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Research Article

Towards Virtual Twinning of Underground Mines: An Information-Model-Based Framework for Air Quality Monitoring and Ventilation Management

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Abstract

Digitalisation in the mining industry remains constrained by fragmented data flows, isolated software tools and the lack of unified information structures that support integrated, regulation-compliant decision-making. While Building Information Modelling (BIM) is well established in construction, its systematic application to underground mining operations is still limited. This study addresses this gap by presenting an automation-ready, BIM-based framework for underground air-quality (AQ) information management, centred on a parametric Mine Information Model (MIM) and an integrated Virtual Twin (VT). The framework unifies tunnel geometry, ventilation infrastructure, equipment data and AQ sensor measurements within a coherent, semantically structured 3D MIM. On this basis, a VT environment is implemented to integrate time-stamped field measurements with multi-scale ventilation simulations, including network-based airflow modelling and hybrid computational fluid dynamics (HCFD).

The shared parametric geometry and identifier structure enable consistent spatial and temporal alignment of heterogeneous data sources, supporting scenario-based analysis of airflow and contaminant dispersion. The primary contribution of the study is the demonstration of a reproducible MIM–VT integration workflow that enables structured ingestion, harmonisation and visualisation of measured and simulated AQ data within a single operational environment. The resulting architecture improves traceability, documentation and reporting in accordance with European Union underground air-quality directives, while enhancing situational awareness for ventilation planning and post-blast safety assessment. A proof-of-concept implementation at an operating underground mine shows that the approach reduces data fragmentation and supports reflective and predictive VT operation. While fully automated, bi-directional control is beyond the scope of this study, the presented framework establishes a scalable and transferable foundation for future prescriptive virtual-twinning developments in underground mine ventilation management.

Keywords: Building Information Modelling (BIM); Mine Information Model (MIM); Virtual Twin (VT); Automation-oriented Data Integration; Underground Mine Ventilation and Air Quality; Regulation-compliant Environmental Monitoring.

Introduction

Ensuring adequate air quality (AQ) in underground (UG) mines remains a fundamental requirement for safe and efficient operations and a key prerequisite for the ongoing automation and digitalisation of mining systems, particularly in the transition toward autonomous and remotely. Operated mines. Limited space, complex tunnel geometries, and various pollutant sources-such as blasting, rock loading, and diesel-powered machinery-create challenging conditions for ventilation and environmental control. Exhaust gases (CO, CO_2, NO_x, VOCs) and particulate matter (PM) are the main contaminants, while non-exhaust emissions originate from mineral dust, explosives, and evaporative compounds. Elevated concentrations of these pollutants have been associated with respiratory and cardiovascular diseases, reduced cognitive performance, and, in severe cases, acute health risks for mine personnel and, in severe cases, acute health risks for mine personnel, directly constraining safe work scheduling, re-entry decisions after blasting, and the automation of underground operations [1-6].

Because of the dependence on forced ventilation and complex airflow paths, pollutant accumulation may vary significantly between tunnel sections. Therefore, continuous monitoring of key indicators -CO, NO_x, and PM concentrations ($PM_{2.5}$, PM_{10})- is essential for both regulatory compliance and operational safety, forming a critical operational data source for ventilation control and decision-making, Table 1. Particle number (PN) and chemical composition are also important, as combustion-related nanoparticles (<100 nm) can dominate toxicity even when their mass contribution is low.

Table 1. Typical pollutants in mine air and unit of measure.

Pollutants	Unit
Exhaust emissions	
Particle number (PN)	cm-3
Gaseous compounds (CO, CO2, NOx)	ppm, ppb
Black carbon (BC)	µg/m3
Volatile organic compounds (VOC)	ppm, ppb
Non-exhaust emissions	
Mineral dust (PM2.5, PM10)	µg/m3
Explosive fumes (CO, CO2, NOx)	ppm, ppb
Evaporative emissions	ppm, ppb

All UG spaces, including underground mines, are basically indoor spaces where the dilution of harmful air pollutants by ventilation is carried out either by gravity or by mechanical means. Fumes from the use of explosives during rock extraction and from diesel-powered vehicles significantly influence the concentration of harmful substances in UG mine air [7-9]. Ensuring compliance with AQ standards through ventilation systems and implementing continuous monitoring has consistently posed challenges in the harsh mining environment [10]. From an automation perspective, this makes UG mines comparable to large-scale industrial indoor environments, where ventilation performance must be continuously monitored, modelled, and adjusted based on dynamic operational conditions.

The EU Directives 92/104/ETY and 2017/164/EU [11] define exposure limits and measurement and monitoring obligations for UG workplaces. National regulations derived from these directives require mine operators to maintain efficient ventilation systems and to perform regular AQ monitoring. Furthermore, the directives specify obligations for ongoing surveillance, verification, documentation, and traceability of actual AQ values to ensure compliance [11-13]. Based on these regulations, various AQ measurement routines [14] are conducted in UG environments to provide a comprehensive understanding of AQ conditions.

Data generated by fixed or mobile sensors serve as the foundation for real-time situational modelling of UG AQ [15]. Monitoring arrangements may be permanent, fixed installations, or temporary, movable units that can be deployed at specific worksites [16]. Additionally, miners and other personnel often carry personal, portable measuring devices to monitor AQ directly. In many instances, measurement data from fixed or mobile sensors can be remotely collected over a network and stored in cloud-based services for subsequent processing [17,18]. However, it is not uncommon for measurement data to remain undigitized, rendering it inaccessible for subsequent use or analysis. In the broader context of mining data, this underscores a recurring issue: the underutilisation and lack of recognition of the intrinsic value of data generated by various production processes throughout the data processing chain. This reflects a broader automation gap in mining, where large volumes of potentially valuable operational data are generated but remain disconnected from decision-support and control workflows.

Another significant challenge lies in avoiding both over- and under-ventilation and in optimising the energy-intensive ventilation process-an objective that requires not only accurate measurement and advanced modelling, but also automation-ready data structures capable of supporting real-time or near-real-time control. Advanced monitoring devices are capable of transmitting georeferenced measurement data directly to local databases via network connections, facilitating real-time storage and analysis [19]. Alternatively, measurement records can also be collected manually and stored in local databases for future analysis and application. In recent years, advances in air quality monitoring technologies have expanded beyond conventional manual sampling and spot measurements. Continuous Monitoring Systems (CMS), supported by IoT-based sensor networks, now enable real-time acquisition and spatial distribution of key AQ parameters throughout the mine. In practice, meeting these requirements has remained challenging due to harsh environmental conditions, sensor limitations, and the fragmented handling of measurement data. The resulting datasets are often underutilised and lack systematic integration into mine information management frameworks.

Recent developments in Computational Fluid Dynamics (CFD) and predictive modelling have enhanced understanding of airflow and contaminant transport that allow for proactive management of ventilation and pollutant dispersion. Ensuring the reliability of such monitoring systems requires regular calibration and validation against high-precision reference instruments. However, such simulations are seldom coupled with spatially accurate, parametric mine geometries or systematically linked to real-time measurement data in a manner that supports automated integration and operational use. In other industries, BIM and VT concepts have been successfully applied to integrate multi-source datasets within a 3D environment, enabling dynamic monitoring and decision support. Their adoption in the mining sector, however, remains limited, and no established approach exists for combining ventilation simulations, AQ data, and parametric tunnel models. Based on the above, it can be said that existing mine data management systems lack the capability to combine geometric tunnel information with dynamic AQ data to enable effective ventilation control and situational awareness. Consequently, mine operators are unable to visualise, predict or report AQ conditions efficiently across the tunnel network. The core problem addressed in this study is the lack of an integrated, information-model–based (IM-based) framework that can merge geometric mine data with dynamic AQ measurements and simulations into a single automation-ready environment supporting real-time visualisation, analysis, and ventilation control.

The main objective is to establish an IM-based approach for the representation and management of UG ventilation and AQ. The study specifically aims to answer the following research questions:

1. How can a MIM-based VT support rapid decision-making and automation-oriented process control through the visualisation of simulated and measured AQ data?
2. In what ways can parametric IM enhance ventilation analysis and management in UG mines?
3. How can conventional and hybrid-CFD (HCFD) simulations be effectively combined within a single VT environment?
4. How can integrated measurement and simulation data be applied to support automated and auditable assessment of compliance with EU AQ requirements?

This study is motivated by the persistent challenges of managing UG air quality within complex mining environments, where fragmented data practices and limited digital integration hinder regulatory compliance and efficient ventilation control. By integrating AQ measurements, simulations, and 3D mine geometries, this research contributes a novel methodological and technological framework for data-driven mine ventilation management. The proposed MIM–VT approach enhances real-time situational awareness, supports predictive ventilation control, and strengthens the linkage between environmental monitoring and digital my planning.

Although the framework is demonstrated using a single mine site, the research does not report a site-specific engineering project. Instead, it develops a generalisable and transferable methodological framework that can be applied across different mines, simulation platforms, and information-model structures. The focus of the contribution is therefore methodological and conceptual rather than project-specific. The proposed framework is designed to be transferable across different underground mining contexts and adaptable to other industrial environments facing similar challenges in automated environmental monitoring and control.

Literature Review

Mine ventilation and optimisation

Mine ventilation is essential for maintaining AQ, ensuring regulatory compliance, and enabling safe and efficient automated operations in UG environments [20,21]. Its main function is to remove contaminants such as gases, dust, and heat while delivering fresh air to operational areas [21-23]. As ventilation represents one of the most energy-intensive processes in mining—accounting for roughly one-third of total electricity use [24]- optimising airflow distribution offers major potential for improving both safety and energy efficiency, provided that ventilation systems can be monitored, modelled, and controlled dynamically [25,26]. The air flow systems, as shown in Figure 1, require the continuous movement of large air volumes at high velocities, which results in considerable electrical demand and substantial costs for heating and cooling [27]. Consequently, achieving an optimal balance between energy use and adequate airflow is a central challenge in UG mine ventilation management.

General ventilation systems deliver pressurised air from the surface to the entire mine, whereas local systems serve specific work sites and are often manually controlled [21-28]. In contrast, local ventilation systems serve specific work sites across different levels of tunnels and production areas, drawing air from the main system and distributing it via local fans and ducts [21-29]. Local systems are often non-automated or only partially automated, requiring miners to manually manage operations such as duct closures and auxiliary fan activation, which limits scalability and responsiveness. Large mines may operate hundreds of auxiliary fans, consuming substantial power. Hence, the challenge lies in maintaining adequate airflow while minimising unnecessary energy consumption.

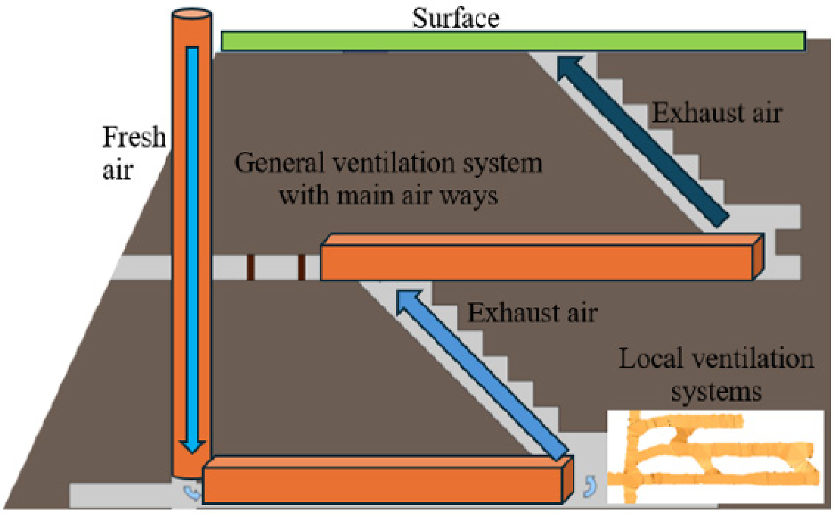


Figure 1. General and local mine ventilation systems.

Ventilation On Demand (VOD) has emerged as a modern solution to this challenge. VOD systems dynamically adjust airflow according to operational demand, ensuring that fresh air is directed to active areas while inactive zones receive minimal supply [30-32]. Data from fixed and mobile sensors, together with equipment and personnel tracking, feed into central databases and control logic systems that regulate fans, Variable Frequency Drives (VFD), and regulators [26]. This approach improves AQ control and energy performance while enabling real-time automation and monitoring, but its effectiveness depends heavily on the availability of integrated, spatially accurate data and reliable system-level models.

Visualisation and information modelling

Mine ventilation simulation and optimisation software can provide detailed insights, but their use typically requires specialised expertise. To enhance relevant information accessibility, data must be visualised intuitively for all required personnel, ideally through mobile and interactive platforms. Parametric IMs and VTs offer such a solution by integrating geometric, simulated, and measured data into a shared operational environment [33,34]. These approaches promote shared situational awareness, enabling faster and better-informed operational decisions [35-36].

In this study, the term Virtual Twin (VT) refers to an integrated cross-domain environment that aggregates multiple component-level Digital Twins (DTs) and harmonises their data structures, semantics, and simulation updates within a shared Mine Information Model (MIM). Continuously updated with both real-time and historical data, either one- or two-way data transfer (digital shadow/digital twin modes), the VT supports decision-making through simulation, machine learning, and human input [37][38]. Developing a dynamic and functional VT requires automated data acquisition and processing to ensure its reliability in operational settings [39]. Unlike traditional 2D or 3D model representations, VTs establish a live connection between the digital and physical mine environments, allowing dynamic monitoring and control with feedback [40-41]. Depending on their scale, VTs can represent components, units, or entire processes, and provide a holistic view of system interactions and support performance optimisation [42,43].

Positioning the VT within digital twin typologies

The concept of the VT proposed in this study builds upon established DT typologies but reframes them from an operational integration perspective rather than as standalone classification constructs [44][45]. The proposed VT operates across multiple DTs and integrates their data under a shared Mine Information Model (MIM) environment. The VT differs from a single DT because it orchestrates multiple DT instances through the MIM. This integrative capability is the primary reason for using the VT terminology. No prior publications describe how multiple DTs can be federated through a MIM to form an operational VT layer. To position the VT appropriately, it is important to clarify how the different typologies of DTs [46-48]-descriptive, reflective, predictive, and prescriptive — relate to one another and to the higher-level construct introduced here.

- Descriptive DT represents a static digital replica of the physical system and focuses on documentation and geometric fidelity. The parametric MIM constitutes the descriptive layer, providing a geometric and semantic representation of the UG environment. It integrates static mine geometries, asset information, and metadata derived from CAD and sensor databases.
- Reflective DT includes one-way data flow from sensors to the model, providing real-time visualisation and descriptive analytics. The integration of live and historical AQ data into the MIM enables a reflective, or digital shadow, mode where measured conditions are visualised and replayed over time.
- Predictive DT incorporates simulation and forecasting capabilities, allowing users to explore “what-if” scenarios based on parameter variations or data trends. The coupling of Ventsim and hybrid-CFD simulations introduces a predictive

dimension, allowing the estimation of contaminant dispersion and ventilation efficiency under various operational scenarios.

- Prescriptive DT adds decision-making and actuation functionalities, forming a closed-loop system with validated, bi-directional feedback and control. The bi-directional communication interface under development — linking the VT to local VOD control systems — forms the prescriptive layer. This enables user-defined feedback and adaptive fan control directly through the VT dashboard, supporting closed-loop ventilation control.

In the context of mine ventilation management, multiple DTs can coexist — each focusing on a specific subsystem or process (e.g., airflow, gas dispersion, energy efficiency, or fan operation). The VT integrates these distributed DTs within a unified information and visualisation framework, referred to here as the MIM. Unlike individual DTs, the VT is not merely another modelling entity; it acts as a meta-twin or integrative layer that coordinates data exchange, model validation, and decision support across several DT instances. Figure 2 illustrates this relationship: smaller, domain-specific DTs operate as sub-models feeding data into the overarching VT environment, which aggregates, synchronises, and visualises their results.

Table 2. Comparative overview of DT typologies and their implementation maturity.

