

IoT-Bayes fusion: Advancing real-time environmental safety risk monitoring in underground mining and construction

Milad Mousavi ^a, Xuesong Shen ^{a,*}, Zhigang Zhang ^b, Khalegh Barati ^a, Binghao Li ^c

^a School of Civil and Environmental Engineering, UNSW, Sydney, NSW 2052, Australia

^b Chongqing Research Institute of China Coal Technology & Engineering Group, Chongqing, China

^c School of Mineral and Energy Resources Engineering, UNSW, Sydney, NSW 2052, Australia



ARTICLE INFO

Keywords:

Real-time safety risk monitoring
Underground mining and construction
Bayesian networks
Internet of Things
Environmental safety knowledge modeling
Coal mining

ABSTRACT

Effectively managing environmental hazards in underground mining and construction sites is a formidable challenge for project managers and site engineers. These complex underground systems are characterized by inadequate ventilation, hazardous gases, and elevated levels of heat and humidity. However, conventional approaches to underground risk management often rely on static and oversimplified methodologies, which limit the ability to accurately predict and control these multifaceted hazards. This research aims to develop an innovative real-time safety risk monitoring system tailored to underground environments. The proposed system facilitates dynamic and remote monitoring, analysis, and control of safety risks within underground workspaces. The methodology integrates data streams from Internet of Things (IoT) sensors to perceptively capture the underground environment, combined with the application of Bayesian networks (BNs) as a robust probabilistic risk modeling engine. To demonstrate the practicality of the proposed system, two proof-of-concept examples using real datasets collected from underground coal mines in Poland and China are presented. The demonstration effectively showcases the system's applicability and potential benefits. Upon implementation, the proposed system will enable real-time and remote monitoring of underground ecosystems, significantly enhancing the safety and reliability of underground operations.

1. Introduction

In recent years, the global economy and mineral prices have experienced substantial fluctuations, coupled with persistent political uncertainties. These challenges have significantly impacted the underground sector, raising concerns not only about economic viability but also about the safety and well-being of the workforce operating in these environments. The industry faces numerous issues, including declining productivity, a shortage of skilled workers, and increasing concerns about its social and environmental impacts [1]. As shallow coal seams become unsustainable, underground coal mining ventures deeper in search of viable deposits [2]. However, deeper mining brings worsening environmental conditions that directly affect worker safety, including poor ventilation, hazardous gas releases, and high heat levels [3].

Despite technological advancements, historical assessments of coal mine accidents show that major explosions and safety incidents remain difficult to prevent, and current safety measures are often inadequate

[4]. The complex nature of coal mine accidents, influenced by a combination of factors rather than a single cause, adds layers of complexity to risk management in this industry [5]. Additionally, underground construction environments pose further safety hazards, such as wall inclination, water level fluctuations, ground surface settlement, and pillar settlement [6], which significantly threaten worker safety and well-being. Given these complex and multifaceted risks, accurately predicting and managing them effectively is a significant challenge. Therefore, adopting innovative approaches, promoting best practices, and implementing additional safety measures are crucial to ensuring worker safety and maintaining productivity in underground operations.

In underground environments, real-time processing capabilities are crucial due to concerns about environmental hazards. To address this, the widespread use of sensing devices, such as environmental sensors, has become prevalent [7]. These sensors provide immediate measurements of key environmental indicators, allowing for the identification and monitoring of potential dangers [8]. In coal mines, integrating monitoring, supervision, and dispatching systems with machinery,

* Corresponding author.

E-mail address: x.shen@unsw.edu.au (X. Shen).

devices, and transportation networks is a common practice. These systems primarily monitor natural hazards such as methane levels, seismic activity, and fires. However, the data collected from these systems is typically used for visual purposes and lacks the in-depth analysis needed to enhance various coal mining processes [9]. Often, the expertise of safety managers and site engineers is relied upon to monitor and interpret real-time sensing data. However, this expertise is often subjective and heavily dependent on individual experiences. Additionally, its transient nature, combined with the potential turnover of these experts, makes it an unreliable and insufficient long-term organizational asset.

