Real-Time Risk Assessment for Underground Space Using IoT, Online Learning, and Bayesian Networks

Milad Mousavi[1], Xuesong Shen[1], Zhigang Zhang[2], Khalegh Barati[1], and Binghao Li[3]

[1] School of Civil and Environmental Engineering, UNSW Sydney, Australia
[2] Chongqing Research Institute of China Coal Technology & Engineering Group, Chongqing, China
[3] School of Mineral and Energy Resources Engineering, UNSW Sydney, Australia
milad.mousavi@unsw.edu.au, x.shen@unsw.edu.au, zzg-2@163.com, khalegh.barati@unsw.edu.au, binghao.li@unsw.edu.au

Abstract –

Underground working environments are inherently hazardous, with explosion risks posing a persistent threat. Traditional static risk assessments struggle with dynamic conditions. This paper presents a novel real-time explosion risk prediction framework integrating Internet of Things (IoT) sensor data, Long Short-Term Memory (LSTM) networks, and Bayesian Networks (BNs). The system monitors critical indicators (e.g., methane, wind speed) via IoT. The LSTM captures temporal patterns via online learning, and its outputs feed into a BN, which combines predictions with expert knowledge for interpretable risk levels. A case study on a real underground coal mine demonstrated accurate methane concentration forecasting (R^2 = 0.93), with errors decreasing over time. The BN assessment dynamically reflected increased explosion risk upon introduction of an ignition source. This integrated approach offers real-time, interpretable support for explosion risk mitigation.

Keywords –

Explosion Risk Prediction; Dynamic Risk Assessment; Process Safety; Internet of Things; Long Short-Term Memory; Bayesian Networks

1 Introduction

Developing and operating underground spaces poses unique hazards characterized by spatial opacity, geological uncertainty, and dynamic environmental fluctuations such as gas emissions and seismic activity [1]. These risks, exemplified by fatal gas explosions, endanger workers and infrastructure, causing substantial economic losses [2]. Traditional static risk analysis methods, assuming stable environments, fail to incorporate time-dependent fluctuations [3]. Consequently, there is a pressing need for dynamic, real-time risk monitoring and prediction systems that can adapt to the evolving conditions characteristic of underground industrial settings.

Recent technological advancements offer promising avenues to address these challenges. The proliferation of the Internet of Things (IoT) enables continuous, real-time data collection on critical environmental indicators through wireless sensor networks. However, current monitoring systems primarily visualize data, leaving it untapped for deeper risk insights [4]. Furthermore, compatibility issues among data sources and the complexity of analyzing multivariate sensor streams hinder generalization [5]. Simultaneously, data-driven models, particularly deep learning architectures like Long Short-Term Memory (LSTM) networks, have demonstrated superior capability in capturing complex temporal patterns in time-series data. However, these models often operate as "black boxes," providing limited interpretability and failing to integrate crucial domain expertise [6]. On the other hand, knowledge-driven probabilistic models like Bayesian Networks (BNs) excel in representing expert knowledge and facilitating transparent, causal reasoning but may lack the adaptive learning capacity required for highly dynamic environments [7].

This paper addresses these limitations by introducing a novel dynamic risk prediction system that integrates IoT sensors, LSTM networks, and BNs into a unified, real-time framework. The technical novelty of this framework lies in an automated, real-time pipeline coupling continuous online LSTM learning (updating weights per time-step) with instantaneous Bayesian probabilistic inference via an Application Programming Interface (API), providing dynamic adaptability and interpretability for high-risk mining environments.

2 Literature Review

This section surveys the current state of research and technological applications in underground risk management.

2.1 Risk Management in Underground Settings

Traditional risk analysis in underground domain employs both qualitative techniques, such as safety checklists and the Delphi method, and quantitative techniques, including event tree analysis, fault tree analysis, and neural networks [8]. Typically, these methods rely on expert knowledge, historical data, and static models that assume stable conditions, thereby failing to capture the rapid environmental shifts common underground.