Type	Definition	Data directionality	Example mining application	Benefits and limitations
Descriptive DT	Static digital replica (geometry, topology, attributes), “Digital model”	None (offline)	3D mine layout models (as-built documentation)	Improves data accessibility; no real-time functionality
Reflective DT	Real-time data ingestion and monitoring, “Digital shadow”	One-way (physical → digital)	Sensor-based monitoring dashboards	Enables situation awareness; lacks predictive capability
Predictive DT	Simulation-driven forecasting and scenario analysis, “Digital shadow”	One-way (enhanced)	Simulation network models	Provides foresight and optimisation support; requires calibration
Prescriptive DT	Validated model with control feedback, “Digital twin”	Two-way (bi-directional)	VOD control system	Enables real-time decision-making; needs robust validation
Virtual Twin (VT)	Integration of multiple DTs within a shared MIM for synchronised visualisation and control, “Digital twin”	Multi-directional (coordinated across DTs)	Hybrid system combining monitoring, simulation, and control	Enables holistic management and interoperability across models

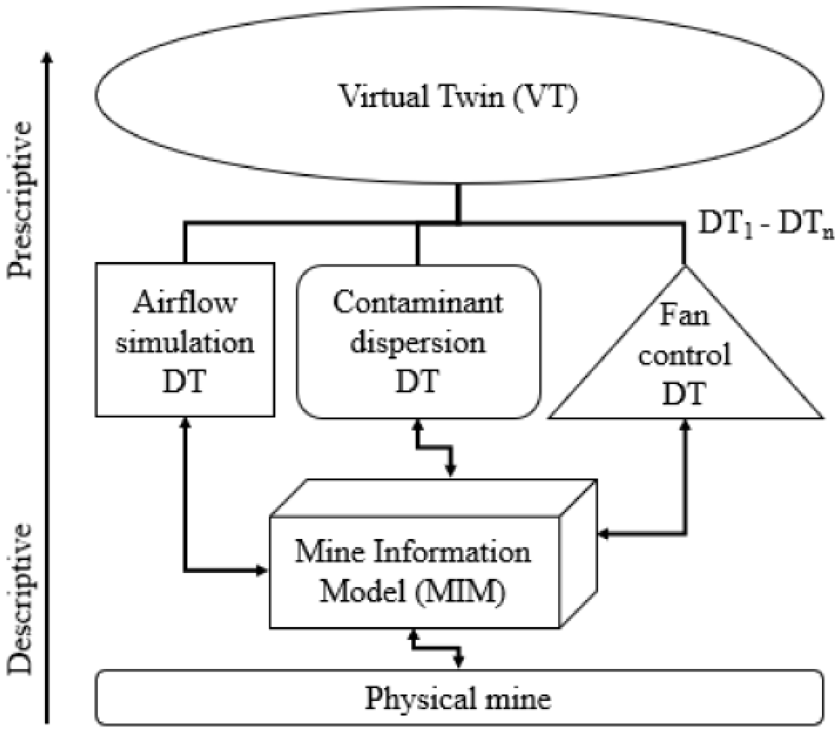


Figure 2. Conceptual positioning of the Virtual Twin (VT) within Digital Twin (DT) typologies.

To clarify the conceptual position of the proposed VT within established DT typologies, Table 2 summarises the main characteristics, data exchange capabilities, and validation maturity across four commonly recognised DT categories: Descriptive, Reflective, Predictive, and Prescriptive. This classification is used here not as a theoretical exercise, but to clarify the operational maturity level at which the proposed VT currently functions and how it enables progression toward automated control. The table highlights how existing mining-related applications typically operate at the Descriptive or Reflective levels, lacking the real-time, bi-directional feedback and validated simulation capabilities required for higher DT maturity. The VT developed in this study aims to integrate these principles conceptually — serving as an operational tool for environmental monitoring and control rather than as a dedicated DT research prototype.

The proposed VT currently operates at a reflective/predictive level but is expanding towards a prescriptive level with real-time guidance. The VT in this study serves as a tool for testing integration and control workflows, rather than as an end-point prescriptive DT itself. In relation to established DT typologies, the VT developed in this study primarily operates at the Reflective level-synchronising multi-source data through the MIM-and partially at the Predictive level through integration of simulation updates. The conceptual architecture and the prototype control loop demonstrate a clear trajectory toward Prescriptive DT operation, where validated simulation behaviour can be used for automated decision-making.

The key distinction is that the VT functions as an integrative "meta-layer", orchestrating several DT instances rather than representing a single DT itself. This federated approach has not previously been described in the mining DT literature. The VT is therefore used not as an end-point DT artefact but as a methodological tool for testing interoperability, simulation synchronisation, and control-readiness across heterogeneous digital subsystems. According to established DT typologies, the present VT corresponds to a Reflective–Predictive level implementation, with the proposed architecture enabling a gradual transition toward Prescriptive real-time control.

Machine control and automation

Machine control (MC) systems integrate sensors, computing units, and communication devices to automate or assist operational processes, including ventilation control, in industrial environments [49]. Within this framework, MC combines on-site measurements with simulated AQ data to regulate local ventilation fans through the VOD system. These models form a bridge between human operators and machine systems, improving responsiveness and efficiency. As shown in Figure 3, the MC system is derived from sub-models of the MIM alongside various measurement and communication technologies [50]. Although MC models represent only a minor portion of the overall MIM, they are essential for facilitating automation and establishing control-readiness within the MIM-based VT environment and effective communication between humans and machines, as well as between machines within machine swarms Figure 3.

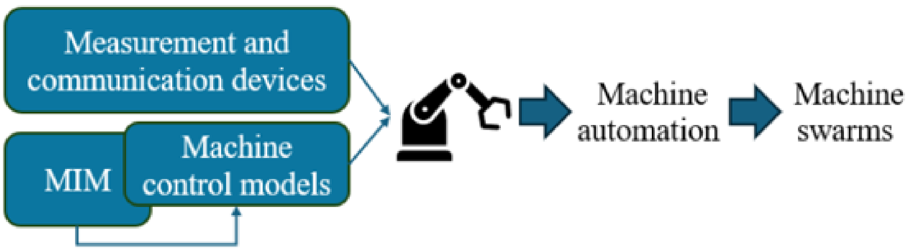


Figure 3. Establishing machine control automation using parametric models based on the MIM.

Comparison with prior work and identification of the literature gap

Existing literature on DTs and BIM applications in built environments commonly addresses one or two of the following: geometric information modelling [51], high-fidelity CFD or network ventilation simulation [52], or sensor networks for environmental monitoring [53]. Studies on mine ventilation have traditionally focused on either network simulation tools (e.g., Ventsim-type analyses) [54] or local CFD investigations [55], and separately on the adoption of sensor networks for safety and monitoring [56]. Likewise, BIM in construction and manufacturing has been leveraged to provide descriptive and asset-management functionality for surface infrastructure [57,58].

However, a systematic review of these streams reveals three recurring limitations: (i) lack of a shared, operational parametric geometric reference that binds multi-scale simulations and sensor observations to the same information units; (ii) limited integration between high-fidelity local CFD and network-scale ventilation models within a cohesive workflow, resulting in mismatched boundary conditions and limited transferability of local results to system-level decisions; and (iii) paucity of validated, bi-directional operational deployments where simulation outputs are actively used to control physical ventilation equipment in situ, combined with rigorous validation against field measurements.

The MIM–VT framework developed in this work addresses these specific gaps by (a) using a parametric BIM representation (5-m cuts and PLM object IDs) as the canonical spatial reference, (b) implementing a hybrid simulation workflow that formalises the exchange between network models and CFD derived parametrisations, and (c) introducing both a validation pathway (empirical comparison of model outputs with collocated sensors) and a roadmap for safe, incremental bi-directional control integration. While earlier studies have proposed digital twins for single aspects (e.g., monitoring, or simulation), few- if any -present a practical, parametric information model that explicitly supports multi-scale model fusion, operational decision support and verifiable validation steps in underground mines.

Therefore, the primary literature gap is not the absence of individual technologies but rather the absence of an integrated, validated methodology that (i) anchors heterogeneous data and models to a shared BIM-derived geometry, (ii) prescribes the data and metadata flows necessary for reproducible model-to-sensor comparisons, and (iii) demonstrates operational readiness pathways from reflective to prescriptive DT modes. This study contributes to closing that gap by providing the methodological scaffolding and an initial Proof-of-Concept (POC) evaluation (workshop validation and comparative model vs. sensor checks) that together define a replicable route for future, fully operational deployments.

Research gap and contribution

Previous studies on DTs [45-58], BIM-based modelling [47-51], and ventilation optimisation [55,56] have contributed significantly to understanding UG environments. However, most remain limited to isolated models, simulations or static monitoring tools. The integration of real-time AQ data, parametric 3D representations, and control automation within a unified framework has rarely been achieved. In addition, interoperability issues, lack of data harmonisation and standardisation, and minimal synchronisation against field arrangements continue to constrain practical deployment. This study addresses these gaps by developing a comprehensive MIM-based approach that fuses simulation and measurement data to support adaptive, data-driven ventilation management and real-time visualisation in UG mining.

The purpose of this paper is not to validate ventilation physics, but to validate the VT architecture for data integration and control readiness in an automation-oriented context. This study focuses on the technical implementation and system-level verification. The importance of this study lies in its contribution to bridging a persistent technological and informational gap in mining. Despite the extensive use of VTs and IM in other industrial sectors, their adoption in the mining domain remains in its infancy. The integration of dynamic AQ and ventilation data into a MIM represents a novel approach that directly addresses the challenges of fragmented data, inefficient ventilation management, and regulatory compliance. By enabling real-time visualisation and analysis of AQ conditions through a VT, this study not only advances the application of parametric IM in a new context but also provides practical means for improving occupational safety, energy efficiency, and operational decision-making in UG mines.

Although demonstrated using a single mine site, this paper does not present a project-specific system build. It proposes a generalisable, software-independent methodological framework that can be replicated and transferred to other underground mines.

Novel scientific contributions generated in this study are:

- A technically implemented data pipeline (sensors/simulations → MIM → VT → control loop).
- A novel MIM-based integrative framework that coordinates multiple DTs under a unified VT environment.
- A validated POC demonstrating functional bi-directional interaction between user input and ventilation simulation.

The scientific novelty of this work lies not in the development of new ventilation physics or simulation algorithms, but in the creation and demonstration of a reproducible, BIM-based methodology for integrating multi-source mine data, heterogeneous simulation models, and interactive control inputs within a VT environment.

First, the study introduces a new MIM-centric integration architecture that enables multiple domain-specific DTs — including ventilation network models, hybrid-CFD (HCFD) simulations, and environmental monitoring datasets — to operate coherently within a unified information backbone. To our knowledge, no earlier mining-related VT or DT efforts have demonstrated this type of multi-model federation under a shared semantic model.

Second, the paper presents a technically implemented and validated scalable data pipeline that connects sensors, cloud storage, PLM entities, simulation tools, and the VT dashboard using common identifiers and structured metadata. This contributes new methodological insight into how disparate engineering systems can be aligned through a BIM-based MIM.

Third, the study offers a POC demonstration of bi-directional interaction, where user inputs in the VT dashboard modify simulation parameters and propagate back to the visualisation environment. This establishes a validated foundation for future prescriptive control and moves beyond the descriptive or reflective levels common in earlier mining DT research.

Together, these contributions provide a methodological advancement for DT research in the mining domain and lay the groundwork for full-scale, real-time VT-controlled ventilation optimisation in future work.

Methodology

This study adopts a structured, three-stage methodological framework to develop and demonstrate an automation-oriented digital workflow for underground (UG) mine air quality (AQ) monitoring and management through parametric information modelling (IM) and Virtual Twin (VT) technology. The process evolves from (i) generation of a parametric 3D design model, to (ii) integration of multi-source AQ datasets for digital shadowing, and finally to (iii) bidirectional data exchange between the model and the real world to enable control-readiness and progression toward full Digital Twin (DT) functionality. The framework combines field measurements, numerical simulations, and data-driven visualisation within a unified MIM environment. This enables the systematic representation, simulation, and evaluation of mine ventilation and contaminant dispersion dynamics, thereby supporting situational awareness and data-driven decision-making across the mine lifecycle.

Although the case study is implemented at a specific mine site, the purpose of this research is not to document a site-specific project application. Instead, the study develops a generalised and transferable methodology for integrating multi-source mine data, hybrid simulations, and interactive control functions within a VT environment. The workflow is built on parametric PLM entities and a BIM-based MIM, which provide an abstraction layer separating the method from any individual mine layout, data system, or simulation platform. All data objects, boundary conditions, and process steps are defined using generic identifiers, schemas, and automation-ready interfaces rather than manual, site-specific procedures.

This design ensures that the proposed framework is scalable, reproducible, and portable to other UG mines and modelling environments with minimal reconfiguration. The methodological value therefore lies in the framework and processes themselves, rather than in the characteristics of the particular mine used for demonstration.

Framework design

The methodology integrates three main components:

1. **Data acquisition**, encompassing geometric mine data and multi-temporal AQ measurements;
2. **Numerical simulation**, combining network-based and CFD techniques; and
3. **Integration and visualisation**, embedding all datasets within the parametric MIM–VT structure.

This integrated framework establishes a reproducible and operationally oriented approach for analysing both system-wide and local ventilation phenomena, bridging the gap between mine design models, operational mining data, and predictive simulation outputs.

Conceptual model for integrating MIM, simulation and control

A layered conceptual model is proposed that organises the MIM–VT environment into six interoperable layers, forming a clear automation architecture for data acquisition, simulation, decision support, and control. This model clarifies how parametric BIM objects act as the geometric and semantic backbone that unifies sensor feeds, multi-scale simulations and actuation for VOD. The layers are presented in Figure 4.

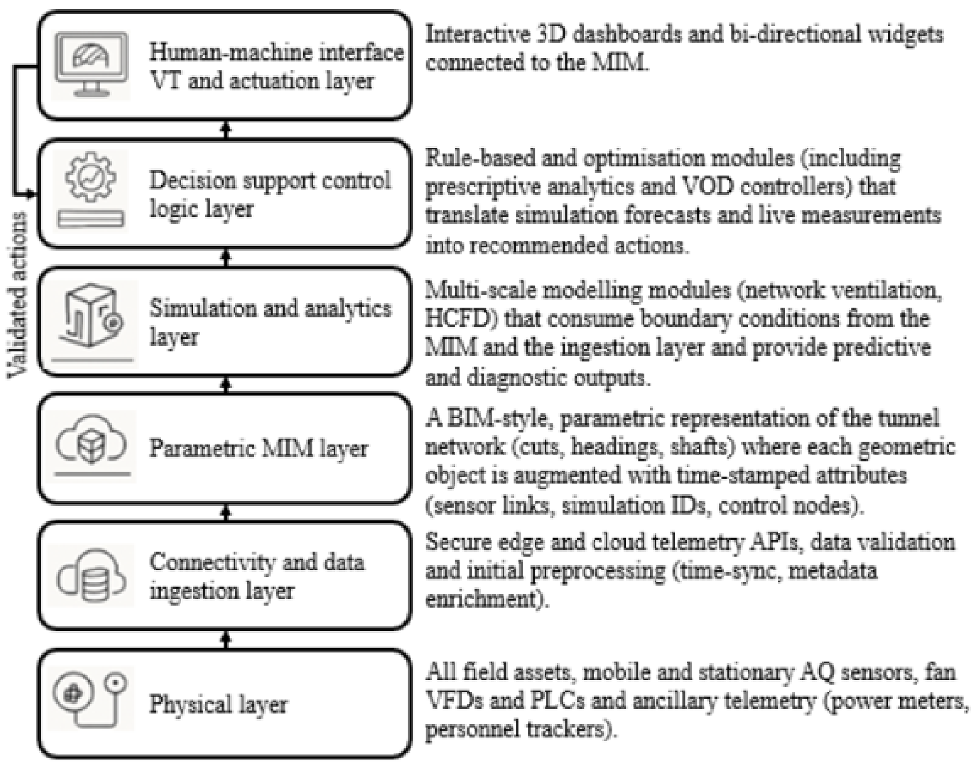


Figure 4. Conceptual architecture of a BIM-based MIM integrating sensors, multi-scale simulation and fan control.

Information flows along two principal axes. The vertical information axis moves from raw observations through preprocessing into the MIM and up into simulation and decision modules, while the horizontal control axis carries validated actuation commands from decision logic back down to the physical devices through logic layer, closing the operational control loop. The MIM serves as the geometric and semantic backbone that interlinks all layers, ensuring that each measurement, simulation domain, and control point refers to the same spatial entity. This structure allows progressive development from reflective operation (monitoring and replay) to predictive (forecasting ventilation performance) and, ultimately, prescriptive modes where validated commands adjust ventilation parameters in near real time.

This layered structure supports incremental deployment: initial stages can operate in a digital-shadow mode (read-only—reflective), progressing to predictive operation with scheduled simulations and alerts, and ultimately to prescriptive operation with automated VOD control under operator supervision. The model also prescribes minimal metadata requirements for each layer (timestamps, device IDs, model versioning, uncertainty bounds), which are essential for rigorous validation, traceability, and regulatory audit trails.

Data acquisition and processing

Effective mine AQ management requires systematic organisation of monitoring and measurement data in a form suitable for automated processing, integration, and control, consistent with EU directives and digital IM practices. Modern AQ sensors already provide real-time environmental data that can be leveraged for manual or automated airflow optimisation in underground environments.

Two complementary datasets were acquired to capture both transient and long-term variations in mine AQ conditions:

- **Mobile short-term measurements**, recording rapid fluctuations during work shifts; and
- **Stationary long-term measurements**, monitoring gradual concentration decay following blasting operations.