In many regions worldwide, the mining and construction industries still rely on manual methods to evaluate safety risks [10]. However, numerous studies have highlighted the limitations of traditional analysis techniques in quantitatively assessing risks, managing uncertainty, and implementing dynamic control measures [11]. In the highly competitive construction and mining sectors, any disruption in production can lead to missed targets, increased costs, and reduced profitability. Abnormalities or deviations in environmental conditions can hinder smooth underground operations, resulting in productivity losses and financial setbacks. Similarly, delays or inefficiencies in sensor data processing within underground spaces can have the same detrimental effects [12]. Conventional data analysis methods often struggle to manage the large volume, high speed, and diverse nature of data generated in underground environments [13]. Most existing advanced risk assessment methods are predominantly offline and static, making them inadequate for addressing the dynamic nature of underground risks and failing to explore the non-linear relationships within safety data [14,15]. Therefore, it is crucial to develop efficient and timely processing methods for the continuous influx of sensor data to ensure optimal safety and productivity in underground operations.

Despite advancements in sensing technologies and data collection in underground environments, several critical gaps remain. Current monitoring systems mainly focus on visual data representation and lack the analytical depth needed to provide actionable, real-time insights. The reliance on human expertise to interpret sensor data introduces subjectivity and inconsistency, undermining long-term safety management. Furthermore, conventional risk assessment methods are largely static and offline, making them ill-suited for the dynamic and complex nature of underground risks. These methods struggle to handle the vast, rapidly changing, and diverse data generated in underground operations and fail to explore the non-linear relationships inherent in safety data. As a result, there is a clear need for an integrated, data-driven approach that enables proactive, real-time monitoring, assessment, and control of safety risks.

This paper aims to develop a real-time safety risk monitoring and assessment system tailored for underground working environments. The system seeks to address the limitations of conventional static methods by enabling dynamic, remote monitoring, analysis, and control of safety risks in underground spaces. To achieve this, the study employs Bayesian Networks (BNs), renowned for their robust risk assessment capabilities, to effectively represent the complex and probabilistic nature of safety risks in underground mining and construction environments. The system integrates real-time data streams from Internet of Things (IoT) sensors as inputs to the BNs, facilitating continuous monitoring of safety risks. The practicality of the proposed system is demonstrated through two proof-of-concept examples using real data collected from underground coal mines in Poland and China. By meeting these objectives, the research aims to enhance underground safety by providing a comprehensive and efficient approach to real-time environmental safety risk monitoring, empowering safety decisions, and mitigating potential hazards.

The paper is structured as follows: **Section 2** offers a comprehensive review of the relevant literature. **Section 3** introduces the proposed methodology, highlights its key components, and outlines the steps involved. **Section 4** presents two proof-of-concept case studies, demonstrating the significance and practical implications of the proposed

framework. Finally, **Section 5** concludes the paper by summarizing the main findings, highlighting their contributions, and providing suggestions for future research directions.

2. Background and context

This section reviews the latest methods and techniques for enhancing safety in underground construction and mining operations.

2.1. Underground safety challenges and risk assessment methods

Li, et al. [16] established a comprehensive database of underground construction safety risks by integrating knowledge structuring, questionnaires, interviews, and group decision-making. They highlighted the complexity of underground construction risks, which are influenced by factors such as architectural forms, construction techniques, geological conditions, and surroundings. In underground mines, ventilation systems that address gases like CH₄, NO_x, SO₂, CO, and CO₂ significantly impact energy expenditure [1]. Gas accidents are common in coal mines, with methane-related incidents occurring frequently [11]. Mine fires and explosions are typical hazards in underground coal mining, often caused by the spontaneous combustion of coal, ignited firedamp (methane-air mixture), and coal dust [17].

Risk analysis techniques in underground engineering include both qualitative methods (e.g., safety checklists, Delphi technique, interviews) and quantitative approaches (e.g., event tree analysis, fault tree analysis, neural networks) [11]. In the mining industry, there has been increasing emphasis on risk assessment and management, considering ecological, social, and economic factors, as reflected in the growing number of publications and reports on these topics. Given the extensive nature of mining operations and their interactions with the environment, thorough risk analysis is essential for ensuring operational accuracy, equipment safety, and minimizing environmental impact [18].

