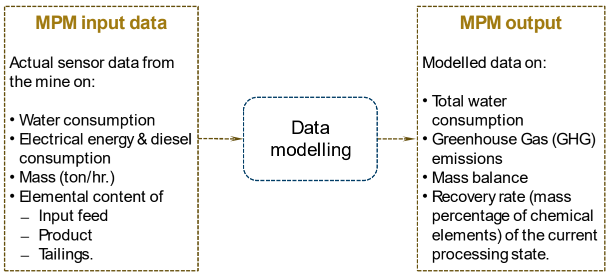

Fig. 1. MPM inputs and outputs.

This implementation focuses on the Skaland Graphite AS (SKA GRAPH) pilot facility located in Troms, Norway. The Skaland operation is an underground mining facility that continuously extracts and processes graphite ore year-round. Unlike other pilot sites that utilize zero-waste or co-product workflows, the material flow at Skaland is characterized by a three-stream mass balance pipeline consisting of the input graphite ore feed, the recovered final product (graphite concentrate), and the discarded waste rock. To resolve this multi-stream processing network, continuous time-series observations are captured at multiple critical nodes to monitor mass flow rates, volumetric variations, and elemental chemical compositions. These streams are matched with real-time tracking of operational inputs, specifically electrical energy, water consumption, and diesel fuel usage, to link plant utility demands directly to instantaneous equipment operation and material throughput.

B. Sensor Network Deployment Framework

To generate the necessary time-series inputs for the core model, a comprehensive sensor infrastructure was deployed across the Skaland mine site and processing plant. The online sensor layout consists of 22 individual tracking assets classified across key operational categories to enable continuous data capture. The primary sensor nodes deployed at the Skaland facility include the following units:

- Vehicle trackers: Deployed on the mobile mining fleet to record engine revolutions per minute (RPM) continuously, providing the primary inputs for real-time diesel consumption tracking.
- Power consumption meters: Online electrical power meters that continuously monitor electricity usage (kWh) across the mine site and processing plant.
- Gas sensors: Installed across in the processing plant to continuously monitor the amount of propane consumed.
- Flow meters: In-line industrial flow sensors that monitor water usage rates, outputting continuous flow percentages to evaluate freshwater demands and process water recycling efficiency.
- Conveyor belt LIBS sensor: A customized online LIBS analyzer developed by Spectral Industries (SPI), installed directly over the primary input conveyor belt up to the autogenous (AG) mill to determine the elemental carbon concentration (%C) of the input ore feed in real time.
- Combustion elemental analyzer (EA): Located in the on-site processing laboratory to determine the carbon grade of the final graphite concentrate via traditional combustion methods, generating high-accuracy reference values five times per shift.
- Weight meter: An integrated industrial belt scale that measures the mass flow rate and cumulative tonnage of the raw ore feed entering the plant in real time.
- Silo level sensors: Continuous distance and level sensors mounted on the storage silos to determine the instantaneous fill percentages of the various final product streams.

Online sensors transmit automated high-frequency data to the central data platform. For monitoring nodes where online instrument installation was technically impractical or cost-prohibitive, a standardized manual data entry protocol was implemented. Plant operators collect physical sub-samples from the product and waste streams five time per shift, complete laboratory analyses using the combustion EA and XRF systems and upload the results via a web interface or structured local CSV/Excel templates.

This hybrid sensor infrastructure allows the MPM script to compute localized mass balances. The total input feed is directly quantified by the belt scale weight meter. The mass accumulation of final graphite concentrate is determined indirectly through a localized formula that processes volumetric changes from the silo level sensors multiplied by the specific bulk densities of the respective graphite grades. The remaining waste mass stream is then computed as the algebraic difference between the total recorded input and the estimated output mass.