Measurement systems employed electrochemical (EC), non-dispersive infrared (NDIR), and optical particulate sensors, calibrated against reference instruments to ensure accuracy. Automated validation and redundancy mechanisms were implemented to mitigate common issues such as missing data, drift, and sensor malfunction.

Monitoring systems were installed in a van and deployed at selected locations within the tunnel network. Each six mobile measurement campaign lasted approximately 1.5–2 hours, with data recorded at one-second intervals to capture short-term variations in AQ during work shifts. Recorded parameters included concentrations of CO, NO, NO_x, and CO_2. Ten long-term stationary measurements, collected over a 12-hour period at one-second intervals, additionally included CO_2 and H_2O concentrations to characterise background AQ trends.

Raw AQ data were logged primarily in TXT or DAT formats, which provide transparent, human-readable structures for subsequent parsing and validation. Each dataset included metadata on instrument configuration, calibration, and sampling intervals. After validation, all measurements were harmonised into standardised tabular formats (CSV) compatible with the MIM–VT environment and interoperable across simulation and control workflows.

Table 3. Example of AQ measurement results with converted and harmonised data table for further data management.

Design_ ID	Site_ ID	Heading_ID	Cut_ID	True_cut_ ID	AQ_Measurement_ ID	AQ_Measurement_ Date_ (dd/mm/yyyy)	AQ_Measurement_ Time_	CO2_ (ppm)	H2O_ (ppt)
Design1	Site1	Heading5	Cut10	D1_S1_H5_ C10	Measurement20230511_0200	11-05-2023	2:00:29 AM	454.68	8.89635
Design1	Site1	Heading5	Cut10	D1_S1_H5_ C10	Measurement20230511_0200	11-05-2023	2:00:30 AM	455.25	8.89999
Design1	Site1	Heading5	Cut10	D1_S1_H5_ C10	Measurement20230511_0200	11-05-2023	2:00:31 AM	454.72	8.88536
Design1	Site1	Heading5	Cut10	D1_S1_H5_ C10	Measurement20230511_0200	11-05-2023	2:00:32 AM	454.48	8.87028
Design1	Site1	Heading5	Cut10	D1_S1_H5_ C10	Measurement20230511_0200	11-05-2023	2:00:33 AM	455.1	8.88828

Simulation process

Modelling approach

Two complementary modelling approaches were employed to simulate airflow and pollutant transport:

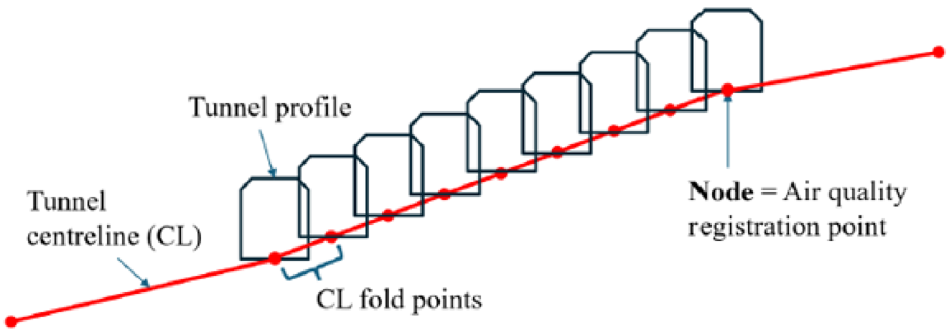
- **Ventsim**® DESIGN - a one-dimensional (1D) network-based ventilation model calculating airflow and gas concentrations through pressure-differential equations; and
- **HCFD** - a 3D Large Eddy Simulation (LES)-based model providing detailed insight into localised turbulence, diffusion, and contaminant behaviour.

This dual approach enables multi-scale interpretation and decision support: Ventsim provides global boundary conditions: Ventsim provides global boundary conditions and pressure-driven flow patterns, while HCFD resolves fine-scale turbulence and contaminant evolution near working faces.

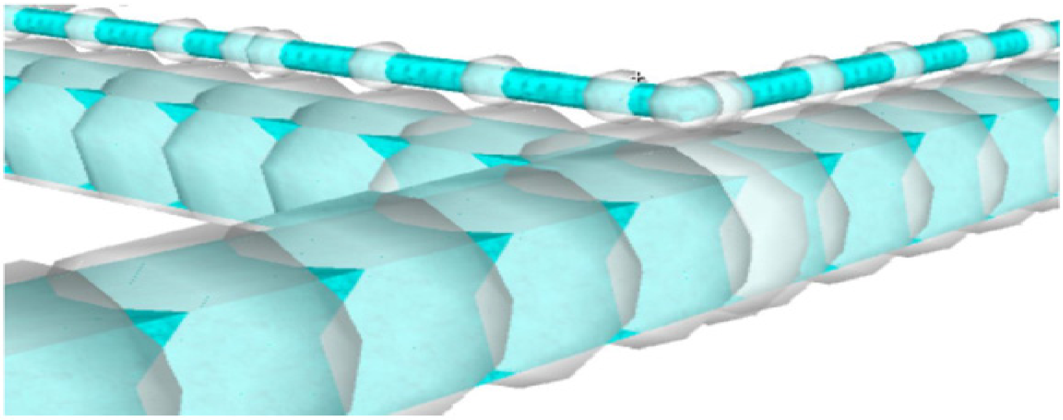
Ventsim simulation setup and parameterisation

The Ventsim model was built using the 3D geometry of the mine tunnel network derived from the MIM centreline data. Airflow paths were automatically computed based on pressure gradients, simulating realistic air mass movement across connected tunnels. Ventsim® DESIGN software, developed by Howden [59], is a very commonly used 1D network simulation tool for mine ventilation design, enabling the generation of detailed 3D models of tunnels, shafts, and raises based on designed mine geometries. The software calculates and visualises airflow volumes and quality across the tunnel network, providing continuous simulation results suitable for integration into automated data pipelines. These outputs are used to estimate temporal AQ values between successive node points along the tunnel centreline.

As shown in Figure 5, the tunnel network is segmented into individual branches, with registration nodes placed at each junction point. During simulation, AQ values are calculated at each node and recorded over time, enabling detailed monitoring of AQ fluctuations throughout the mine.



(a) AQ registration nodes and tunnel cross-sections.



(b) Simulation nodes (white) positioned along the tunnel and ventilation duct centrelines (cyan).

Figure 5. Principle of Ventsim® ventilation simulation model generation based on the PDM tunnel centrelines.

In the simulated tunnel network, each five-metre segment is represented by a node that logs air contamination (CO) levels within its specific area at defined time intervals, as illustrated in Figure 6. The simulation results are presented at the timestamp t = 2 minutes, showing the calculated and colour-coded air quality value at each node along the tunnel network. Each node represents a 5 m tunnel segment, where contaminant concentrations are computed based on the local airflow and mixing dynamics. The model captures both main headings and intersecting tunnels, which are not single-ended tunnel cavities but are treated as discrete nodes influencing airflow patterns and pollutant dispersion. Color-coded cross-sections depict relative contaminant levels, allowing a quick assessment of high and low concentration zones along the tunnel network.

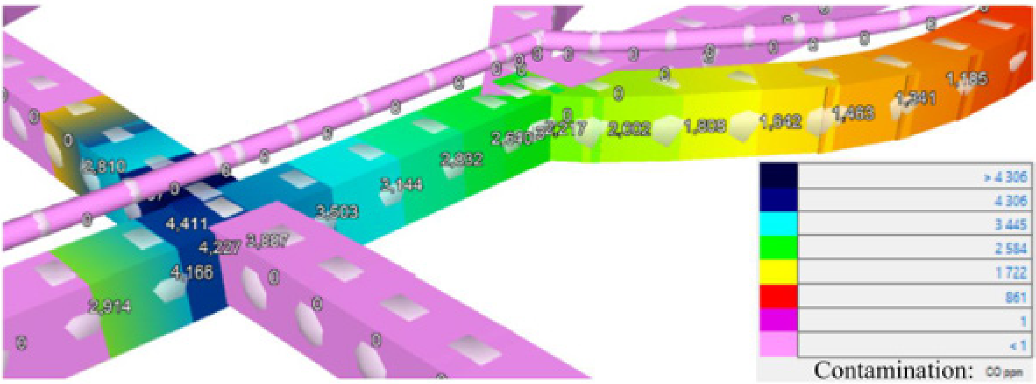


Figure 6. Visualisation of simulated AQ results at time t = 2 min, showing colour-coded tunnel cuts based on contamination levels.

The resulting dataset is stored in a tabular format, Table 4, and subsequently converted into a simplified spreadsheet format for harmonisation. AQ readings are captured at one-minute intervals into separate data sheets. Each heading and its cuts are clearly labelled to ensure accurate linkage between the recorded data (Unique_Node_Number) and the corresponding model segments (True_cut_ID). The dataset includes concentrations of gases such as CO and NO, with additional metadata.

Table 4. Example of AQ simulation results for one tunnel segment at t = 2 min, showing node-based contamination values and corresponding model identifiers.

Unique_Node_ Number	True_cut_ID	Distance_from_start_(m)	Velocity_(m/s)	Airflow_(m3/s)	CO_(ppm)	NO_(ppm)
24	D1_S1_H1_C24	393	0.031	0.786	0.038	79
24	D1_S1_H1_C24	398	0.031	0.786	0.038	79
25	D1_S1_H1_C25	388	0.031	0.786	0.038	79
25	D1_S1_H1_C25	393	0.031	0.786	0.038	79
26	D1_S1_H1_C26	383	0.037	0.932	0.038	79
26	D1_S1_H1_C26	388	0.037	0.932	0.038	79

HCFD simulation setup and parameterisation

The purpose of introducing HCFD in this framework is not to replace network-level ventilation simulation, but to enable localised, automation-compatible parameterisation of post-blast contaminant behaviour. The HCFD model utilised the same initial parameters (air velocity, pressure, and contaminant concentrations) as the Ventsim setup but applied boundary conditions defining a single dominant exhaust path to capture local dispersion dynamics. While no direct data transfer currently exists between the two models, their combined interpretation demonstrates the potential for multi-source data fusion, where large-scale Ventsim simulations could provide boundary conditions for local HCFD domains in future work.

The capability of the VT framework to host and process AQ simulation datasets is further demonstrated by integration of a novel HCFD analysis module. This HCFD system combines high-fidelity 3D LES model PALM [60] with a reduced-order CFD analysis tool (TV2D, an in-house model) within a mine tunnel network. This hybrid approach enhances and partly overlaps with the capabilities of the other simulation software used by providing greater temporal detail on the evolution of pollutant concentration after blasting within a chosen section of a tunnel network. The principal methodology of the HCFD approach is described herein.

Hybrid-CFD 1: LES modelling of working face ventilation after blasting

The HCFD approach exploits LES modelling to resolve the primary ventilation of the active mining tunnel after blasting. This is carried out by using the PALM LES model, which has been carefully validated for indoor dispersion problems [61]. It should be recognised that the turbulence-resolving LES method represents the most reliable CFD approach for capturing the relevant flow physics governing such inherently transient phenomena. Here, the objective is to establish the relevant dilution rates, or mores specifically the concentration time series at the outlet of the tunnel section in a generalisable manner which is exploitable in the reduced reduced-order CFD analysis of the tunnel network. Figure 7(a) illustrates the 3D LES model for the primary blasting ventilation problem. The model depicts a generic working face where active mining operations take place. Flexible ventilation ducting (shown in light green) is mounted to the top of the tunnel 30 metres away from the end where blasting occurs.

The outlet of the working face leads to the access tunnel and the rest of the tunnel network. For the LES analysis, all walls were assigned no-slip boundary conditions, while the inlet flow rate was specified by imposing a constant velocity profile across the upstream section of the inlet duct. The outlet was modelled as an open boundary satisfying overall mass conservation. The computational grid resolution was 2 cm, which was sufficient to resolve more than 90% of the turbulent kinetic energy of the flow. Further details on the modelling of indoor flows using the PALM LES framework can be found in reference [61]. Figure (b) and (c) depict vertically averaged normalised concentration fields <C*>z=<C>z/C0 (scaled with initial concentration C0) under two different ventilation flow rates after 8 min from the start.

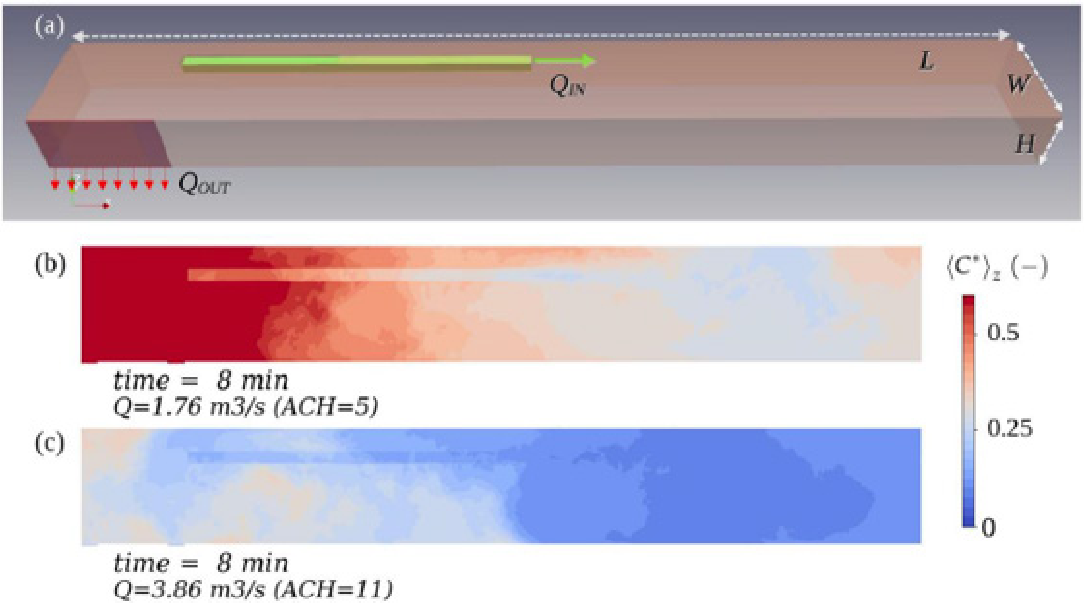


Figure 7. Illustration of the 3D LES model representing the working face ventilation after blasting. (b–c) Horizontally averaged normalised concentration fields (viewed from above) from two simulations with airflow rates of (b) 1.76 m³/s and (c) 3.86 m³/s at t = 8 min.

In order to examine ventilation process in a generalisable manner, multiple simulations are performed initialising the entire volume with a constant concentration C0 while varying the ventilation volume flow rate QIN (=QOUT). The volume flow rates can be scaled by the volume of the working face V, yielding ACH= QIN/V (air change rate) which is a commonly used ventilation flow rate metric. The time series of the outlet concentration COUT(t) is recorded from each LES simulation. These signals are parametrised as a function of ACH in three parts:

1. Initial delay *t0=t0(ACH)* such that *COUT(t)=0* for *t < t0*
2. Period of constant outlet concentration COUT(t)=CC(ACH) for t0 < t < tD where tD=tD (ACH) is the starting time of decay
3. Exponential decay *COUT(t) = b*CC* exp(-a(t-tD))* where *b=b*(ACH) and *a=a*(ACH) for *t>tD*

The initial delay can be ignored if the exhaust gas from blasting can be assumed uniformly distributed within the working face at the onset of ventilation. Figure 8(a) depicts the temporal evolution of the outlet concentration for five different ACH values, whereas Figure 8(b) illustrates their parametrised counterparts. In Figure 8(c) two simulated and parametrised (fitted) outlet concentration signals are compared. The parametrisation is carried out such that the total amount of mass flowing through the outlet is equal for all cases.

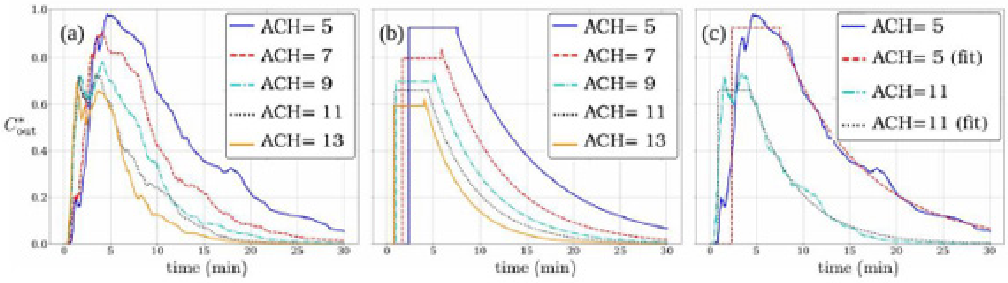


Figure 8. (a) Scaled outlet concentration time series (C*OUT = COUT/C0) for different ventilation flow rates (ACH). (b) Parametric representations of outlet concentration signals. (c) Juxtaposition of model and parametrized (fit) time series for two ventilation flow rates.