Cascading hazards in underground projects present significant risks due to the interconnected nature of various infrastructure systems and the complexity of the environment. Zhang, et al. [19] proposed an improved risk assessment methodology that integrated Failure Mode and Effects Analysis (FMEA) with normal wiggly hesitant fuzzy sets (NWFHSS) to enhance expert evaluations of risk factors. The approach gathered insights from experts, grouped them effectively, and ranked the potential risks to identify the most critical ones. This helped improve safety and decision-making in utility tunnel construction projects. Bai, et al. [20] proposed an innovative energy-based coupling risk assessment (CRA) model to quantitatively analyze the risks associated with utility tunnels, which housed various hazardous pipelines. They identified six types of energy and numerous cascading accident scenarios, emphasizing the generalized coupling effect, where changes in one component impacted another. The case studies demonstrated significant fatality and economic risks from natural gas explosions, cable fires, and rain-triggered ponding, underscoring the need for improved preventive measures. Hai, et al. [21] identified several limitations in existing risk assessment methods for cascading underground hazards. They pointed out that many studies focused on static analyses of individual risk factors, neglecting the dynamic interactions between multiple risks. Additionally, there was a lack of dynamic models that accounted for multifactor conditions. To address these issues, the authors called for improved risk indicator systems to enhance efficiency and objectivity, as well as the incorporation of coupling effects between risk factors in risk management practices to ensure comprehensive assessments.

2.2. Leveraging Bayesian networks for underground risk assessment

BNs are graphical models that analyze probabilistic relationships among variables using directed acyclic graphs (DAGs). These models consist of nodes representing variables, connected by arrows that

indicate causality. Since their initial adoption in the late 1990s, BNs have been widely used in risk assessment, reliability analysis, accident modeling, diagnostics, and prognostics [14]. Typically, both the structure and parameters of a BN are determined by learning from sufficient data. For example, Li, et al. [22] used BNs to predict rockburst risks in underground spaces. They estimated conditional probabilities from a dataset of 135 rockburst case histories, including 83 rockburst cases and 52 non-rockburst cases.

In some research areas, data collection can be challenging. In such cases, expert knowledge can be used to determine the BN structure. Wu, et al. [23] presented a quantitative risk assessment method for urban underground utility tunnels using BN modeling. The study identified the worst-case accident scenario involving gas pipeline leakage and incorporated domino effects into the risk analysis. Due to the scarcity of utility tunnel accident data, expert elicitation and traditional data were used to determine conditional probability tables (CPTs). The proposed method was able to quantitatively evaluate risks, support safety management, and assist in emergency decision-making for urban utility tunnel accidents. Tong, et al. [24] developed a BN to explore factors contributing to mine gas explosions. The model integrated expert knowledge and probabilities derived from the Delphi method, addressing the complex interplay of multiple gas sources and their impacts. The model effectively represented influential factors, accounted for uncertainties during disaster evolution, and allowed for dynamic probability updates. Wu, et al. [25] introduced a Dynamic Bayesian Network (DBN) to analyze the gradual damage to road surfaces caused by tunneling activities over time. The authors used relevant standards, technical reports, expert experiences, and fault trees to construct the DBN and establish relationships.

Recent advancements in integrating BNs with various tools and modeling frameworks were comprehensively examined by Marcot and Penman [26]. Notably, the literature reflects a growing trend of incorporating BN models into management decision networks, causal network modeling through structural equation modeling, Bayesian neural networks, hybrid discrete and continuous variable models, object-oriented and agent-based models, state-and-transition models, geographic information systems, and even quantum probability. The authors highlight a significant research gap, emphasizing the need for self-updating and self-improving BNs capable of learning from real-time continuous inputs derived from monitoring data.

2.3. IoT for enhanced underground safety monitoring

The IoT technology has been extensively used in various sectors, including manufacturing and transportation, offering effective solutions [27]. Recently, IoT integration has led to positive changes in underground safety, resulting in improved safety protocols and operational efficiency. Wu, et al. [4] conducted a study on an IoT-based dynamic information platform specifically designed for underground coal mines. This platform used IoT technology to monitor and record operational data related to coal mine production systems and track the locations of underground equipment and miners. Key components of the platform included a 3D virtual mine system, a safety diagnosis system, a safety inspection system, and an emergency rescue system. In a separate study, Zhang, et al. [28] proposed an Artificial Intelligence Internet of Things (AIoT) system for real-time monitoring of tunnel construction. IoT sensors were effectively deployed to capture real-time shield data parameters. Before tunnel construction, a detailed determination of geometric and geological parameters was carried out. The authors used Random Forest models to achieve accurate predictions of operational parameters for successive rings and resulting settlement.