III. Implementation Flowsheet and Modeling Framework

A. Technical Software Architecture

The technical architecture of the MPM system is structured as a standalone computational engine that communicates with the central ISM-PM platform (Fig. 2). The system uses a secure TCP-IP protocol to achieve bi-directional data flow, retrieving raw sensor inputs and publishing computed process indicators back to the platform. The software infrastructure consists of four primary modules:

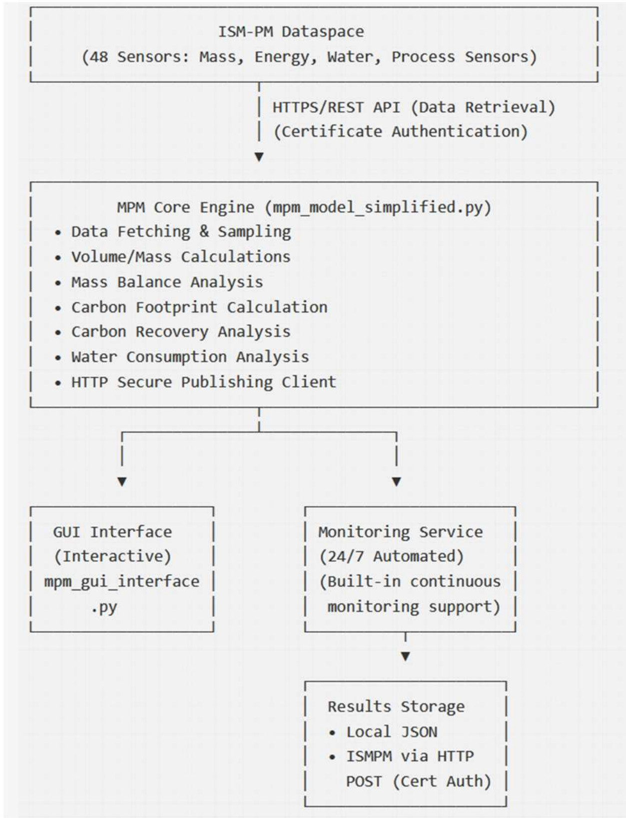

Fig. 2. MPM technical architecture.

(1) ISM-PM interface: Establishes secure communication with the central platform using certificate-based SSL/TLS client authentication. It handles time-ranged data queries using pagination and manages the structured upload of results.

(2) Core analysis engine: Implements the primary analytical classes. It handles chunked data fetching for large datasets, performs 5-minute time-series resampling and interpolation, executes geometric silo volume modeling, and runs the mass and energy balance scripts.

(3) GUI interface: A Web-based user interface that allows operators to manually configure analysis windows, select security certificates, preview settings, validate sensor availability, and view summaries of mass recovery and carbon balances.

(4) Continuous monitoring service: An automated background service that handles continuous 24/7 operations, checking data at configurable intervals (from 5 minutes to 24 hours) using rolling time windows.

The underlying technology stack is built entirely on open-source libraries, utilizing Python 3.8+, NumPy and Pandas for data manipulation, Matplotlib for data visualization, and Requests for secure HTTPS communication using JSON payloads.

B. Industrial Process Flowsheet and Time-Delay Compensation

To contextualize the data pipeline, the physical processing layout at the Skaland facility requires a multi-stage refinement flowsheet. Extracted graphite ore from the underground mine is delivered to the plant's storage bins. The material is then processed through a primary crushing circuit and an autogenous grinding mill (AG Mill). The slurry flows into secondary grinding systems (comprising Grinding Mills 1 to 4) and passes into multi-stage flotation circuits (including the Aker flotation cells and Denver flotation batteries) to separate the graphite flakes from the silicate gangue. The recovered graphite concentrate is sent to thickeners, pre-dried using drum filters, and processed through a high-temperature propane-fuelled drying oven. The dried product is classified via sieving and grading circuits and stored in six dedicated final product silos based on commercial size fraction and bulk density characteristics: Flake 1, Flake 2, Medium 1, Medium 2, Fine medium, and Powder 1 and 2. A major challenge in modelling this flowsheet is accounting for physical process lag. Material entering AG mill requires a significant retention time before reaching the final product silos.