Hybrid-CFD 2: Reduced order advection-diffusion modelling for tunnel network

The parametric representation of the scaled outlet concentration $C^*OUT=C^*OUT$ (time, ACH) is implemented as a boundary condition into a numerical framework which solves the evolution of concentration C along a predetermined exhaust route through a tunnel network. The route is defined in 1D by a coordinate s and discretised into $ds=5$ m steps in accordance with the PDM convention. The exhaust path begins from the working face and terminates at the ventilation exit duct (i.e. return air raise).

The numerical solution along the exhaust route considers the interaction between the flow in the main path and the intersecting tunnel segments which act as stagnant "cavities" that influence the mass balance in the ventilation path by initially storing contaminants from the main path and eventually releasing them back into the main flow. The governing equations for this reduced order advection-diffusion modeling system are given in Equation 1 and Equation 2,

$$\frac{\partial c}{\partial t} = -U\frac{\partial c}{\partial s} + v_{eff}\left(\frac{\partial^2 c}{\partial s^2}\right) - \frac{\partial c^{(i)}cav}{\partial t}\left(\frac{L^{(i)}cav}{\Delta y}\right)I^{(i)}cav \qquad \textit{Equation 1.}$$

$$\frac{\partial c^{(i)}cav}{\partial t} = \kappa\frac{U}{L^{(i)}cav}\left(C - C^{(i)}cav\right) \qquad \textit{Equation 2.}$$

where C is the concentration, U the bulk velocity along the ventilation path and ν_{eff} is the effective viscosity in the direction of the flow. The bulk velocity is computed $U=QIN/A$, where A is the cross-sectional area of the tunnel and QIN is predetermined by means of the other network-wide ventilation simulation software. $C^{(i)}CAV$, and $L^{(i)}CAV$ are the mean concentration and tunnel length of i^{th} cavity (intersecting tunnel section) and $I^{(i)}CAV$ is an indicator function which is unity when $s=s^{(i)}CAV$ and otherwise zero. Finally, κ is the cavity exchange coefficient, which is estimated from experimental studies [62], and Δy is the width of the tunnel section at the cavity intersection.

By accounting for the cavity interactions, this modeling approach allows the mine ventilation time scales to be examined with greater detail enabling mine operators, for instance, to assess the representativeness of local AQ measurements or the limitations of numerical predictions from more idealized models. As previously discussed, the simulation results of the current mine ventilation simulation software are limited in their ability to provide detailed insights into the conditions at the intersections of neighbouring tunnels. Similarly, the HCFD model, while effective in simulating local AQ dynamics, does not account for the broader network-wide effects following a blast. Thus, by combining the simulation results with the advection-diffusion analysis of the exhaust route, a more comprehensive understanding of the ventilation process can be achieved throughout the tunnel network. The seamless integration of these model outcomes into a unified digital environment is essential for their operational usability within automated ventilation management workflows.

Integration and visualisation in the MIM environment

Following preprocessing and simulation, the datasets were spatially aligned and integrated within the MIM framework, which functions as the operational interface between data, models, and control logic. The MIM serves as a parametric 3D representation of the tunnel system, linking geometric data to measured and simulated environmental parameters through georeferenced and time-stamped attributes.

Model creation

Utilisation of geometric mine raw data

Geometric mine data were obtained from conventional mine design software [63], and exported in CAD-compatible formats containing centreline coordinates and minimal metadata, as shown in Figure 9.

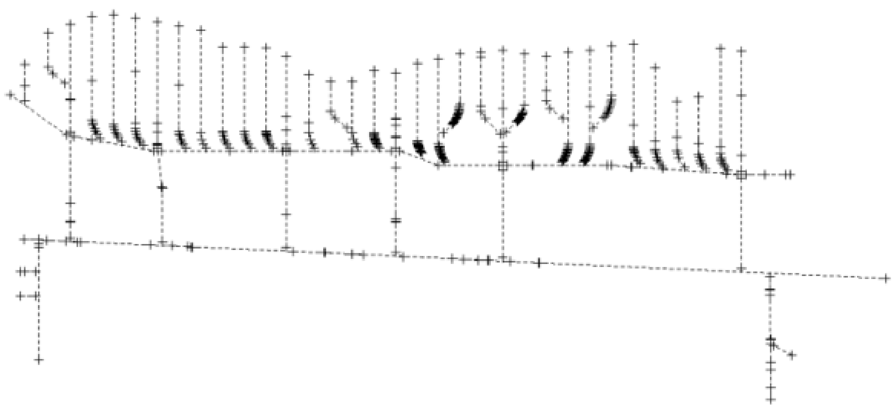


Figure 9. Original tunnel centrelines generated from raw mine design data using CAD tools.

Tunnel geometries were exported in STR format from Surpac software, defining tunnel centrelines through XYZ coordinates at each fold point. The network comprised multiple interconnected tunnel segments, with fold points positioned according to the designed tunnel location and orientation. A common limitation of CAD-based mining design is that tunnel fold points are irregularly distributed and connected by varying directions, gradients, and lengths. Although these points can store metadata for reporting and calculations, their non-uniform placement reduces the accuracy and efficiency of detailed spatial data management. However, during excavation, tunnels are constructed in well-defined units of approximately 5 metres in length, known as cuts, with the planned drilling length typically 5.0 metres and the actual cut length post-blasting generally around 4.8 metres. In the following subsection, these centrelines are used to generate parametric data processing units, 5-meter-long cuts, that are repeated at regular intervals with the aforementioned dimensioning.

Parametric Design Model and PLM objects

In the Parametric Design Model (PDM) of the tunnel network, AQ parameters, such as measurement and simulation results, are linked in this study to the smallest selectable tunnel network objects, cuts. This integration allows dynamic datasets stored in various database tables to be associated with each individual tunnel information unit, thereby establishing georeferenced condition information for each unit, as shown in Figure 10. Each unit is uniquely specified by its PLM (Product Lifecycle Management) object identifier (ID) using Dassault Systèmes **3D**EXPERIENCE® platform [64]. Together with all other cuts related to one tunnel they form a unique tunnel segment, i.e. heading. These interconnected headings make up the tunnel network, which constitutes the most comprehensive component of the MIM in this study. This hierarchical structure facilitates detailed monitoring and management of AQ across the tunnel network.

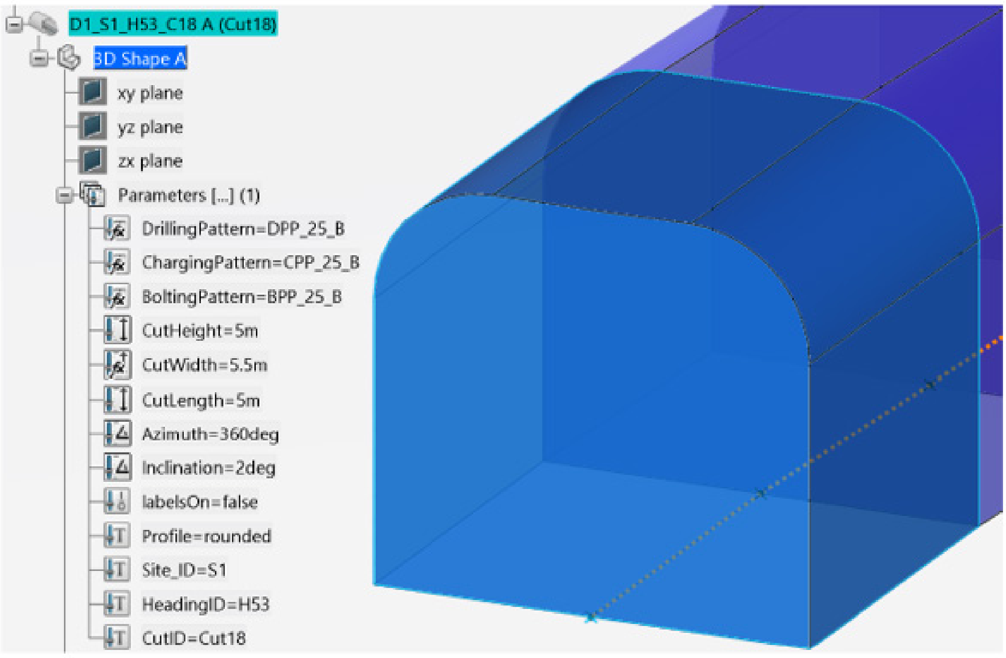


Figure 10. Example of a 5 m tunnel cut as a PLM object in the 3DEXPERIENCE® platform, with associated geometric and air quality parameters for MIM-based management.

The PDM, shown in Figure 11(a), goes beyond the limitations of traditional CAD representations composed of disconnected lines and points by using parameterised objects or "bodies" whose dimensions and attributes can be centrally adjusted, enhancing the model's adaptability for various applications. Figure 11(b) shows the centre lines of the tunnel network with 5 metre cut intervals to be exported from the PDM, which are then used to create individual simulation models Figure 11.

Inheritance of geometries in model generation

In this study, the original geometric output data of the exported tunnel centreline is used to generate multiple distinct 3D models, following a specific hierarchical inheritance structure of geometries, as depicted in Figure 12. The first tunnel model, the PDM, is created from the raw mine data from mine design. PDM serves as the foundation for the secondary tunnel models generated in this study: the Ventilation Simulation Model (VSM) (based on Ventsim simulation model) and a HCFD model. The PDM is also developed further to serve as MIM, which outputs various VT models (VTM) for visualisation and interaction, and even separate Machine Control Models (MCM) for the VOD optimisation purposes.

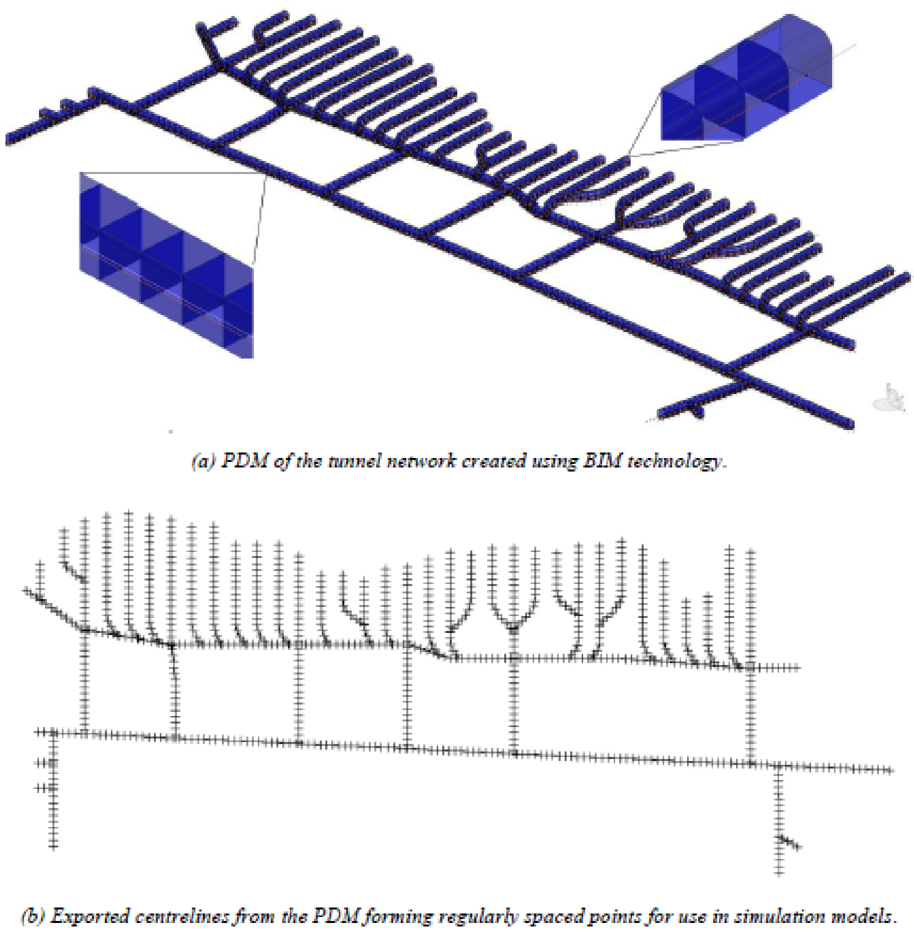


Figure 11. A Parametric Design Model (PDM) is created based on geometric raw mine datasets. It generates modified centreline data for the creation of corresponding simulation models with synchronised geometries.

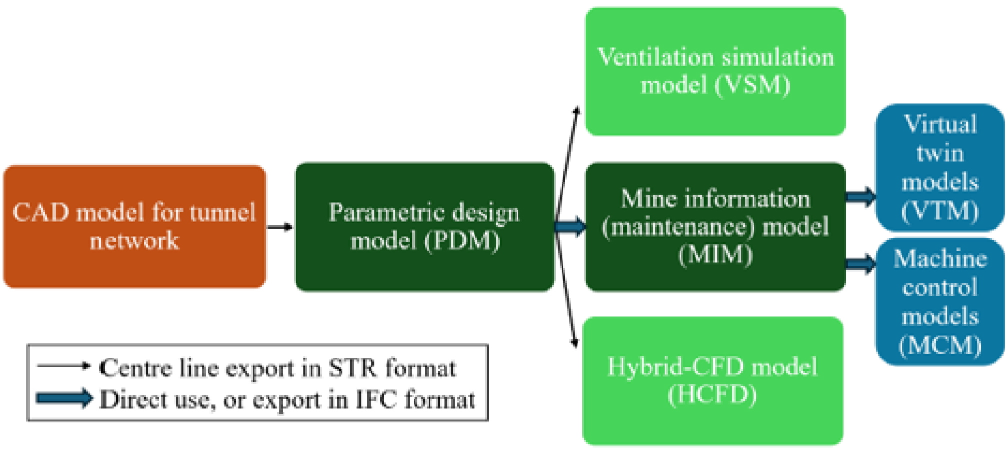
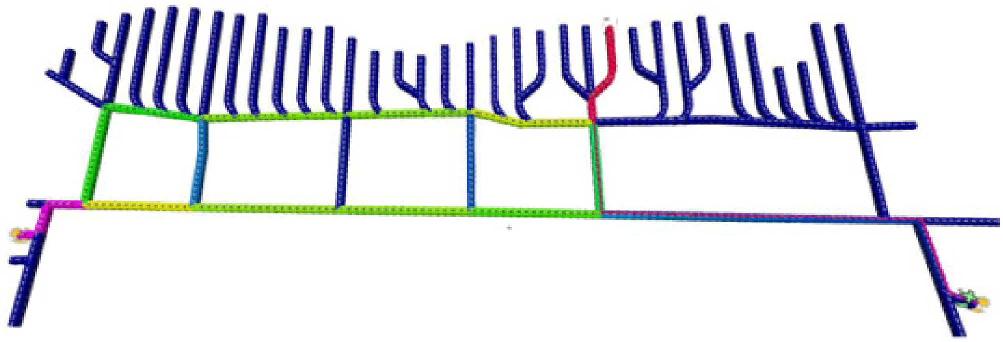


Figure 12. Inheritance structure of tunnel geometry showing how the PDM serves as the basis for simulation, information, and machine control models.

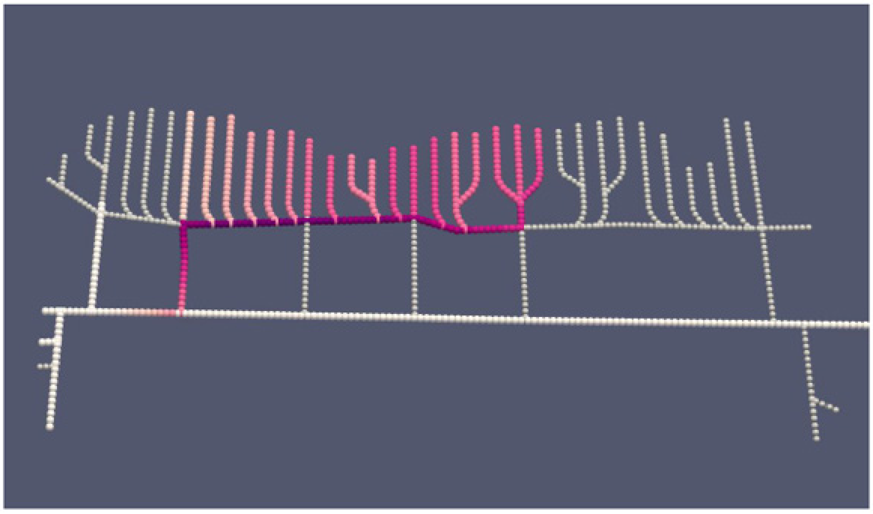
When switching from CAD tools to BIM technology and creating a separate PDM, both can be maintained and updated separately for different operational purposes. This transition is particularly advantageous when more precise and adaptable modelling units with specific spacing and volume are required for analysis and optimisation. It also allows for the storage and attachment of all possible other relevant georeferenced data at designated locations.