Ye, et al. [29] emphasized the critical role of IoT in enhancing safety management and early warning systems in tunnel construction, which often faces accidents due to challenging geological conditions. Their proposed digital twin (DT) platform utilized IoT technologies to facilitate real-time data collection and monitoring through wireless sensor

networks, enabling dynamic interaction between physical and virtual environments. By integrating multi-source data, the platform improved safety management accuracy and allowed for timely responses to potential hazards. Liu, et al. [30] focused on optimizing fire emergency response in metro systems, using the Simenkou metro station in Wuhan as a case study. The authors developed a multi-objective optimization model to minimize both the number of firefighters deployed and the total emergency response time during a fire. A key element of their approach was the integration of IoT, which allowed commanders to make informed decisions based on real-time data from sensors. This method improved the coordination of firefighting teams and ensured a more efficient allocation of resources during emergencies. The study highlighted that IoT's ability to provide immediate feedback was crucial for enhancing the overall effectiveness of emergency response strategies in urban environments.

Zhou, et al. [31] examined the technical challenges associated with deep underground activities, particularly focusing on rockburst risks and rock mass instability. The authors reviewed various assessment methods, including empirical approaches, simulations, mathematical modeling, and microseismic monitoring, while emphasizing the importance of control strategies for effective energy utilization within rock masses. The paper suggested six directions for implementing intelligent management techniques to mitigate hazards during underground operations. It highlighted the role of IoT technology in mine monitoring and management, which enabled equipment connectivity and real-time data collection, thereby enhancing the accuracy and efficiency of rockburst prediction and prevention. Zhang, et al. [32] introduced the concept of the Mine Internet of Things (MIoT) and discussed its potential contributions to enhancing mine safety. MIoT was described as a network of interconnected sensors and actuators installed at mine sites, designed to enable real-time monitoring, accident prediction, process optimization, and effective personnel and equipment management. The authors outlined the fundamental structure of MIoT systems, which consists of three layers: the perception and control layer, the network layer, and the application layer. The study highlighted various MIoT applications, including environmental monitoring, fire detection, personnel and equipment positioning, and production safety management.

2.4. Research gaps

State-of-the-art literature highlights significant progress in enhancing underground safety monitoring and risk assessment through advanced probabilistic models and IoT technologies. BNs have been widely adopted for modeling complex underground risk scenarios, using both data-driven and expert-based approaches to establish probabilistic relationships among critical variables. These models have proven effective in analyzing accident causes, predicting risks like gas explosions, and supporting decision-making processes. Additionally, IoT technologies have revolutionized underground safety by enabling real-time monitoring of environmental conditions, equipment, and personnel. Integrated platforms now offer a comprehensive view of operational data, enhancing situational awareness and facilitating better emergency response and resource allocation. The incorporation of AI algorithms, such as machine learning models, has further improved predictive accuracy, allowing for timely interventions to prevent accidents.

Despite these advancements, current systems often struggle to provide real-time, actionable insights essential for effective risk management in dynamic underground environments. Most existing BN-based risk assessment models rely on static data or human interpretation, limiting their ability to adapt dynamically to real-time changes. This lack of adaptability reduces their effectiveness in rapidly evolving conditions, where timely risk predictions are crucial. Moreover, while IoT systems have significantly enhanced data availability, their integration with advanced probabilistic models like BNs remains underexplored, particularly in real-time risk prediction and decision-making contexts.