This limitation has prompted a shift towards dynamic modeling. For instance, Wu, et al. [9] proposed a quantitative risk assessment method for coal mine gas explosions based on BNs and Computational Fluid Dynamics (CFD), emphasizing that a dynamic model integrating real-time conditions could enhance production safety. Furthermore, the interconnected nature of underground systems leads to cascading hazards. Bai, et al. [10] developed an energy-based coupling risk assessment model for utility tunnels, identifying multiple cascading accident scenarios and stressing the need for stronger preventive actions. Hai, et al. [11] noted that existing methods often perform static analysis on individual risks while overlooking dynamic interactions, recommending the development of better risk indicator systems and the incorporation of interdependencies among risk factors.

2.2 IoT Applications in Monitoring Underground Hazards

The adoption of IoT technology has significantly advanced the monitoring of factors such as gas, dust, temperature, humidity, airflow, and seismic activity in underground mining. IoT devices enable swift data transmission, facilitating a dynamic approach to risk assessment. Onifade, et al. [12] highlighted how IoT enables smart ventilation systems that deliver precise amounts of fresh air to specific areas, using sensor networks to transmit real-time data to control rooms for immediate alerts and automated adjustments. Wu, et al. [13] developed a dynamic information platform for underground coal mine safety using IoT, integrating data acquisition, transmission, analysis, and application layers to collect and analyze vast amounts of operational data. Despite these advancements, a significant challenge remains. Ślęzak, et al. [4] pinpointed that the big data collected is typically used for raw data visualization and monitoring, with deeper analytical potential largely untapped. Applying intelligent forecasting models and data analytics to this data could predict near-future conditions and substantially enhance decision support systems.

2.3 Bayesian Risk Assessment in Underground Environments

BNs have become a crucial tool in underground risk management due to their probabilistic nature and ability to handle complex, uncertain relationships. Their applications range from accident cause analysis to dynamic risk modeling. Xuecai, et al. [14] developed a data-driven BN model for analyzing coal and gas outburst accidents, learning its structure and parameters from a comprehensive dataset of real-world incidents. In scenarios with insufficient data, expert knowledge is integrated. Tong, et al. [15] constructed a BN for mine gas explosions using expert knowledge and the Delphi method to establish conditional probabilities, featuring multi-scale nodes with dynamic probability updates. Mousavi, et al. [16] introduced an IoT and BN framework for online safety risk management, emphasizing the need for accurate BN structures and comprehensive sensor data. However, large and diverse data streams can challenge BN accuracy and computational efficiency. Moradi, et al. [17] noted that relying solely on BNs for complex assessments with numerous sensors and heterogeneous data becomes impractical, underscoring the importance of integrating BNs with data-driven prediction engines for proactive, dynamic risk monitoring.

2.4 Data-Driven Risk Prediction in Underground Spaces

Data-driven models, particularly LSTM networks, have emerged as powerful tools for uncovering complex patterns in time-series data from underground environments. Their application focuses on predicting critical parameters to provide early warnings. Kumari, et al. [18] proposed a UMAP and LSTM model for predicting fire and explosibility risks in sealed-off areas of coal mines, using historical and real-time gas sensor data to forecast concentrations and calculate fire ratios. Dey, et al. [19] implemented a hybrid CNN-LSTM model with IoT sensors to predict miner health quality and gas concentration levels, achieving high prediction accuracy.

Despite these strides, significant concerns remain. A primary issue is the black-box nature of these deep learning models, which fail to deliver context-specific insights or support interactive what-if scenario analysis, limiting customized decision-making guidance [20]. This lack of interpretability challenges trust in the algorithms, necessitating careful integration with engineering knowledge [21]. Furthermore, a notable gap in the literature is the absence of online learning frameworks specifically tailored for underground spaces. Online learning, which involves continuously training a model on newly arriving data streams [22], is essential for real-time adaptability in dynamic environments but has not been extensively explored. This gap highlights the need for methodologies that seamlessly integrate deep learning with online learning to ensure predictive models can evolve continuously in response to changing underground conditions [23].

3 Research Methodology

The proposed IoT-LSTM-Bayesian system, as illustrated in Figure 1, operates through three modules, with static segments occurring pre-operation and dynamic segments occurring periodically during operation. The first module involves IoT deployment for real-time data acquisition and preprocessing. The second module updates an LSTM model with real-time data and predicts future values. The third module evaluates target risks using a pre-developed BN and the LSTM predictions, reporting risk evolution to users.