Simulation models

Both simulation models were developed using tunnel centrelines exported from the PDM. The ventilation simulation model (VSM), generated with Ventsim software, Figure 13(a), integrates the tunnel geometry with a baseline airflow dataset to simulate scenarios such as the displacement of contaminated air following blasting. Similarly, the HCFD model Figure 13(b) was created using the in-house TV2D simulation tool.



(a) VSM generated from PDM data.



(b) HCFD model created using the PDM for detailed airflow analysis.

Figure 13. Exported centrelines from PDM are utilised for creating spatially accurate and equivalent simulation models.

Visualisation and digital twin integration

The results were visualised through the VT application, enabling temporal playback and spatial analysis of AQ conditions. The VT provides a dynamic and intuitive platform for graphically combining empirical field data with simulation outputs, facilitating 3D information management into a coherent and reproducible workflow and real-time evaluation of ventilation performance and pollutant migration patterns. The overall framework for AQ measurement, simulation, modelling, and visualisation is illustrated in Figure 14. A 3D MIM was constructed from geometric mine design raw data using cut-level tunnel objects in a parametric design environment. This MIM formed the basis for both the VSM and HCFD models developed in their respective software and was subsequently integrated into the VT application.

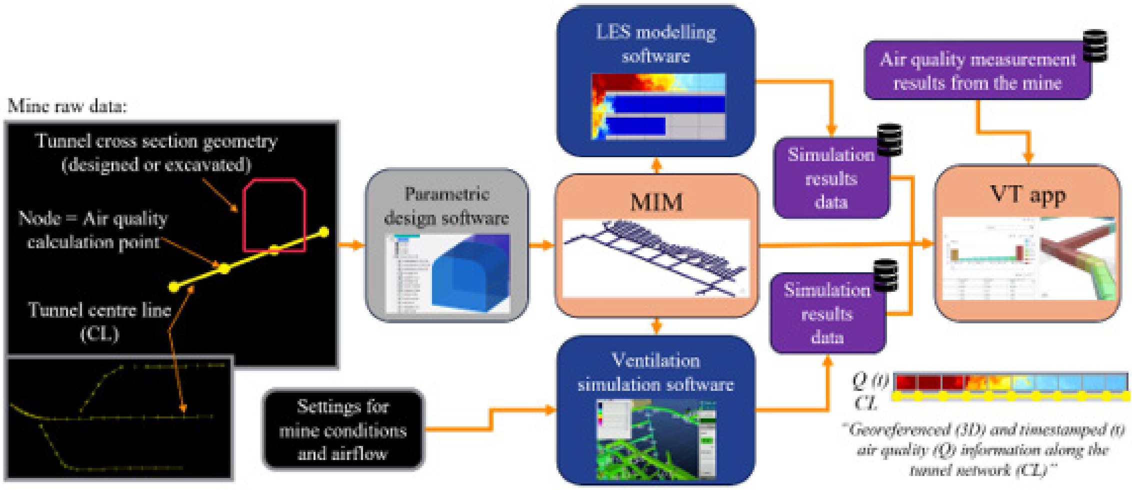


Figure 14. Overall framework of AQ measurement, simulation, modelling, and visualisation. Geometric mine data and AQ datasets are integrated within the VT application to support real-time parametric AQ management.

All datasets from various sources are stored in CSV format and transferred to Amazon Web Services (AWS), which functions as the project's central data repository and is updated regularly to ensure synchronisation and currency. The platform retrieves data from AWS, integrates it with the geometric model generated through parametric design, and visualises the combined dataset. Within the VT framework, a custom Flask-based Python service processes user inputs, updates the corresponding CSV files, and automatically synchronises the revised data with the AWS environment. Within the VT environment, users can inspect spatio-temporal AQ variations, replay simulation results, and compare measured and modelled data in real time. Initially, the system operates as a digital shadow, where information flows unidirectionally from data repositories to the MIM. With bidirectional connectivity enabled, the VT transitions into a digital twin, allowing data exchange with control systems—for example, to optimise local ventilation fan operations or VOD processes.

This integrated digital workflow — spanning data collection, simulation, and real-time interaction - provides a robust methodological foundation for advancing mine ventilation management, improving environmental safety, and supporting the evolution toward fully autonomous underground operations. The REST API and the harmonised PLM identifiers ensure reproducible, software-independent data exchange across the MIM-VT-simulation pipeline.

Real-time feedback architecture and control flow

Building upon the conceptual model described above, Figure 15 illustrates the implemented architecture that enables real-time data feedback and control between the physical mine and its VT representation. The architecture includes bidirectional data transfer capability, although real-time control is only partially implemented at this stage. The system comprises six interconnected layers arranged vertically to form a complete data and control pipeline.

The real-time feedback architecture links the physical environment, the simulation engines and the VT dashboard through a structured data-flow designed to support future bi-directional operation. Sensor measurements are first transmitted to the server-side data-processing layer, where they are aligned, validated and assigned to their corresponding MIM entities. These updated attributes are then made available to the VT dashboard, which refreshes the 3D visualisation and time-series panels without manual interaction, ensuring near-real-time situational awareness. On the simulation side, ventilation models can be triggered either automatically at predefined intervals or manually in response to user input. Once a simulation is completed, its results — airflow, pressure or contaminant concentrations — are mapped back to the same MIM objects via shared identifiers and pushed to the VT interface using the API. This creates a continuous information loop in which physical measurements and model predictions are updated through a common spatial framework.

To prepare the system for supervised bi-directional control, an intermediate validation layer checks any outbound user actions or proposed parameter changes. This layer ensures that values fall within allowable ranges and that safety constraints are met before commands are forwarded to the operational control system. Although the current implementation employs this mechanism only for conceptual testing, the architecture demonstrates that the VT can support a closed-loop workflow in which measurements, simulations and operator decisions interact coherently. This forms a necessary step toward reflective–predictive DT operation and provides the structural foundation for future prescriptive control.

Proposed interactive POC to verify the functionality of the concept

The POC experiment is designed to verify that the VT environment can receive a user-initiated input, propagate the updated parameter to the simulation engine, and return the resulting output back to the VT for visual inspection. In the test scenario, the user selects a ventilation fan within the dashboard, adjusts a single operational parameter (e.g., duty, pressure rise or volumetric flow), and submits the change through a simplified input form in VT dashboard, like presented earlier in Figure 15.

The updated parameter is transferred via the API layer to the simulation module, which recalculates the affected airflow distribution using the predefined network or HCFD model. Once computation is complete, the resulting airflow values and pollutant fields are packaged into VT-compatible attributes and sent back to the dashboard, where the corresponding 3D segments are refreshed automatically.

The round-trip verification demonstrates that the architecture supports (i) correct mapping between user selections and PLM/MIM entities, (ii) functional transfer of modified parameters to the simulation tool, and (iii) return of updated results into the VT without manual intervention. Although simplified, this POC confirms the feasibility of extending the system toward supervised bi-directional interaction and provides a practical test of the underlying data-flow and control mechanisms.

Model validation and evaluation

The validation conducted in this study focused on verifying the system-level consistency, interoperability, and plausibility of the proposed MIM–VT framework, rather than on direct quantitative comparison between simulated and measured AQ values. At the current stage of development, both the field measurements and simulation datasets from Ventsim and HCFD were used primarily as representative data sources to test and demonstrate the end-to-end data flow within the VT environment.

The objective of validation in this phase is not to confirm the physical accuracy of ventilation models, but to verify the correctness, fidelity, and reproducibility of the proposed MIM–VT data-integration architecture. Quantitative, measurement-based validation of flow, pressure and gas concentration behaviour will be conducted in the next phase of the research programme.

Scope and rationale of validation in this phase

The validation conducted in this study focuses on verifying the technical integrity, semantic consistency, and functional behaviour of the MIM–VT integration pipeline. Because the available measurement and simulation datasets are representative and not temporally synchronised, the objective of this phase is not to validate the predictive accuracy of airflow or contaminant simulations. Instead, the aim is to demonstrate that (i) multi-source data can be reliably ingested, mapped, and visualised within the VT; (ii) simulation outputs retain spatial and semantic coherence when transferred between platforms; and (iii) the system responds consistently to user-initiated parameter changes within the prototype control loop. In this phase, the objective is to validate the consistency, interoperability and functional behaviour of the VT–MIM integration, rather than the numerical accuracy of the underlying simulation models, which will be addressed in the next research phase.

This staged approach follows established DT development practice, where system-level validation precedes model-level validation. Quantitative comparison between simulated and measured values — including root mean square error (RMSE), systematic deviation (bias) and coefficient of determination (R^2) metrics—will be conducted in the next research phase once synchronised time-series datasets become available.

Conceptual validation and system-level verification

At this stage of the research, validation focuses on demonstrating data transfer and system functionality. Physical validation of the model (simulation results vs. measurements) will be the objective of the next research phase in the series of articles. Accordingly, validation was performed at three complementary levels:

1. **Data integrity and interoperability validation**. The first step ensured that all components of the MIM–VT pipeline could exchange information reliably and without data loss. The process included schema validation between the AWS data repository, the Flask API, and the MIM. Test datasets representing CO and NO_x time-series from mobile sensors were successfully ingested, converted into the VT format, and visualised in the 3D model, confirming correct temporal alignment and metadata mapping.
2. **Model-to-model consistency validation**. The second step assessed the consistency between Ventsim network simulations and the HCFD results used for local refinement. Parameter exchange between the two models was verified through boundary-condition matching and variable naming conventions. This step demonstrated that simulation results from different modelling domains can be linked and visualised within the same MIM environment without manual post-processing.
3. **Logical and conceptual validation**. Finally, the overall logic of the VT was validated through a structured expert workshop involving ventilation engineers and other related specialists from the Kemi mine. Participants reviewed the system behaviour by comparing visualised simulation results with their qualitative operational knowledge of airflow and post-blast conditions. The feedback confirmed that the model responses, e.g., plume propagation trends and recovery dynamics, were plausible and consistent with expected field behaviour. Participants also verified that measured data, simulation outputs, and fan-control parameters were correctly referenced to their physical locations in the mine model.

These steps established that the MIM–VT framework functions as an internally coherent and technically valid integration environment. Although a quantitative full numerical validation against measured concentrations is beyond the scope of this current development phase and is therefore still pending, the structural and process-level verification carried out here ensures that the model is ready for such testing in future work. The objectives, methods, and maturity level achieved in the validation are discussed in more detail in Table 5.

Table 5. Validation objectives, methods, and achieved maturity level.

Validation dimension	What was validated in this study	Method used	Achieved maturity level
Data flow integrity	End-to-end sensors → MIM → VT data transfer	API logging, data tracking, consistency checks	**Intermediate**
Interoperability across platforms	Compatibility between AWS, Flask API, Ventsim/HCFD, and VT	Format harmonisation, schema mapping	**Intermediate**
Logical consistency between models	Agreement of boundary conditions and variable definitions between Ven	Expert review, model comparison	**Initial–Intermediate**
Spatial consistency	Correct mapping of simulation values to 3D mine geometry	Coordinate matching, PLM ID linkage	**Intermediate**
User-oriented face validation	Perceived plausibility and usefulness of VT outputs	Expert workshop, structured feedback	**Intermediate**
Bi-directional parameter update	VT dashboard input affecting simulated fan/airflow parameter in POC	Prototype testing	**Initial**
Quantitative model accuracy	Comparison of simulated vs. measured time-series values	Not covered in this phase	**Not assessed**

Evaluation of the applied methodology in a workshop

The modelling methodology presented in earlier sections was then evaluated in a workshop attended by Kemi mine personnel representing various organisational roles and involved in mine ventilation in some way. The objective was to assess the applicability of IM in mining and to explore its potential benefits and challenges, particularly in managing and visualising air quality data through a VT. Five key mine representatives participated, covering responsibilities in planning/design, production, ventilation, line management and research/development. The session began with an introduction to the proposed modelling methodology and its results, followed by individual responses to structured questions and a subsequent group discussion. The first question focused on how useful the participants considered IM and the use of VT to be in the management and utilisation of mine ventilation and AQ data. Four different options were given; No benefits, Few benefits, Moderate benefits and Significant benefits. Each participant had one vote. Voting results are summarised in Figure 16.

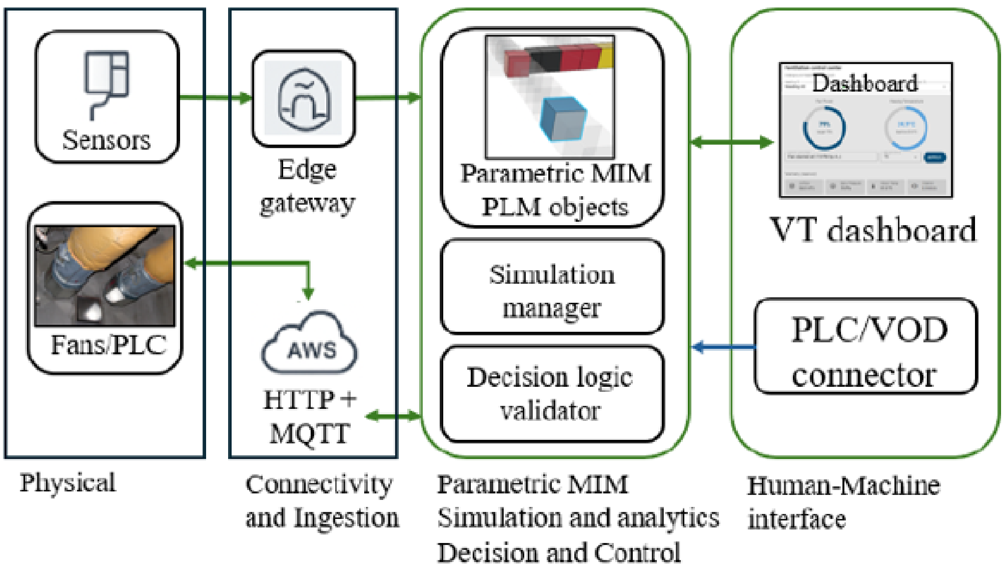


Figure 15. Real-time feedback and control architecture for the MIM–VT framework. The diagram illustrates the integration of a VT user interface, bi-directional widget/API, command validator and decision logic, simulation manager, AWS state store and messaging layer, and PLC/VOD connector.

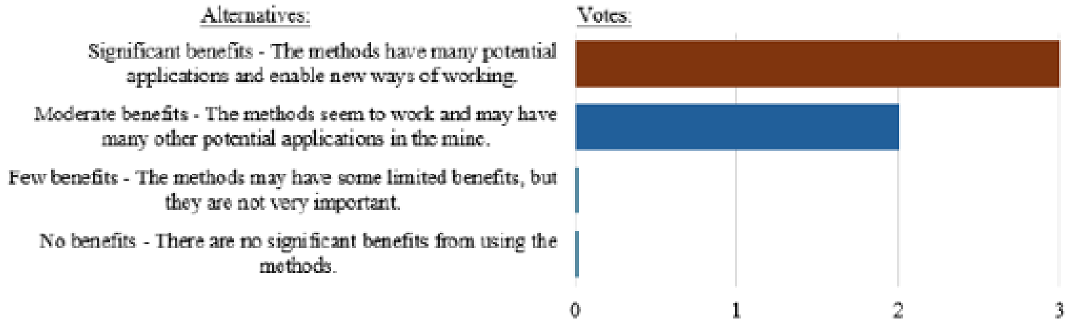


Figure 16. Workshop voting results on the perceived usefulness of IM and VT for mine ventilation and AQ management.

Participants reached a consensus that information modelling constitutes a beneficial approach, offering substantial opportunities for the mining sector. Its potential was considered particularly pronounced in the areas of asset management, financial and cost monitoring, as well as in supporting workforce communication and visualisation. The survey further identified operational areas where IM was perceived as most valuable, requiring participants to rank the domains shown in Figure 17. Six alternative areas were given: Production, Design, Safety, Ventilation, Maintenance, or Something else. In addition to these, potential applications were identified in the monitoring of ore and other material flows, as well as in enhancing communication and collaboration through the use of dedicated communication tools.