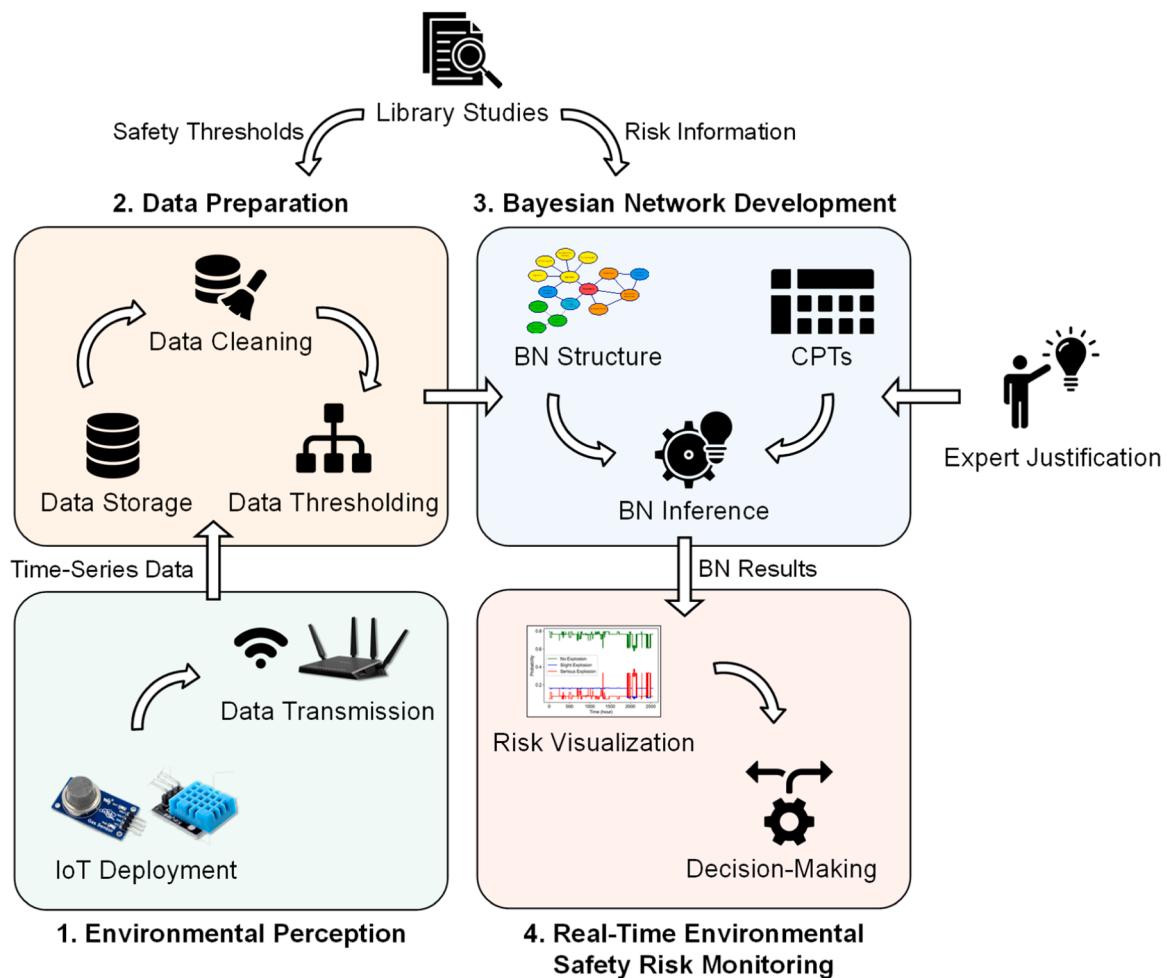


Fig. 1. Proposed IoT-Bayes framework for real-time underground environmental safety risk management.