3.1 Data Specifications and Preparation

Data is derived from IoT sensors (e.g., for methane, wind speed, temperature, dust) deployed in critical locations like work fronts and ventilation corridors. Data is recorded at intervals from minutes to hours and transmitted via technologies like Wi-Fi. The real-time nature is crucial for adapting to dynamic conditions but requires robustness against sensor failures.

Data preparation involves three key tasks. First, missing values are imputed using forward fill to maintain temporal order. Second, anomalies, such as test-induced sensor readings, are identified via domain knowledge and replaced with the last known correct value. Third, the sliding window technique segments input data into overlapping fixed-length windows to capture temporal dependencies for the LSTM.

3.2 Online LSTM Learning and Prediction

LSTM networks are chosen for their ability to model long-term temporal dependencies in sequential data, such as methane concentration patterns. This memory mechanism is particularly critical in underground environments where gas accumulation and dispersion exhibit complex, time-lagged trends that simpler models fail to capture. An LSTM cell contains forget, input, and output gates that regulate information flow via sigmoid and hyperbolic tangent functions [24].

The model undergoes online learning, updating itself with each new data sample at every time step. This enables adaptation to evolving trends. Model performance is evaluated at each step using Mean Squared Error (MSE), Mean Absolute Error (MAE), and

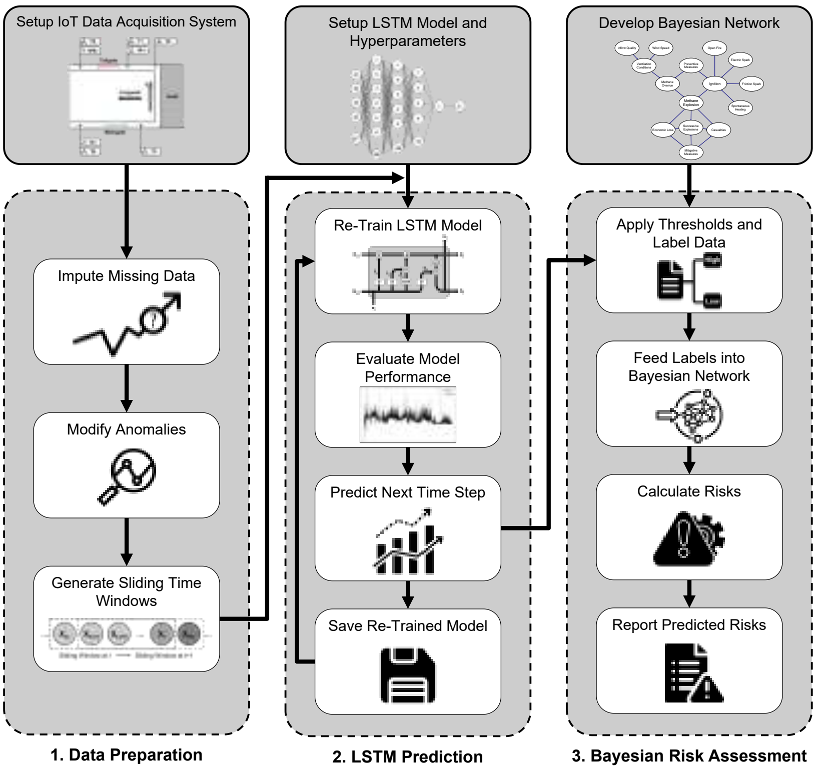

Figure 1. Overview of the proposed IoT-LSTM-Bayesian risk prediction system.

the Coefficient of Determination (R^2). Lower MSE/MAE and an R^2 closer to 1 indicate better performance. The trained model then predicts the next step's values. This model is saved and reused for subsequent retraining.