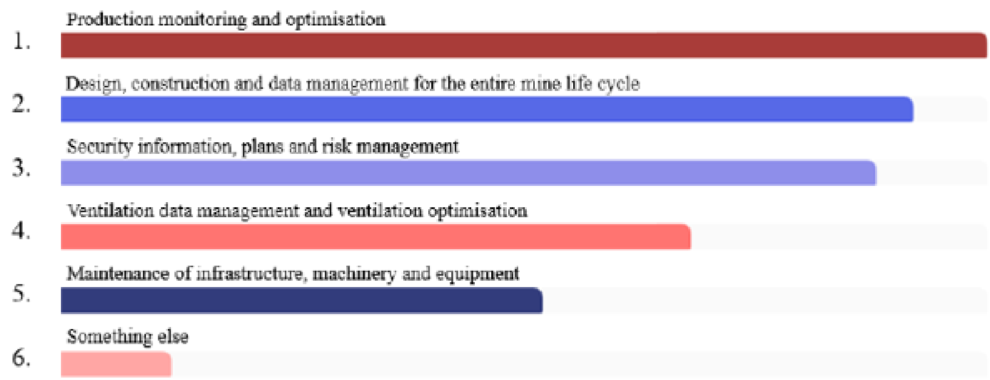


Figure 17. Ranking of mining operation domains where IM was considered most beneficial (Production, Design, Safety, Ventilation, Maintenance, Other).

Finally, the benefits and challenges of applying IM in mining operations were evaluated using an impact–probability matrix, see Figure 18, in which respondents positioned predefined benefits (a) and challenges (b) according to their perceived impact and probability. Four top benefits and challenges were predefined, all of which are well recognised in the use of information models. Each participant first assessed the impact and probability of each benefit/challenge on a scale of 0 to 4, and the software then calculated the averages from the results, which are shown in the figures.

The discussion further highlighted that increased data availability enhances process control, standardisation of practices, and the management of exceptional situations. Modelling was considered to support resource monitoring and improve decision-making. The main challenges were identified as relating to practical implementation, including resourcing, costs, and the systematic nature of maintenance. Defining a clear business case was therefore deemed essential to justify the required investments. Sustained and demand-driven model maintenance was recognised as requiring time, trust, and the establishment of consistent practices. Nonetheless, even incremental progress was seen as valuable in reducing potential resistance to change, which diminishes over time as the benefits become evident.

Importantly, once data collection is underway, process development can commence immediately. Participants confirmed that the displayed behaviour aligned with their expectations based on operational experience, providing expert-based face validation of the model responses. They also emphasised the improved interpretability of simulation outputs when viewed through the integrated 3D VT interface, supporting the system's suitability for operational decision-making. This expert-based evaluation provides qualitative validation of the operational relevance and interpretability of the VT outputs.

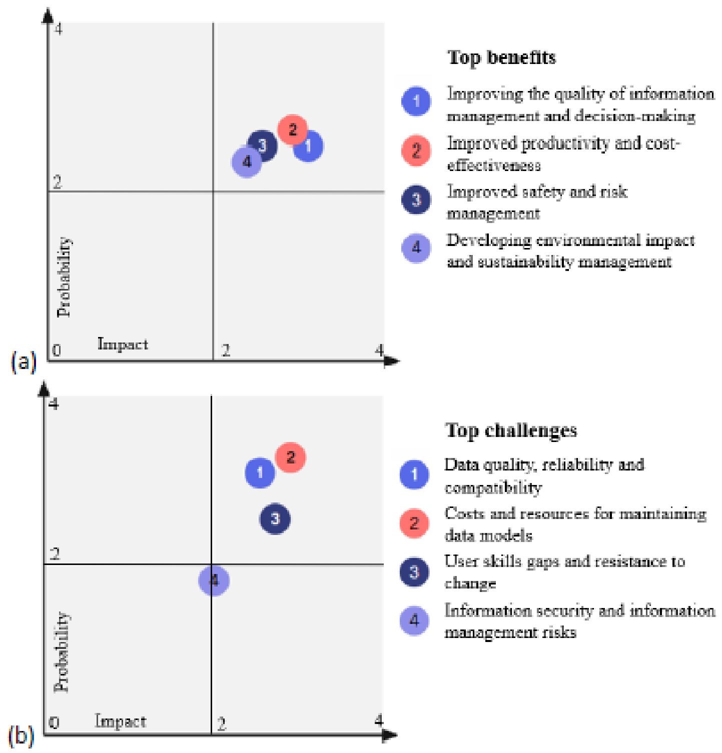


Figure 18. Perceived impact and probability of (a) key benefits and (b) main challenges of applying IM in mining operations, based on workshop responses.

Performance improvement enabled by the model

The adoption of the MIM–VT framework improved several aspects of data management, situational awareness, and decision-making processes compared with the previously fragmented workflows used in the mine. Even though no direct time-series measurements of latency or computation speed were conducted, the observed and reported performance enhancements were evident in the areas of information accessibility, data reliability, and cross-departmental collaboration. The assessment combined both technical performance indicators (e.g., data completeness, interoperability, update frequency) and operational indicators derived from user feedback during the Kemi mine workshop (e.g., perceived situational awareness, decision-making support, and system usability).

These indicators reflect the maturity of the system and its readiness for operational deployment. The overall evaluation is summarised in Table 6. The qualitative assessment indicates that the main benefits of the MIM–VT approach arise from improved data integration and transparency, rather than purely computational performance. The transition from isolated measurement and simulation systems to a harmonised, parametric information model markedly improved the traceability and interpretability of AQ data. Workshop participants highlighted that the VT environment made AQ information accessible beyond the ventilation engineering team, enhancing cross-functional communication and confidence in data accuracy. Approximately 80% of respondents rated the system's usefulness as "high" or "very high," citing the ability to visualise both measured and simulated parameters within the same 3D context as a major advantage.

Table 6. Qualitative performance improvements observed with the MIM–VT framework.

Performance Indicator	Baseline (conventional practice)	MIM–VT framework	Qualitative improvement	Description
Data accessibility	Distributed files, limited user access	Centralised cloud-linked model accessible via VT dashboard	**High**	Unified access to measurements, simulations, and geometry via a single interface

Data completeness and consistency	Inconsistent datasets, missing metadata	Harmonised, validated CSV datasets linked to parametric objects	**High**	Improved data traceability and reduced risk of missing records
Information interoperability	Manual data transfer between tools	Automated import/export between Surpac, Ventsim, and 3DEXPERIENCE®	**Moderate–High**	Standardised exchange formats enabling multi-software integration
Visual clarity and interpretability	2D reports and separate charts	Interactive 3D representation of measured and simulated AQ data	**High**	Enhanced understanding of spatial patterns and airflow behaviour
Situational awareness (user perception)	Limited to expert engineers	Shared across engineering, production, and safety teams	**High**	Workshop participants reported improved communication and transparency
Decision-making support	Reactive, manual review of AQ data	Proactive visual forecasting and scenario comparison	**Moderate–High**	Enables early detection of poor ventilation conditions
System scalability and reusability	Standalone models per site	Modular architecture adaptable to different mines	**High**	Facilitates replication and standardisation across operations
User adoption and perceived usefulness	Low engagement outside R&D	Broad interest and acceptance confirmed in workshop	**High**	80% of participants rated the system as "useful" or "very useful"
Validation readiness	No structured validation process	**Data-model alignment supports quantitative validation**	**Moderate**	Establishes foundation for future field-based model validation

These findings, although primarily qualitative, substantiate the claim that the proposed model improves performance at the information and decision-making level. Together with the validation results presented in Section 3.5, this provides strong evidence that the MIM–VT framework represents a credible and operationally relevant step toward data-driven and automation-ready ventilation management and the gradual realisation of a full VT for mining environments.

Case Study

This study was conducted within the Finnish NEX-EL project (Non-Exhaust Emissions in Electrifying Mining and Urban Environment, 2023–2026), specifically under Work Package 3, Towards a Digital Twin of Mine Air Quality [65]. The case study serves as a demonstration and verification environment for the proposed MIM–VT framework under realistic underground operating conditions. The primary objective was to demonstrate and verify a realistic, automation-ready AQ modelling and visualisation workflow by integrating measured and simulated datasets into a commercial VT environment. The Outokumpu Chrome Oy Kemi mine in northern Finland served as the pilot site.

Air quality monitoring

The visualisation of local AQ conditions experienced by personnel at specific locations and times is primarily based on measured data, which may include both real-time values and extended historical records. The visualisation of local AQ values for a person working at any time in a mine can be most easily based on collected measurement, Figure 19. Mobile stations captured short-term AQ variations during active work phases, such as drilling or bolting, while stationary stations along access routes provided long-term background data. All datasets were georeferenced to the MIM and visualised in the VT app, enabling location-specific analysis and comparison across time and space. This enables both immediate situational awareness and retrospective analysis of exposure conditions during different operational phases.

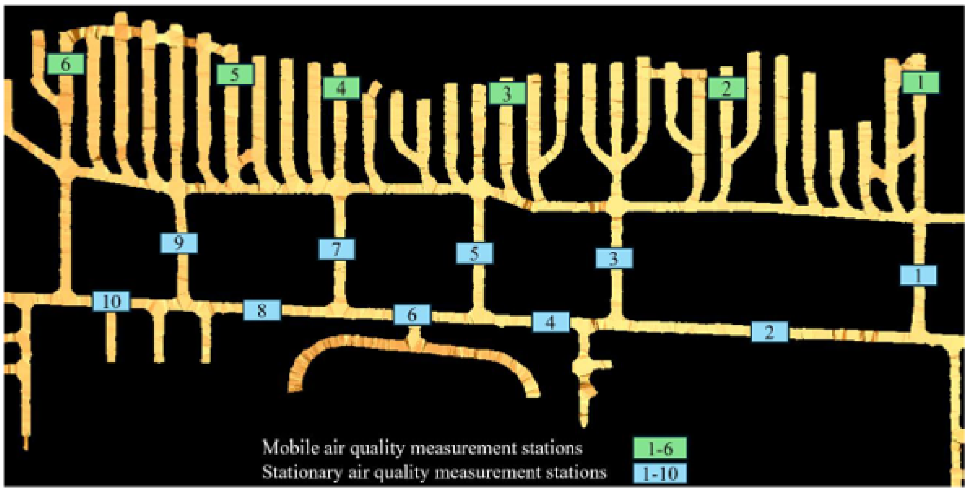


Figure 19. Locations of mobile (green) and stationary (blue) AQ measurement stations within the pilot tunnel network used for data collection and visualisation in the VT app.

Forecasting post-blasting air quality

In underground mining operations, AQ forecasting relies on simulation data that estimate the time required to restore safe conditions following blasting events. To predict post-blast ventilation efficiency, two simulation tools were applied: Ventsim for network-scale ventilation analysis and a HCFD model for detailed contaminant transport in intersecting tunnels. The combined results were used to estimate the time required to restore safe AQ levels and to support re-entry decision-making through time-resolved visualisation within the VT environment.

Ventsim simulation

A 5 × 5 m tunnel network was modelled using Ventsim software to simulate post-blast airflow and contaminant clearance over a 180-minute period, see Figure 20, with two selected timestamps t(min)= 15 and 30. The fresh air fan supplies fixed fresh air flows of 6 m3/s and 12 m3/s to the duct, delivering flow rates of 5 m^3/s and 10 m^3/s respectively to the duct ends, while exhaust air was vented through designated routes. The simulation tracked the displacement of blast contaminants, illustrating how clean air gradually replaced polluted air along the network. Model parameters - including dispersion factors - were based on validated field applications, ensuring realistic post-blast conditions. Within the proposed framework, the Ventsim model provides system-level boundary conditions and baseline ventilation dynamics for subsequent integration with localised HCFD analyses.

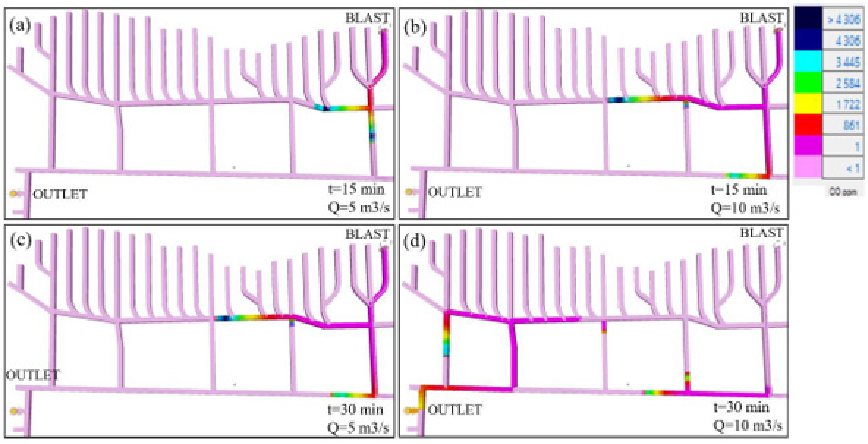


Figure 20. Visualisation of Ventsim simulation results showing dispersion and clearance of blast contaminants at two airflow rates (5 and 10 m³/s) and two time steps (t = 15 and 30 min). Contaminated air moves from the blast origin (top right) toward the outlet exhaust raise (bottom left) as ventilation progresses.

The contaminant sources are positioned at the end of the airway where the blast event is defined. A dispersion factor of 0.2 is applied to regulate the rate at which contaminants are released into the airstream. This factor represents the delayed clearance of contaminants from the ventilation flow. In a development heading like this, where the duct exhaust terminates some distance short of the tunnel face, the dispersion factor accounts for the slower removal of contaminants resulting from reduced local air velocities near the heading end. The amount of emulsion explosive used in the blasting is 400 kg, which produces the air pollutant concentrations shown in Table 7.

Table 7. Composition of detonation products from the simulated emulsion explosive (density = 1.0 g/ml) used in ventilation and AQ dispersion simulations.

	Mass %	g/kg
N_2	27.107	271.07
CO_2	12.885	128.851
CO	2.48	24.798
H_2	0.171	1.71
NH_3	0.383	3.833
CH_4	0.025	0.247
NO	0	0
NO_2	0	0
H_2	0	0

Hybrid-CFD simulation

The Hybrid-CFD (HCFD) analysis focused on a 600 m exhaust route, see Figure 21, to capture local contaminant transport phenomena that are not resolved by network-scale ventilation models but are critical for operational clearance time estimation. Simulations were run for flow rates of 5 m^3/s and 10 m^3/s to examine contaminant transport and storage effects in intersecting tunnels. Normalised concentration fields (*C*= C/C0)* were recorded at 30 s intervals for 3 hours.

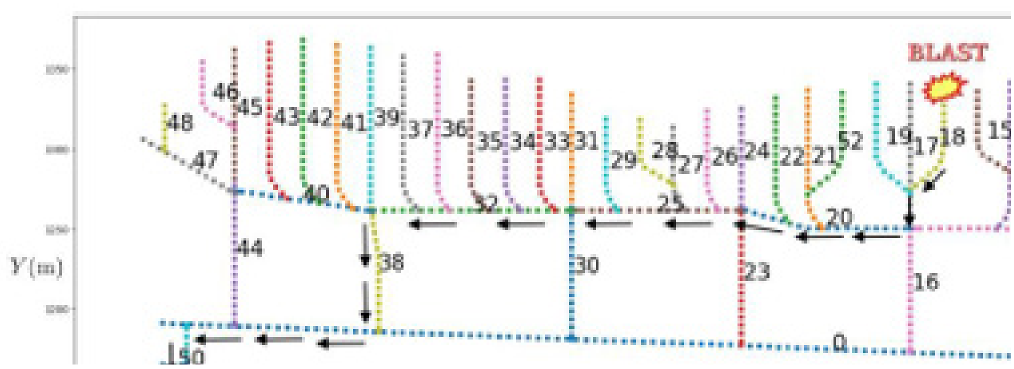


Figure 21. Pilot tunnel geometry with numbered headings. The example exhaust route (black arrows) runs from the blasting site (Heading #18, BLAST) to the exhaust air raise (OUTLET), total length 612 m.

Results in Figure 22 illustrate the *C** distribution within the relevant tunnel network under two different ventilation flow rates and at two different time instances (*t=15* min and *t=90* min). These results revealed how intersecting tunnel cavities temporarily store and slowly release contaminants, significantly delaying clearance times — an effect that directly informs ventilation planning and safe re-entry assessment.

The concentration results visualised in Figure 22 are plotted in Figure 23 to present the concentration distribution along the exhaust path's s-coordinate (blue line) in juxtaposition with the mean concentration of each intersecting tunnel or cavity (red dots). Three tunnel cavities are tagged with yellow, red and green symbols to assist a direct comparison between the plots. Such ventilation analysis lays bare the role of intersecting tunnels, which initially, when the high concentration peak passes by, absorb part of the contaminants while slowly releasing them back into the main flow when the peak has passed. This mechanism causes the concentration distribution to eventually become uneven along the tunnel coordinate as shown in Figure 23(c) and (d), delaying the ventilation process significantly.