To prevent errors in instantaneous mass balance calculations, the Core Analysis Engine implements a time-alignment algorithm compensating for a 80-minute process delay between raw ore input and final product "*Output*". The compensation "*Aligned_output*" and mass recovery "*Mass_recovery_rate*" with current timestamp T, are given as:

$$Aligned_output(T) = Output(T).shift(periods = 80min) \quad (1)$$

$$Mass\_recovery\_rate\ (T) = \frac{Aligned\_output\ (T)}{Input\_ore\_mass\ (T)} \quad (2)$$

C. Carbon footprint and fuel combustion formulations

The carbon footprint module operates as an integrated script within the MPM architecture to evaluate operational greenhouse gas emissions, reported in metric tons of CO_2-equivalent. The total carbon footprint A_{CO2e} represents the combined greenhouse gas contributions from diesel fuel combustion A_{diesel}, propane usage $A_{propane}$, and grid electricity consumption A_{kWh}, described by:

$$A_{CO2e} = A_{diesel} \cdot SE_{CO2\text{-}diesel} + A_{propane} \cdot SE_{CO2\text{-}propane} + A_{kWh} \cdot SE_{CO2\text{-}kWh} \quad (3)$$

where the standard specific emission factors (SE) [6] [7], are defined based on Norwegian grid and fuel compliance standards [8], given as:

$$SE_{CO2\text{-}diesel} = 2.68 \text{ kg } CO_2 \text{ per liter of diesel} \quad (4)$$

$$SE_{CO2\text{-}gas} = 3.03 \text{ kg } CO_2 \text{ per kg of gas} \quad (5)$$

$$SE_{CO2\text{-}kWh \text{ (Norway Grid Mix 2025)}} = 0.028 \text{ kg } CO_2 \text{ per kWh} \quad (6)$$

Because diesel fuel flow meters are not directly installed on the individual mobile mining assets, the MPM-CF subscript utilizes vehicle engine parameters and high-frequency RPM sensor readings to calculate fuel usage mass (m_{diesel}, in grams) over an time interval t (in second):

$$m_{diesel} = V_d \cdot \rho_{air} \cdot \left(\frac{1}{2}\right)\left(\frac{1}{CR}\right) \cdot \left(\frac{RPM}{60}\right) \cdot t \quad (7)$$

where V_d represents the engine displacement volume in liters, CR is the compression ratio, ρ_{air} = 1.225 g/L is the reference air density, and factor 1/2 accounts for the physical combustion cycles of 4-stroke industrial diesel engines. The computed fuel mass is converted to kilograms and multiplied by the specific emission factor to establish continuous asset-level emission logs. For grid electricity tracking, the model applies the Norwegian grid mix factor (0.028 kg CO_2e/kWh in 2025) for international compliance and benchmarking. However, the model can also apply an emission factor of zero because Skaland facility operates under commercial contracts ensuring electricity sourcing from certified renewable sources.

IV. Results and Discussion

A. Baseline Energy Consumption Analysis

Baseline modelling was conducted using historical operational records from the complete calendar year 2022 to evaluate the distribution of energy consumption and pinpoint the major sources of greenhouse gas emissions at the Skaland facility. The consolidated carbon footprint indicators are summarized in TABLE 1.

TABLE 1. ANNUAL CARBON FOOTPRINT INDICATORS FOR SKALAND GRAPHITE BASELINE OPERATIONS.

Operational section	**Diesel emissions** (t CO_2e)	**Gas emissions** (t CO_2e)	**Electricity emissions** (t CO_2e)
Mine site operations	218	0	46
Processing plant operations	0	1048	133
Total cumulative emissions	218	1048	179

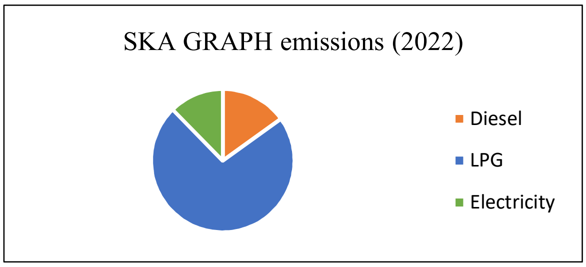

Fig. 3. CO_2 emissions in Skaland Graphite in 2022.

The total annualized greenhouse gas generation reached 1,445 metric tons of CO_2e. Proportional distribution analysis shows that thermal drying via the gas-fueled concentrate oven is the dominant environmental driver at the site, accounting for 73% of the total carbon footprint. Diesel-powered hauling and loading machinery contributes 15%, while electricity usage across the crushing and milling systems accounts for the remaining 12% under grid comparison conditions (Fig. 3).