3.3 Bayesian Risk Assessment

BNs are chosen for their ability to integrate data-driven insights with expert knowledge into a transparent, interpretable probabilistic framework. A BN is a directed acyclic graph where nodes represent variables and edges represent conditional dependencies, quantified via Conditional Probability Tables (CPTs) [25]. The joint probability distribution is calculated using Eq. (1). Inference, updating probabilities given new evidence, is performed using Bayes' theorem (Eq. 2).

$$P(U) = P(X_1, \dots, X_n) = \prod_{i=1}^{n} P(X_i | Parent(X_i)) \quad (1)$$

$$P(Parent(X_i)|X_i) = \frac{P(Parent(X_i))P(X_i|Parent(X_i))}{P(X_i)} \quad (2)$$

In the dynamic system, predicted environmental indicators from the LSTM are discretized using predefined thresholds (e.g., methane concentration labeled as negligible or serious) and fed as evidence into specific BN nodes. The BN then updates probabilities throughout the network, providing real-time, interpretable risk insights.

4 Case Study on Underground Coal Mine

Methane explosions, resulting from methane concentrations reaching 5-15% in the presence of an ignition source, are among the most severe hazards in underground coal mining [26]. Concentrations exceeding 1% are typically considered hazardous, triggering safety protocols that halt production and incur significant financial losses [13]. This case study evaluates the proposed system using environmental monitoring data from a real longwall underground coal mine in China, focusing on methane concentration prediction and explosion risk assessment.

4.1 Data Characteristics and Preparation

Data was collected from eight sensors deployed at the mine's working face: five methane concentration sensors (T0-T4), one temperature sensor (TP1), one wind speed sensor (WS1), and one dust concentration sensor (D1). Figure 2 shows the spatial distribution of the sensors used in this study. Data spanned 3 January 2022 to 12 May 2023 (494 days) at one-minute intervals, yielding 710,367 samples. Table 1 presents the data characteristics. The raw dataset contained missing values and outliers. Missing values were imputed using forward fill, replacing them with the last recorded value to preserve temporal order. Outliers, primarily caused by controlled sensor calibration tests that artificially raised methane levels above 1%, were identified using domain knowledge from mine experts and replaced with the last known valid reading. Data from all eight sensors formed a six-step sliding window to capture multivariate spatial-temporal dynamics, targeting the critically located T0 sensor for prediction.

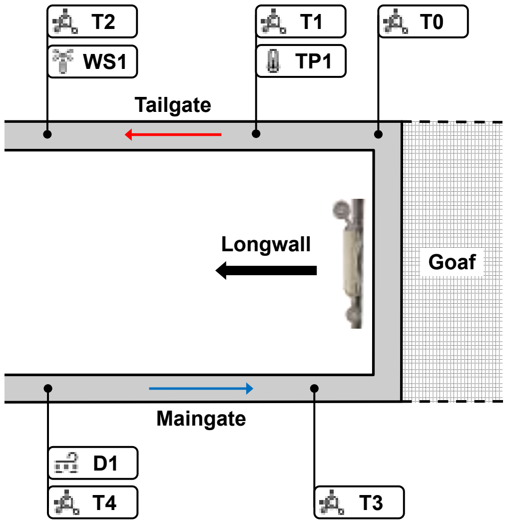

Figure 2. Deployment layout of the environmental sensors within the coal mine.

4.2 Online LSTM Learning and Prediction

A predictive LSTM model, whose architecture is shown in Figure 3, was constructed with two LSTM layers (256 and 128 units, respectively) followed by two dense layers (32 and 1 unit). The Rectified Linear Unit (ReLU) activation function was used, and the model was compiled with the Adam optimizer having a learning rate of 0.001. The hyperparameter selection, including the six-step window length, was based on domain knowledge and empirical testing related to gas dynamics in mines. The model was trained using online learning; at each one-minute time step, a single data sample (the current sliding window) was used to update the model weights via the *train_on_batch* function in *Keras*. Subsequently, the *predict_on_batch* function was used to forecast the T0 methane concentration for the next immediate time step.

Table 1. An overview of the characteristics of the sensor readings.