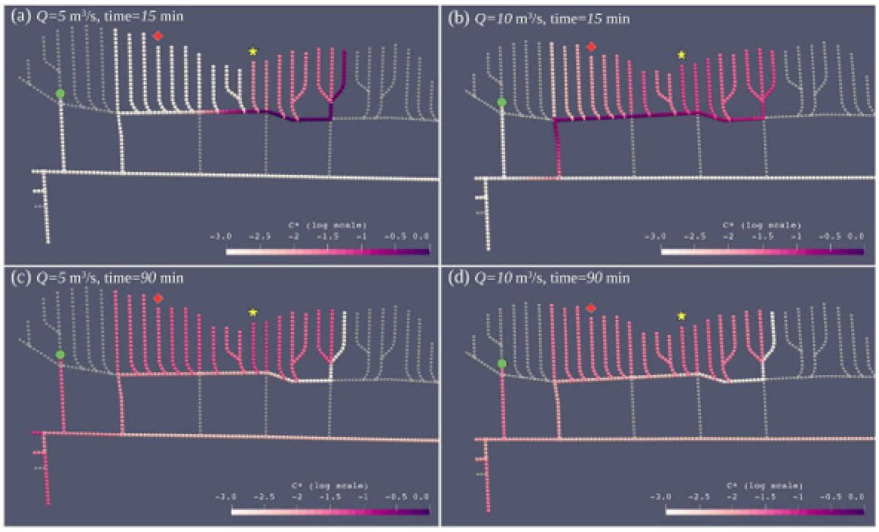


Figure 22. Normalised concentration (C*) distribution along the exhaust path and intersecting tunnels under two ventilation flow rates: Top: t = 15 min — (a) Q = 5 m³/s, (b) Q = 10 m³/s; Bottom: t = 90 min — (c) Q = 5 m³/s, (d) Q = 10 m³/s. Three tunnel cavities are tagged (yellow, red, green) for comparison with Figure 23. Logarithmic scale applied.

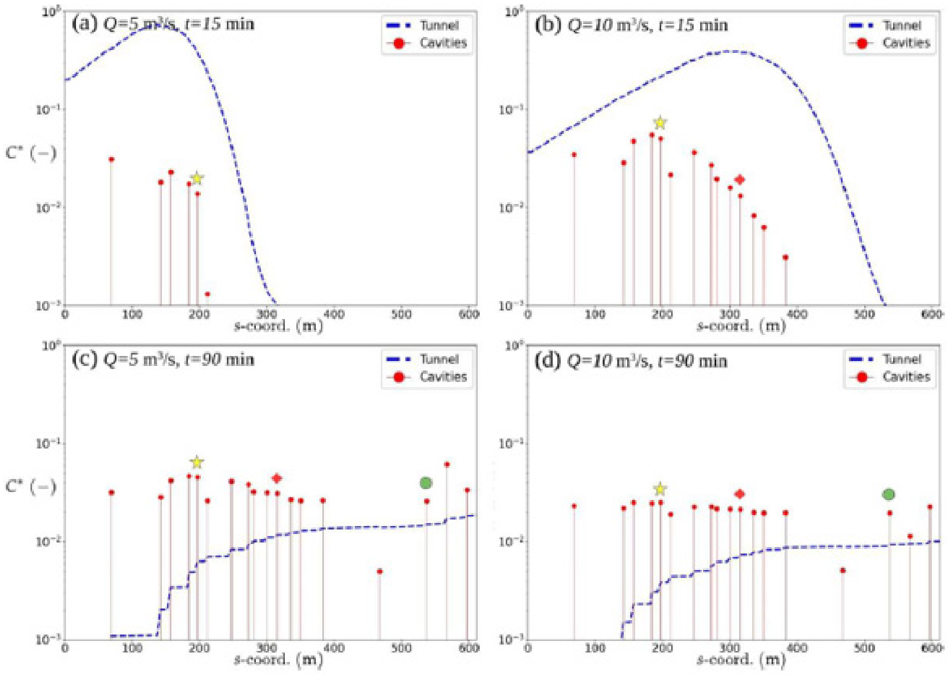


Figure 23. Normalised concentration along the tunnel exhaust path (s-coordinate). The exhaust path concentration is shown by the dashed blue line; intersecting tunnel cavities appear as red dotted bars. Three cavities (yellow, red, green) correspond to Figure 22.

Citation: J Salmi*, D Mikulich, M Auvinen, A Hellstenc, J Hoivala, T Rönkköd, M Griffith, Zehao Ye and R Heikkilä. Towards Virtual Twinning of Underground Mines: An Information-Model-Based Framework for Air Quality Monitoring and Ventilation Management. Adv in Mining & Mineral Eng. 2(1): 2026. AMME.MS.ID.000526. **DOI:** 10.33552/AMME.2026.02.000526

The long temporal tail of the concentration evolution along the exhaust path is made evident by inspecting local concentration values over time. Figure 24 illustrates a time series of normalised concentration at two different probe locations s=150 m and s=500 m along the exhaust path. These results facilitate a direct comparison against experimental measurements and temporal AQ outcomes under different ventilation conditions. The integration of the novel Hybrid-CFD analysis results into the proposed VT environment is demonstrated in the Results section.

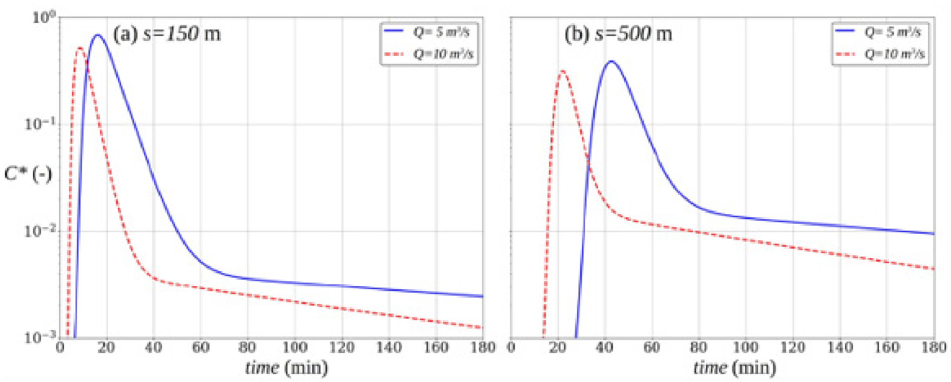


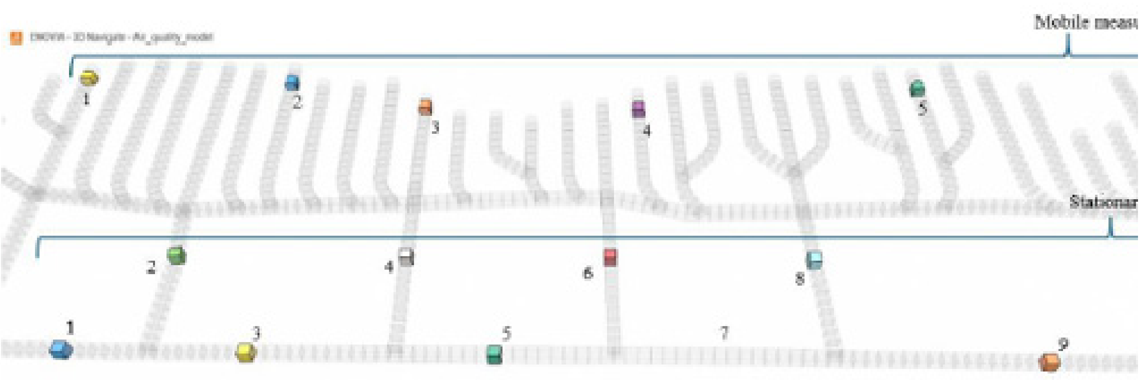
Figure 24. Normalised concentration time series for two probe locations along the exhaust path: (a) s = 150 m and (b) s = 500 m. Results illustrate temporal decay of contaminants under two airflow rates (5 and 10 m³/s). Logarithmic scale used.

The apparent differences between airflow directions in previous figures arise from modelling principles: Ventsim computes flow paths from pressure differentials across the full network, while HCFD analyses a single exhaust route in detail. No data exchange currently exists between the two tools; both utilise identical initial parameters. Their combined use demonstrates the operational complementarity of the approaches - Ventsim provides system-level airflow patterns, whereas HCFD resolves local concentration gradients.

Integration and visualisation in the VT environment

Measured and simulated datasets were harmonised and linked to parametric objects within the PDM, enabling the VT to function as an operational interface for AQ monitoring, analysis, and control exploration. The VT was implemented on the Dassault Systèmes **3D**EXPERIENCE platform using the NETVIBES Data factory Studio solution, as illustrated in following figures. Users can query AQ history at any monitoring location and compare simulation outcomes interactively. The use of a commercial industrial VT platform demonstrates the practical deployability of the proposed methodology beyond research prototypes.

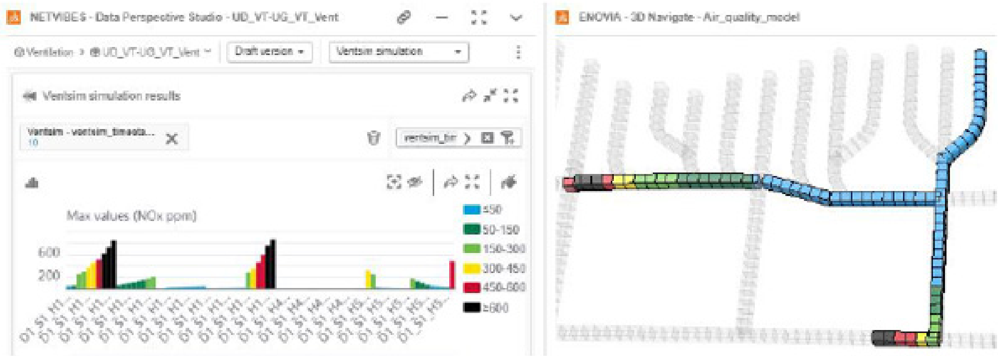
Figure 25(a) shows each location containing different measurement datasets. Mobile measurement datasets are used to represent active working spots at tunnel ends at upper part of the figure, while stationary measurement datasets reflect fixed monitoring stations along access tunnels at lower part of the figure. In the illustrated PLM objects, colour coding could be applied to represent the highest recorded measurement values; however, in this case, only the object locations are displayed. The data and measurement history for each measurement point can be accessed by clicking on the desired object, as presented in Figure 25(b).



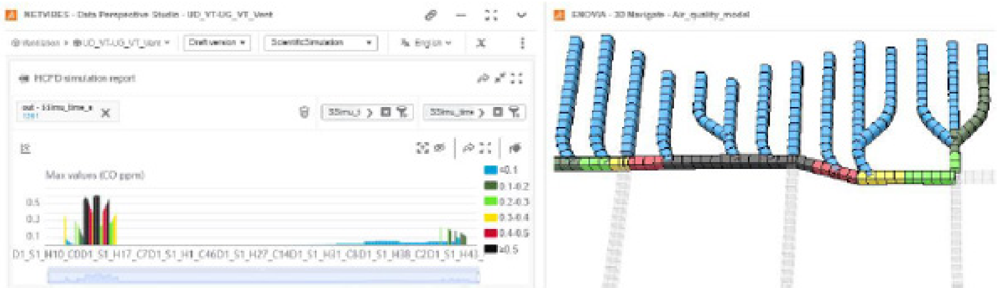
(b) Example of data report form providing historical AQ data for selected PLM objects.

Figure 25. The VT view enables inspection of AQ history at each monitoring location.

Figure 26 illustrates both Ventsim and HCFD simulation visualisations in VT app environment at different time intervals, depicting the progression of AQ following a blasting event. The basic settings of gases and tunnel dimensions are not fully synchronised in both simulations, which is why the smoke from the explosion does not look exactly the same in the figures.



(a) Visualised AQ simulation results in the VT app: Ventsim (NO_x ppm) at t = 10 min.



(b) Visualised AQ simulation results in the VT app: HCFD (CO ppm) at t = 20 min.

Figure 26. Contaminated air flows from the blasting zone (top right) toward the exhaust raise.

All the main access tunnel results can be derived from Ventsim simulations, while all the intersecting single headed tunnels can also have values from the HCFD simulation, as presented in Figure 27. Various simulation data read directly from different databases can thus be displayed side by side in the VT view, which improves the versatility of the information conveyed to the user. Integrated visualisations combine Ventsim and HCFD outputs to provide a unified, time-resolved representation of AQ dynamics across the tunnel network. This enables the identification of poorly ventilated areas lacking sensors and supports safe re-entry planning after blasting. This integrated view allows operators to assess AQ conditions consistently even in areas lacking physical sensors, improving risk awareness and operational planning.

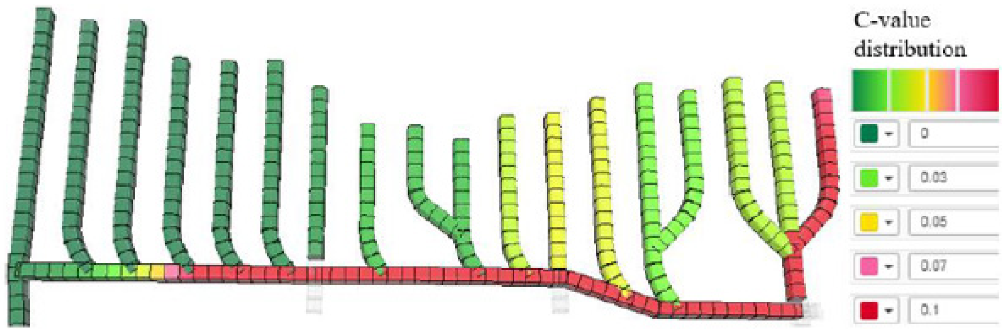


Figure 27. Example of integrated HCFD simulation results in the VT app. Single-ended tunnel cavities are assigned simulated AQ values complementing the Ventsim network simulation, improving overall spatial accuracy.

Finally, after all geometries and AQ data from the parametric tunnel model have been transferred to the VT model in NETVIBES Data Factory Studio, the parameterised AQ values across the tunnel network can be investigated and adjusted in both tabular and graphical formats, with support for various data queries, as presented in Figure 28. The ventilation control centre widget on the right side of the figure supports bidirectional data management, enabling operators to input comments and modify fan control parameters directly within the VT interface.

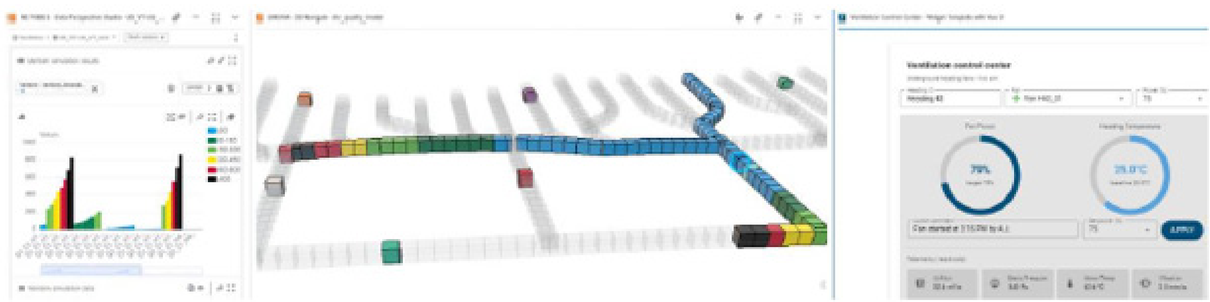


Figure 28. Measured and simulated AQ values displayed in the VT app. Data can be sorted and queried; the ventilation control widget (right) supports bi-directional data management between the VT app and the database.

The system also supports semi-real-time data updating — up to every 10 seconds — through a flexible pipeline linking the VT app with cloud databases (AWS APIs (Amazon Web Services Application Programming Interfaces), Flask (Python programming language web application framework), Python). Bi-directional widgets within NETVIBES dashboards allow operators to input feedback or modify fan parameters directly in the interface, establishing a foundation for adaptive, data-driven ventilation management. This architecture ensures that all data types — static geometry, time-dependent sensor readings, and simulation outputs — can be synchronised and visualised within a unified MIM, both in a unidirectional data flow (digital shadow) and in a bidirectional integration (digital twin).

Current technical implementation

The integration pipeline consists of three stages.

1. **Data ingestion and harmonisation.** Raw CO, NO_x, temperature and airflow measurements are transferred from the mine's IoT system to AWS, where preprocessing scripts unify formats, align timestamps, and append metadata (sensor ID, location, tunnel-cut ID).
2. **Model integration and mapping.** Harmonised datasets are accessed through a Flask-based REST API, which convert them into VT-compatible and automation-compatible attributes. Each record is linked to its corresponding 5-m tunnel-cut object in the MIM via unique PLM identifiers. Ventsim and HCFD outputs are imported using the same schema, allowing measured and simulated values to coexist in a common

Citation: J Salmi*, D Mikulich, M Auvinen, A Hellstenc, J Hoivala, T Rönkköd, M Griffith, Zehao Ye and R Heikkilä. Towards Virtual Twinning of Underground Mines: An Information-Model-Based Framework for Air Quality Monitoring and Ventilation Management. Adv in Mining & Mineral Eng. 2(1): 2026. AMME.MS.ID.000526. **DOI:** 10.33552/AMME.2026.02.000526

geometric reference.