B. Machine-Level Asset Prioritization

While managing data volume, a cutoff threshold was established, focusing real-time sensor integration on assets that contribute more than 1% of total greenhouse gas emissions. This localized machine fleet mapping identifies seven primary assets for direct sensor integration:

(1) Loader 1 (mine site): A Volvo L180 front loader powered by a Volvo D13F engine (12.78 L displacement, 16:1 compression ratio) mapped to online RPM Sensor Node 1.

(2) Dumper (mine site): A Volvo A40 articulated hauler powered by a Volvo D16H engine (16.2 L displacement, 15:1

compression ratio) mapped to online RPM Sensor Node 2.

(3) Loader 2 (crushing area): A Volvo L110 support loader utilizing a Volvo TD70 engine (7.75 L displacement, 9:1 compression ratio) mapped to online RPM Sensor Node 3.

(4) Haul Truck 1 (transport): A Volvo FMX 540 road truck powered by a 13.2 L engine (15:1 compression ratio) mapped to online RPM Sensor Node 4.

(5) Drying Oven (processing plant): A stationary thermal unit running on bulk gas fuel, monitored directly via online gas consumption percentage Sensor Node 5.

C. *Sensor Variability and Data Dispersion Metrics*

Statistical analysis was applied to the sensor streams to verify data quality and evaluate signal dispersion under real operating conditions. The standard deviation (σ) values captured during stable operations for the core sensors are detailed in TABLE 2.

TABLE 2. THE SENSOR STREAM STATISTICAL VARIATION METRICS.

Sensor mapping node name	**Target measurement parameter**	**Quantified dispersion (σ)**
Ore feed scale	Instantaneous mass flow rate (kg)	0.044 kg
LPG consumption meter	Oven fuel consumption grade (%)	0.004%
AG mill power meter	Main crushing energy consumption (kWh)	10.61 kWh
Grinding Mill 1 power meter	Grinding circuit 1 energy consumption (kWh)	22.15 kWh
Grinding Mill 3 power meter	Grinding circuit 3 energy consumption (kWh)	10.27 kWh
Water flow meter	Total plant process flow rate (%)	0.0015%

The low standard deviation recorded for the belt scale (0.044 kg) and the LPG meter (0.004%) demonstrates high baseline signal stability, confirming their suitability for integration into real-time algorithms. The larger standard deviations observed across product storage silos (such as Medium 2 at 1.461%) capture intermittent filling cycles and the physical discharge of completed product batches to packaging sections.

System execution performance logs show that the Core Analysis Engine requires approximately 25 minutes of computation time to process a standard 24-hour sensor block. This comprises 96 data points per sensor node across 21 concurrent core sensor channels using 5-minute sampling intervals, confirming the system's readiness for live 24/7 automated monitoring.

V. CONCLUSION AND FUTURE WORK

The implementation and operational validation of the Mineral Processing Model demonstrates the efficacy of physics-based digital twins for tracking industrial resource allocation and environmental indicators. By deploying a secure architecture that links plant sensor networks directly to chunked processing pipelines, the system generates continuous metrics for mass balance, water efficiency, and carbon recovery rates. Baseline data analysis successfully identified thermal drying via the gas-fuelled oven as the dominant source of emissions at Skaland, accounting for 73% of the site's total carbon footprint. This insight provides a clear, data-driven foundation for targeting future process electrification and carbon reduction initiatives.

Furthermore, real-time tracking of input feed compositions through online LIBS carbon sensors delivers significant operational value. It provides early warnings of high-grade anomalies, allowing operators to adjust parameters proactively, prevent flotation tank overflows, and avoid unexpected production shutdowns.

The completed MPM framework establishes a robust template for automated environmental tracking, reinforcing operational efficiency and corporate sustainability metrics within European critical raw material operations.

Building on the successful implementation of the MPM, future work will focus on integrating machine learning techniques with the existing physics-based digital twin to establish a hybrid framework [9]. This will enable predictive capabilities for key process indicators, and support proactive optimization of operations. In particular, the approach will target the reduction of dominant emission sources, such as LPG-based thermal drying, while also exploring cleaner energy alternatives, including hydrogen [10], to advance both efficiency and sustainability in mineral processing. The impacts of sensor errors, missing data, calibration drift, and model uncertainty on the calculated mass balances and carbon footprint indicators will be further examined.

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