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An Edge-AI Powered Micro-Seismic Digital Twin for Predicting Dynamic Rockburst Risks in Deep Hard-Rock Excavations

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Abstract: As mining operations aggressively push past depths of *2* km to *3* km, underground excavations encounter extreme, non-linear geo-stresses. At these depths, traditional microseismic (MS) systems fail to predict catastrophic, sudden rockburst events due to data transmission latency, manual waveform processing bottlenecks, and static geological models. This paper reviews the emerging paradigm of shifting from centralized cloud processing to decentralized, real-time edge computing integrated into high-fidelity Digital Twins (DTs). By processing massive, high-frequency waveform data directly at the underground sensor level (Edge-AI) and feeding these localized dynamic metrics into a continuously updating 3D physical-virtual model, modern deep mining can achieve automated, low-latency, and predictive hazard zoning. This review contextualizes the transition from legacy empirical seismic monitoring to dynamic, event-driven Edge-AI systems, identifying critical bottlenecks in micro-seismic wave classification, edge-hardware survival, and real-time bidirectional data synchronization.

1. INTRODUCTION: THE DEEP-MINING CRISIS

When mining operations enter the ultra-deep domain (greater than 1,000 meters), the surrounding rock mass stops behaving like a predictable, static solid. Instead, it transforms into a highly stressed, energy-storing environment subject to violent, structurally dominated failures known as **rockbursts** (Ma et al., 2025). The classic approach to managing this hazard involves installing array-based geophones or piezoelectric sensors to capture microseismic (MS) acoustic emissions—the minute cracking sounds rocks make before failing completely (Yu et al., 2022).

However, conventional MS frameworks are structurally bottle-necked:

- **The Bandwidth & Latency Trap:** Geophones generate high-frequency raw acoustic waveforms (*1* kHz to *10* kHz or higher). Transmitting miles of uncompressed raw multi-channel data from a deep active stope up to a centralized surface cloud server induces a severe transmission delay. In an environment where rockbursts can trigger milliseconds after a blast, a 2-minute processing delay is fatal.

- **The Noise Factor:** Deep excavations are incredibly noisy. Heavy machinery, drilling, ventilation systems, and deliberate blasting produce severe acoustic interference. Distinguishing a genuine structural rock micro-fracture from a nearby jumbo drill using manual or simple threshold-based filtering results in high false-alarm rates or completely missed precursor signals (Ma et al., 2025; Zhu et al., 2024).

- **Static Model Blindness:** Classic rock-mechanics modeling relies on static, pre-calculated finite element methods (FEM) built from initial core samples. They cannot adapt on the fly to the physical reality of a working face that advances by several meters every single day (Zhang et al., 2024).

To cross this chasm, current research is focusing on the intersection of **Edge Computing** (bringing machine learning down into the dark, directly onto the sensor node) and **Digital Twins (DT)** (creating a live, breathing 3D simulation of the mine that mirrors reality in real time) (Liang et al., 2023; Sotomayor Sotelo, 2026).