Variable	Unit	Sensor Code	Min	Max	Mean	SD
Methane Concentration	% CH4	T0	0.000	0.985	0.121	0.083
		T1	0.000	0.995	0.146	0.084
		T2	0.000	0.995	0.184	0.093
		T3	0.000	1.000	0.064	0.042
		T4	0.000	0.947	0.052	0.032
Wind Speed	m/s	WS1	0.003	6.345	1.193	0.525
Temperature	°C	TP1	9.400	20.700	15.315	2.600
Dust Concentration	ppm	D1	0.000	238.067	1.250	5.796

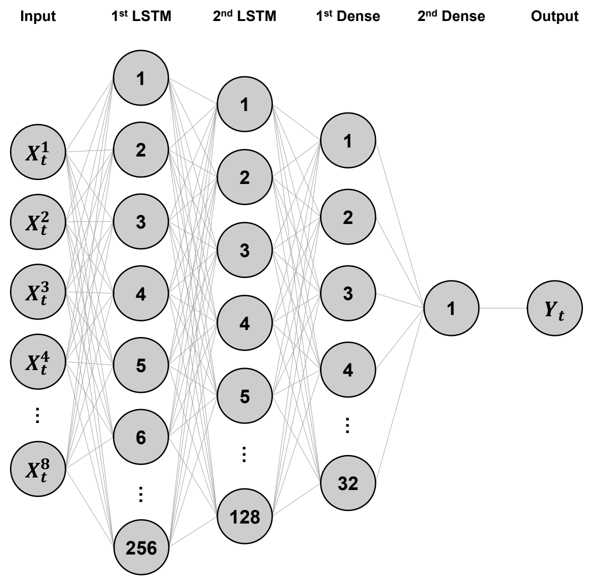

Figure 3. Architecture of the developed LSTM network.

Figure 4 compares the actual methane concentrations measured by sensor T0 and those predicted by the developed LSTM model. The model's performance evolved significantly over time as it engaged in continuous online learning, updating its weights incrementally with each new minute of data using the *train_on_batch* function. Initially, with scant training data, predictions displayed considerable deviation from actual readings; this early phase underscores the importance of expert oversight before deploying model outputs for operational decisions. However, as sequential processing continued, the model rapidly adapted to fluctuations and, aided by spatially distributed multivariate inputs, demonstrated strong responsiveness to sudden spikes. The prediction error, evaluated cumulatively using MAE and MSE, decreased sharply within the first 250 time steps and then plateaued at a low, stable level, indicating successful convergence. Over the entire dataset, the final MAE reached 0.01, MSE reached 0.0005, and the R^2 achieved 0.93. This high R^2 value reflects a strong explanatory power and indicates a high level of predictive accuracy for methane concentration, validating the LSTM's suitability for real-time hazard forecasting in dynamic underground environments.

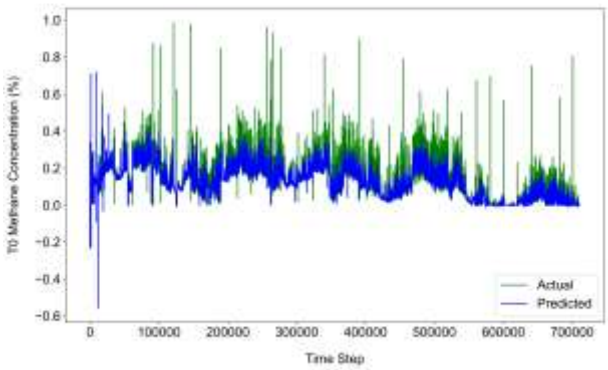

Figure 4. Comparison of the predicted and actual values over time.

4.3 Methane Explosion Bayesian Network

Due to a lack of comprehensive historical data on methane explosions, the BN was constructed using a knowledge-driven methodology. An initial network structure was drafted from literature, identifying causal and consequential variables related to ignition sources, gas accumulation, ventilation, safety interventions, and explosion consequences. This structure builds upon the authors' previous work [27]. This structure was refined through three rounds of expert consultation involving academic specialists and a senior mine ventilation officer. Based on expert feedback, variables like atmospheric pressure and oxygen concentration were removed for being redundant or constant, while practical proxies like wind speed (for airflow) and inflow methane quality were added. Various methane sources were aggregated into a single "methane overrun" node, as sensors measure cumulative concentration.

The final BN, as shown in Figure 5, comprised 15 discrete nodes organized into five groups: (1) Causes: ignition sources like friction spark, open fire; (2) Environmental Conditions: methane overrun, wind speed, inflow quality, ventilation conditions; (3) Accident Trigger: methane explosion; (4) Consequences: casualties, economic loss, successive explosions; and (5) Control Actions: preventive and mitigative measures. Nodes were defined as binary or ordinal states (e.g., negligible/serious, none/slight/severe). CPTs were populated via a structured expert elicitation process, which is fully detailed and validated in [16]. The structure allowed certain nodes (e.g., methane overrun) to receive direct sensor input, while others (e.g., ignition sources) could be set manually for scenario analysis.