3. **Visualisation and interaction.** A **3D**EXPERIENCE® NETVIBES dashboard provides multi-layer visualisation of these datasets. Users can filter by pollutant, time or location, compare measurement–simulation pairs, and inspect heat maps or time-series plots that update automatically as new data arrive. This supports near-real-time situational awareness within a unified 3D environment and enables operators and engineers to interact with complex AQ datasets without requiring direct access to simulation tools.

Transition towards bi-directional integration

The current system functionality is predominantly one-way (physical → VT), reflecting a reflective DT implementation stage, and development is now directed toward secure bi-directional communication with operational control systems. This transition progresses through three stages.

- **Virtual feedback loop**

The VT will generate predictive ventilation responses using surrogate or reduced-order HCFD models. Suggested adjustments (e.g., fan duty, regulator settings) will be displayed directly within the dashboard.

- **Supervised control interaction**

Authorised operators will send parameter updates or setpoints from the VT interface to a validation module that checks ranges, safety thresholds and uncertainty before forwarding commands to the VOD system.

- **Closed-loop control**

After sufficient verification, the VT will support semi-automated or automated control modes in which sensor feedback continuously updates simulation states and informs real-time ventilation adjustments.

A dedicated Command Validator and Safety Gateway will mediate all outbound actions to ensure operational safety. Extending the current unidirectional pipeline into this bi-directional architecture moves the MIM–VT framework from reflective monitoring toward prescriptive, decision-support operation aligned with DT maturity models. This staged transition aligns with industrial best practices for introducing automated control in safety-critical environments.

In summary, the case study demonstrates a practical workflow for integrating heterogeneous AQ datasets into a parametric VT of an UG mine. By coupling measurement data with Ventsim and HCFD simulations inside a unified VT platform, the approach bridges the gap between system-level ventilation design and detailed contaminant transport modelling - providing an operationally useful, visually intuitive, and extendable framework for smart mine ventilation control. The case study therefore provides empirical evidence that the proposed MIM–VT architecture is technically feasible, operationally relevant, and scalable toward automation-oriented mine ventilation management.

Results

The study demonstrates the practical implementation and operation of a parametric Mine Information Model (MIM) derived from geometric raw data, enabling the spatial linkage of condition-specific attributes — such as air quality (AQ) parameters — to individual excavation units. Measurement datasets, alongside two simulation-based AQ datasets from distinct modelling platforms, were integrated into the MIM as dynamic parameters. The resulting VT environment enables seamless visualisation and monitoring of these data through a unified operational interface, supporting near-real-time situational awareness and compliance assessment against AQ directives and national regulations.

The main outcomes can be summarised as follows:

- **Parametric modelling of void spaces:** The developed MIM translates AQ data into spatially explicit parameters, enhancing the management and visualisation of UG ventilation conditions. This enabled spatially explicit tracking of airflow-related parameters and pollutant distributions across the mine network, providing a consistent geometric reference for both measured and simulated AQ data.
- **Application of LES:** The study demonstrates the application of LES-based Hybrid-CFD (HCFD) modelling for operational post-blasting fume dispersion analysis with high spatial resolution. The results complement conventional ventilation simulations by identifying delayed contaminant clearance in intersecting tunnel sections and revealing delayed contaminant clearance and residual concentration zones in intersecting tunnel sections that are not observable through network models or sensor measurements alone.
- **Integrated VT framework:** By combining geometric mine data with measured and simulated AQ datasets, the VT application supports efficient, interactive monitoring and optimisation of underground ventilation. The integration enabled interactive inspection, comparison, and temporal replay of measured and simulated AQ data within a single VT environment.

Furthermore, a stakeholder workshop conducted within the project provided qualitative validation of the proposed MIM–VT concept from an operational and organisational perspective. Participants identified perceived benefits related to asset management, cost control, communication, and process transparency, while also highlighting constraints related to resourcing, cost, and long-term model maintenance. However, they also acknowledged practical challenges related to resourcing, cost, and long-term model maintenance. Incremental deployment and clearly defined business cases were seen as critical to ensuring adoption and continuity. Overall, the workshop results indicate that BIM-based MIM and VT solutions are considered operationally relevant by industry stakeholders, provided that implementation is incremental and supported by clear organisational ownership.

Discussion

The proposed MIM–VT framework demonstrates a scalable and adaptable approach for modelling, visualising, and managing underground air quality (AQ) data under operational mining conditions. By linking parametric 3D models, simulation results, and sensor measurements within a unified structure, the framework enables both local and global monitoring and supports optimisation-oriented analysis of mine ventilation. Its modular architecture allows adaptation to different mining sites through modifications of tunnel geometry, sensor configuration, and ventilation layouts, while maintaining interoperability and consistency through the VT interface.

As detailed in Section 3.4.4, the proposed architecture enables real-time feedback and technically validated control-readiness. This capability represents a step toward prescriptive VT operation and closes the loop between monitoring and automated decision-making. The MIM–VT framework should not be interpreted as a fully operational prescriptive DT, but as a demonstrated reflective–predictive architecture that provides the necessary foundation for later bi-directional control.

Theoretical and practical contributions

The study provides contributions at both theoretical and practical levels by demonstrating how a BIM-based MIM can serve as an integrative backbone for multi-source DTs in UG mining.

Theoretical contributions

First, the research advances the conceptual understanding of VTs by positioning the VT as a meta-level integrator that coordinates several domain-specific DTs - network ventilation, HCFD, environmental monitoring — within a unified parametric model. This clarifies the role of VTs within established DT typologies (descriptive → reflective → predictive → prescriptive), addressing an existing gap in the mining DT literature related to multi-model federation and cross-domain orchestration. Second, the study contributes a repeatable methodology for connecting heterogeneous simulation models and sensor data through PLM-based identifiers and a shared geometric representation. This demonstrates how semantic alignment and spatial anchoring can enable interoperable DT components, offering a transferable and reproducible approach beyond the case study.

Practical contributions

Practically, the study demonstrates a functioning prototype of a MIM–VT system capable of ingesting, harmonising and visualising near-real-time environmental data alongside simulation outputs in a single 3D environment. This improves situational awareness and supports more transparent interpretation of airflow and contaminant behaviour. The POC bi-directional interaction - where user-initiated parameter changes propagate through the simulation engine and return to the VT - demonstrates technical readiness for supervised control under controlled operational conditions. Finally, the approach shows how a parametric and automation-ready information model has the potential to reduce manual engineering effort and allow the workflow to be scaled and replicated across different mines and IT infrastructures.

Practical implications and recommended validation path

Practically, the integration of MIM and VT improves data transparency, reusability, and accessibility across mining operations. The framework facilitates real-time visualisation of AQ conditions through mobile and desktop platforms, supporting operational decision-making and safety management. The case study indicated its potential for improving situational awareness, reducing data latency, and supporting user-specific information retrieval. Workshop findings further validated the applicability of this methodology to production optimisation, mine planning, and lifecycle information management, although resource allocation and systematic maintenance remain essential challenges for long-term implementation.

From a practical perspective, the conceptual model emphasises a staged validation and deployment strategy:

1. **Baseline harmonisation**: enforce metadata and time-synchronisation standards across sensors, simulations and MIM objects to enable automated alignment.
2. **Component validation**: individually validate network and HCFD components against targeted in-situ experiments (e.g., controlled tracer releases or post-blast monitoring at instrumented cuts).
3. **Integrated validation**: compare fused model outputs (hybrid predictions) against independent sensor arrays along representative exhaust routes, quantifying errors and uncertainty envelopes.
4. **Controlled actuation trials**: under strict supervision, execute limited VOD scenarios where the VT issues non-safety-critical setpoints (e.g., incremental VFD changes) while monitoring system response and safety thresholds.
5. **Full operationalisation**: after satisfactory safety and performance verification, enable prescriptive modes with human-in-the-loop oversight and automatic rollback strategies.

This staged validation path aligns with safety-critical automation practices in industrial process control. While the current prototype implements only predictive one-way updates, the architecture has been deliberately designed to support supervised bi-directional control loops once the necessary validation and safety approvals are completed.

Generalisation and applicability to other mining contexts

Although the present study focuses on a single case, the methodological structure — linking parametric geometry, measured and simulation data, and VT-based visualisation — is inherently adaptable to various geological settings and mining methods. By recalibrating input parameters such as tunnel geometries, airflow characteristics, and pollutant source terms, the same framework can be employed to model ventilation processes in both hard-rock and soft-rock environments. Furthermore, the modular nature of the MIM enables integration with diverse data acquisition systems, including IoT-based sensors and autonomous vehicle telemetry, without fundamental modifications to the underlying data schema.

This makes the framework scalable from pilot-scale studies to full-mine implementations. From an operational perspective, adopting the MIM–HCFD methodology across different mines can support standardisation of air-quality management practices, facilitate benchmarking of ventilation performance, and promote interoperability between simulation platforms. These capabilities are particularly valuable for large mining companies managing multiple sites with varying infrastructure and regulatory conditions.

Limitations

This study presents a framework-level and prototype implementation of a VT for mine ventilation management. Several limitations should be acknowledged.

First, the validation is carried out using representative but not fully synchronised datasets, meaning that physical accuracy and predictive performance of the simulation models are not quantitatively assessed by design.

Second, the real-time control loop is implemented as a POC prototype and has not yet been deployed within the operational VOD system.

Third, the hybrid CFD and network model coupling uses aligned boundary conditions but does not yet include dynamic iterative coupling.

Fourth, the demonstration is based on a single case-study mine, although the architectural principles are generalisable.

Novelty and significance

This study presents a novel, operationally demonstrated integration of MIM with VT technology for underground mine ventilation management. While the use of BIM has become well established in construction, its systematic application to mining processes remains limited. The developed approach demonstrates, for the first time in the context of underground mine ventilation, a comprehensive linkage between parametric tunnel geometries and dynamic AQ datasets — derived from both simulations and measurements — within a single MIM environment. This integration enables real-time synchronisation between digital and physical processes, providing a foundation for intelligent and adaptive ventilation control.

Comparison with existing approaches

Conventional mine ventilation management typically relies on disconnected systems in which measurements, simulations, and control actions are handled independently. Such fragmentation restricts real-time data use, introduces latency, and limits predictive capability. In contrast, the proposed MIM–VT framework establishes a machine-readable data exchange with demonstrated unidirectional operation and a validated pathway toward bidirectional integration that unifies real-time sensor data, simulation-based predictions, and operational control parameters within a parametric 3D model. This enables rapid feedback between physical and digital layers, enhancing situational awareness and supporting proactive decision-making. The ability to visualise simulation results alongside live measurements also strengthens predictive ventilation management and reduces risks associated with delayed AQ information.

Conclusions

This study demonstrated the use of BIM-based parametric modelling as an automation-ready information backbone for managing underground mine AQ data through the development of a MIM. CAD-derived tunnel geometries were transformed into a parametric model that served as the basis for air quality simulations, virtual twin (VT) applications, and machine-control (MC)–oriented workflows. The model integrated both simulated and measured AQ parameters — time-stamped and spatially linked to 5 m long tunnel excavation units — providing a unified digital framework for ventilation analysis and management providing a unified digital framework for ventilation analysis and management under operational conditions.

The main contributions of this work are:

- **Parametric integration of AQ data:** Development of a MIM that combines 3D tunnel geometries with dynamic AQ datasets to enable real-time visualisation and monitoring through an automation-oriented VT interface.
- **LES-based simulation for mine ventilation:** Introduction of LES modelling for predicting blast fume dispersion - representing a novel, operationally integrated application in mining ventilation.
- **Operational implementation and validation:** Demonstration of how MIM–VT integration supports daily mine operations, enhances situational awareness, and supports regulatory compliance with occupational air quality requirements.
- **Industry engagement:** Workshop results confirmed industry interest in applying BIM principles for data-driven mine management, identifying both the benefits (efficiency, communication, cost tracking) and challenges (resource needs, maintenance, trust in data accuracy).

These results indicate that the greatest value of parameterised AQ management lies in enabling shared, real-time data access and interpretability through mobile VT applications — broadening the user base beyond engineers and regulators to all mine personnel.

Future work

Future work will focus on advancing the MIM–VT framework from the current reflective–predictive prototype toward a fully validated and operationally deployable prescriptive DT for UG ventilation and AQ control. A central priority is the integration of synchronous measurement–simulation time-series, which will enable rigorous quantitative validation and support automation-safe decision logic of airflow and contaminant predictions using established statistical metrics such as RMSE, bias and R^2. These datasets will also support systematic model calibration and facilitate deeper analysis of temporal behaviour across both network and HCFD simulations.

In parallel, the simulation architecture will be extended to include multi-scale and potentially iterative coupling between Ventsim and HCFD models. This will enhance the fidelity of local flow interactions and strengthen the connection between mine-wide network behaviour and detailed computational domains. Building on the bi-directional prototype demonstrated in this study, future development will introduce supervised control capabilities in which VT-generated ventilation adjustments are evaluated through uncertainty checks and operational rules before being forwarded to the VOD system. This gradual transition from monitoring and prediction toward assisted and eventually prescriptive decision-making forms the next step in the DT maturity path.

Finally, the generalisability of the approach will be examined by deploying the framework in additional mine sites with varying geometries, infrastructure and data availability. Such multi-site evaluation will assess scalability, expose differing data-integration constraints and confirm the transferability of the MIM-based approach across heterogeneous operational environments. Collectively, these developments will move the VT closer to a robust, real-time DT capable of supporting continuous optimisation under supervised operational conditions.

Recommendations

To realise the full potential of IM in mining, process owners must establish clear data collection and governance strategies aligned with organisational maturity. Systematic acquisition, harmonisation, and application of operational data are crucial for achieving long-term returns on digitalisation investments.

The adoption of VT and MC technologies is strongly recommended for safety-critical and data-intensive mining operations. VTs offer interactive, real-time visibility into UG conditions, supporting remote monitoring, simulation, and decision-making. When combined with MC systems - particularly for ventilation and mobile equipment - VTs provide a foundation for semi-automated or autonomous operation, improving safety, efficiency, and environmental performance. Based on the findings of this study and the demonstrated capabilities of the MIM–VT framework, several strategic recommendations can be made for organisations seeking to advance toward a fully functional DT for mine ventilation. The results indicate that the VT implemented here corresponds to the early stages of a broader DT maturity trajectory, and the following steps provide a clear roadmap for continued development:

(1) Strengthen the reflective stage through continuous multi-source data integration

The current VT already supports automated ingestion and harmonisation of simulation and sensor data. To consolidate this capability, it is recommended that the operator deploy systematic routines for maintaining, validating, and synchronising input data for automated processing — particularly environmental sensor streams and updated geometric information.

(2) Expand predictive capabilities by aligning simulations with synchronous measurements

Organisations should prioritise establishing synchronous time-series measurement–simulation datasets. These will enable quantitative validation and enhance confidence in the predictive components of the VT. Validation metrics such as RMSE, bias, and R^2 should be integrated into routine performance monitoring.

(3) Introduce assisted decision-making modules

To move beyond visualisation and prediction, the VT should be extended with decision-support functions that generate recommended ventilation adjustments based on validated simulation behaviour and operational rulesets. Human operators would remain in the loop, but the VT would assume a more active analytical role.

(4) Progress toward prescriptive DT operation through supervised bi-directional control

The prototype fan-parameter update demonstrated in this study shows that bi-directional communication is already feasible. The next step is to implement supervised, real-time VOD control, in which VT-driven recommendations are translated into operational commands under controlled conditions. This will form the basis for a future prescriptive ventilation DT.

(5) Aim for full DT maturity by embedding continuous validation and optimisation loops

Ultimately, achieving full DT maturity requires continuous quantitative validation, automated optimisation of ventilation strategies, and seamless integration with operational decision-making systems. As additional datasets and modelling capabilities become available, the VT framework should be scaled to support dynamic optimisation across the complete mine network.

In summary, while the present implementation covers levels 1–2 of the DT maturity path (Reflective and initial Predictive), the architecture developed in this study provides a robust and automation-ready foundation for advancing toward levels 3–5: assisted decision-making, prescriptive real-time control, and continuous validation. These levels are recommended for organisations aiming to operationalise an end-to-end ventilation and AQ DT.

Declaration Of Competing Interest

Authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration Of Generative Ai and Ai-Assisted Technologies in the Writing Process

During the preparation of this work the author used ChatGPT 4.0 in order to improve the language and readability. After using this tool, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

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