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2. CORE ARCHITECTURE OF AN EDGE-AI MICRO-SEISMIC DIGITAL TWIN

A truly predictive rockburst digital twin cannot operate as a single software platform; it requires a multi-tiered ecosystem capable of converting physical elastic waves into localized, actionable spatial stress maps within seconds.

```
[ PHYSICAL DEEP MINE STOPE ]
            |
            ▼ (High-Freq Elastic Waves: 1-10 kHz)
[ Smart Sensor Nodes (Edge-AI) ] ──► Local Waveform Picking (P/S Wave) & Noise Filtering
            |
            ▼ (Lightweight Parametric Metadata: Energy, b-value, Coordinates)
[ Subsurface Gateway (Fog Node) ] ──► Spatiotemporal Cluster Detection & Event Localization
            |
            ▼ (Bidirectional MQTT / OPC-UA Stream)
[ 3D Virtual Digital Twin Engine ] ──► Live Stress Inversion & Dynamic Hazard Visualization
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2.1. Tier 1: The Smart Sensor Node (The "Edge")

Instead of using passive geophones that simply pass raw electrical voltages up a long copper cable, the system deploy intelligent, micro-controller-equipped sensor packages. Each node features localized processing chips (e.g., edge Tensor Processing Units or low-power ARM Cortex-M processors) running ultra-lightweight neural networks.

- **In-Situ P-wave and S-wave Arrival Picking:** Instead of uploading whole waveform files, the edge node processes the signal locally using tiny 1D Convolutional Neural Networks (1D-CNN) or gated recurrent units to detect the exact millisecond the Primary (P) and Secondary (S) waves arrive (Wang et al., 2025).
- **Real-time Noise Filtering:** Algorithms like Gaussian Mixture Models combined with intelligent signal recognition differentiate blasting signatures and mechanical shear from true stress-induced micro-fractures inside the rock mass right at the source (Ma et al., 2025).

2.2. Tier 2: The Fog Gateway (Local Geomechanical Inversion)

The smart nodes forward only lightweight metadata—such as calculated arrival timestamps, peak particle velocity (PPV), and wave frequency—to a localized underground gateway. This gateway bypasses cloud storage bottlenecks to run automated triangulation routines. By matching multi-node arrival times, it determines the precise 3D coordinates (X, Y, Z) of the rock micro-fractures along with their immediate energy release metrics (Zhu et al., 2024).

2.3. Tier 3: The Virtual Twin Layer (Real-Time Synchronized Engine)

The calculated 3D coordinates and source parameters feed straight into a 3D visualization engine (e.g., WebGL or specialized mining engines). Here, the mine geometry is updated dynamically according to working face advancement records (Zhang et al., 2024). Instead of static rendering, the system performs ongoing geomechanical stress inversions, displaying evolving clusters of seismic activity as an active heat map of rock mass damage (Sotomayor Sotelo, 2026).

3. KEY ALGORITHMIC PILLARS FOR DYNAMIC FORECASTING

Moving from reactive monitoring to proactive forecasting requires translating raw microseismic metrics into geological risk levels on the fly.

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3.1. Advanced Seismological Feature Extraction

To successfully track rock mass degradation, the model continuously calculates key seismic precursor indices across rolling windows (Yu et al., 2022):

- **The Gutenberg-Richter *b*-value:** This evaluates the ratio between minor micro-cracking events and major fractures. A sudden drop in the *b*-value indicates that small micro-cracks are merging into macro-fractures, signaling that a major rockburst is imminent.
- **Energy Index (*EI*) and Seismic Energy Density:** This tracks the accumulation of abnormal elastic strain energy relative to the historical baseline of that specific geological formation.
- **Spatiotemporal Event Density:** This measures how tightly packed the rock fractures are in both space and time. Spatially scattered cracks indicate stable stress redistribution, whereas a dense, rapidly growing cluster points to localized structural shear failure.

3.2. Event-Driven Transformers and Deep Feature Fusion

Traditional temporal models process microseismic streams purely based on sequential timestamps. However, recent developments demonstrate that deep rock mass behavior responds much more directly to physical mining disturbances (like a blast or mechanical extraction) than to time alone.

Advanced deep-learning models, such as event-driven Transformers (e.g., *DynamiXFormer* architecture), mapping mining-induced advance rates and spatial blasting parameters directly against the extracted microseismic feature streams (Zhang et al., 2024). By incorporating attention mechanisms, these networks isolate long-term regional stress trends from the acute, short-term seismic spikes caused by immediate blasting operations, yielding localized rockburst prediction accuracies exceeding 90% (Wang et al., 2025; Zhang et al., 2024).

4. CURRENT ENGINEERING CONSTRAINTS AND RESEARCH GAPS

Despite the immense theoretical value, building an autonomous, edge-driven microseismic twin in deep underground mines presents severe physical and architectural challenges:

- **Harsh Edge-Hardware Survivability:** Edge units must survive extreme conditions, including high ambient humidity, ambient heat, exposure to corrosive dust, and intense physical shock fields from daily blasting. Protecting sensitive TPU/GPU edge devices without degrading sensor sensitivity remains an unsolved packaging challenge.
- **Heterogeneous Data Interoperability:** A true Digital Twin requires the fusion of highly varied datasets (Liang et al., 2023). Blending high-frequency continuous microseismic streams with sparse geological drilling records, localized rock mass classification parameters (RMR/Q-system), and changing daily tunnel geometry plans demands standardized, highly flexible data models (Sotomayor Sotelo, 2026).
- **The "Black Box" Interpretability Problem:** Deep neural networks excel at predicting high-risk zones, but mine engineers cannot easily verify *why* a model suddenly classifies a specific pillar as highly hazardous. Integrating Explainable AI (XAI) frameworks—such as SHAP (Shapley Additive exPlanations)—into localized edge architectures is critical to giving engineers the clear physical rationale they need to confidently order an active stope evacuation (Zhang et al., 2024).

5. CONCLUSION

Developing an Edge-AI powered microseismic digital twin represents a vital paradigm shift for deep geotechnical engineering. By converting passive data gathering into decentralized, real-time edge processing and interactive spatial analytics, this framework systematically addresses the data bottlenecks that long limited traditional microseismic networks. Eliminating telemetry latency and introducing event-driven machine learning models enables mine operators

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to transform raw acoustic emission signals into active, 15-to-30-minute early warning windows. Resolving current bottlenecks in edge-hardware durability and multi-source data fusion will pave the way for fully autonomous, self-correcting subsurface hazard management systems.

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