Figure 5. Refined BN for methane explosion in underground coal mines.

4.4 LSTM-Bayesian Risk Assessment

Figure 6 displays the architecture of the LSTM-Bayesian fusion system. The system integrated the prediction and assessment layers. At each time step, the continuous methane concentration predicted by the LSTM for sensor T0 was discretized using a 1.0% threshold; values above were labeled serious, others negligible. This step converted the numerical prediction into a format compatible with the BN's categorical reasoning framework. This labeled evidence was then input into the "methane overrun" node of the BN via *SMILE Engine* [28], the API of *GeNIe Modeler*. The BN performed automatic probabilistic inference to update the risk levels of all dependent nodes, including the "methane explosion" node.

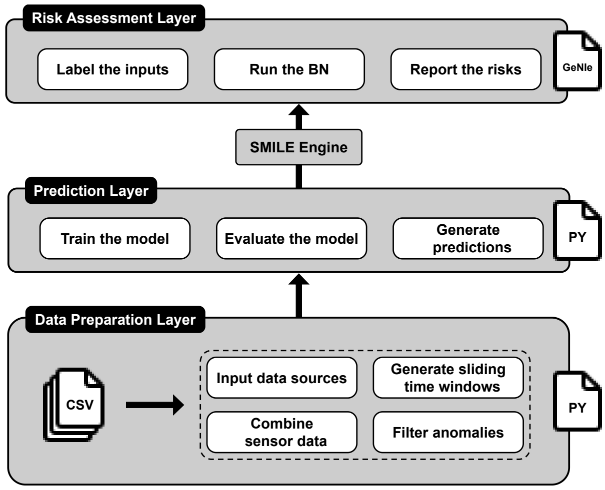

Figure 6. Architecture of the LSTM-Bayesian risk assessment system.

The system's performance was examined under two evidential scenarios. In Scenario 1, representing normal operations, only the predicted methane concentration was used as evidence, while ignition source nodes retained their prior low probabilities. The BN calculated a stable explosion risk probability of approximately 3.5% throughout the period. In Scenario 2, simulating a localized open flame near T0 for three hours, the "open fire" node was set to 1 during this interval. This nearly doubled the explosion risk to 6.8%. Given methane consistently remained below 1% during the study, low absolute probabilities are expected. In practice, operators utilize these relative risk spikes to trigger tiered advisory interventions before deterministic alarms mandate shutdowns.

4.5 Discussion and Implications

The case study validates the framework's core functionalities. The LSTM component demonstrated effective online learning, with predictive accuracy for methane concentration improving to a high level (R^2=0.93) as it adapted to the mine's dynamic environment. The integration with the BN provided a crucial interpretative layer. It translates predicted gas levels into contextualized probabilistic risks, enabling automated safety protocols (e.g., machinery power-offs) within the 1-minute forecast window. Unlike reactive 1% alarms that mandate costly complete operational shutdowns, the system detects ascending trends early. This grants operators crucial lead time to proactively intensify ventilation or slow production, preventing catastrophic financial losses and fatal explosive states. This hybrid approach bridges data-driven prediction and explainable reasoning to support critical decision-making.

5 Conclusions

An innovative system for dynamic risk management in underground environments was introduced, integrating IoT, LSTM, and BNs. A case study in a Chinese coal mine demonstrated its capability to accurately predict methane concentrations and assess explosion risks in real time. The LSTM model achieved high accuracy (R^2=0.93), and the BN provided interpretable, scenario-sensitive risk updates. This integration addresses limitations of purely data-driven or knowledge-driven methods, enhancing safety and operational efficiency.

While the extensive 494-day dataset establishes a robust proof-of-concept, relying on a single mine limits generalizability. Ongoing future work will conduct cross-site validation, benchmark against baseline models, develop 5-10 minute multi-step forecasts for human intervention, apply cost-sensitive learning, and explore digital twin integration.

Acknowledgments

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