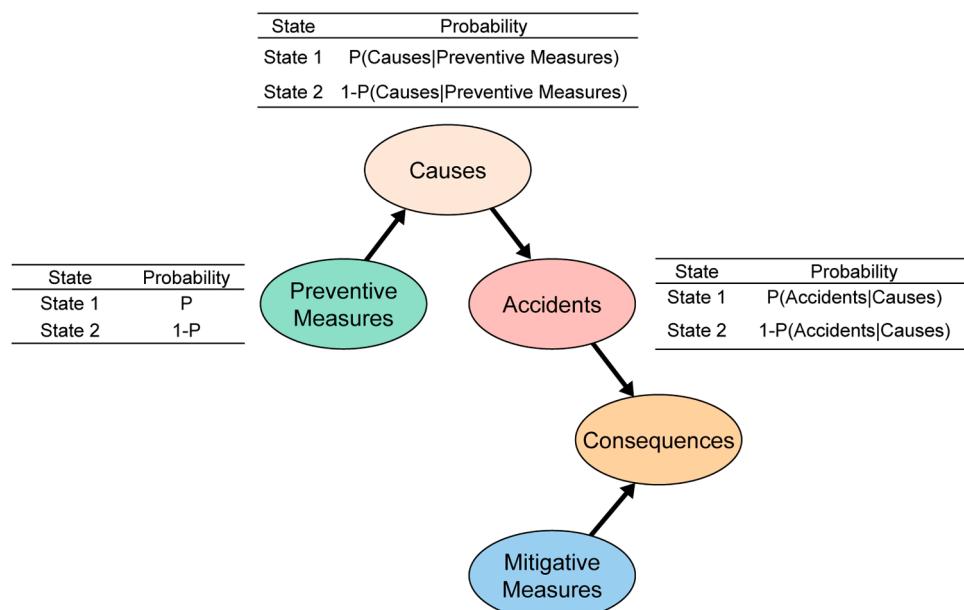


Fig. 2. The cause-consequence correlation and CPTs in a BN for environmental safety accidents.

Table 1

Causes and consequences of methane explosions in underground coal mines.

Category	Influenced By	Influencing On
Causes		
Ignition sources	Friction spark; Open fire; Electric spark; Spontaneous heating	Methane explosion
Methane overrun	Methane emission from goaf; Leakage of methane drainage pipe; Methane discharge from coal seam; Ventilation conditions; Preventive measures	Methane explosion
Concentration of oxygen	None	Methane explosion
Ventilation conditions	Atmospheric pressure change; Wind speed	Methane overrun
Consequences		
Successive explosions	Methane explosion; Mitigative measures	Casualties; Economic loss
Casualties	Methane explosion; Successive explosions; Mitigative measures	None
Economic loss	Methane explosion; Successive explosions; Mitigative measures	None

Addressing these gaps could lead to more dynamic and responsive risk management systems, paving the way for safer underground operations.

3. Proposed framework

Fig. 1 presents an overview of the research framework, which consists of four interconnected modules. The first module involves deploying IoT sensors in the underground environment to collect data on environmental factors such as methane levels, wind speed, temperature, and atmospheric pressure. This environmental data is then cleaned and labeled based on specified thresholds in the data preparation module, before being used as input for the developed BN. The BN assesses safety incidents in real-time, updating the probabilities and outcomes of accidents based on interrelated causes. The BN's risk evaluation results are displayed graphically to compare different scenarios, aiding safety operators in decision-making. Detailed explanations of each framework module are provided in the following sections.

3.1. Environmental perception

The IoT is defined as a multi-layered system that enables the interconnection of devices and real-time data visualization through three key layers: sensing, transmission, and application. The sensing layer consists of various sensors that collect critical environmental data, forming the foundation of IoT. The transmission layer ensures the reliable transfer of these data packets from the sensing devices to a centralized data processing center, often requiring relay nodes such as base stations to maintain efficient communication. Lastly, the application layer processes and analyzes the collected data, enabling improved decision-making and service delivery—crucial for enhancing system control and risk management in industrial environments [33]. IoT is distinguished by its ability to connect all equipment within an industrial system, facilitating the sharing of accurate, timely information essential for effective risk management. By integrating IoT, the system achieves real-time centralized control, minimizing decision-making errors and improving responsiveness to emergencies, thereby reducing the spread of risk. This comprehensive and integrated IoT network significantly enhances the system's ability to manage, avoid, and mitigate risks, addressing the critical need for information integrity in industrial environments [34].

The first module of the proposed framework utilizes IoT sensors to gather real-time underground environmental data. These sensors measure parameters such as gas concentration, wind speed, air pressure, temperature, and humidity. Therefore, the sensors must be strategically installed throughout the underground space, following a deployment strategy that ensures comprehensive coverage of environmental

Table 2

Experts' opinions for enhancing the developed BN.

Modification Type	Subject Variable(s)	Experts' Commentary
Remove a variable	Atmospheric pressure change	Changes in air pressure can cause an increase in the methane emission rate, especially from the extracted areas, and can also alter the explosive range of methane. Since this study measures the final concentration of methane in the mine roadways through sensors, the methane emission rate is not a determining factor. Therefore, changes in air pressure cannot be considered as a direct influencing factor on ventilation conditions.
Remove a variable	Concentration of oxygen	The level of oxygen available in roadways, considering its direct relationship with the quality of the air necessary for personnel respiration, is not a factor that can be altered to control explosions. Therefore, in most cases, the available oxygen level will always remain within a constant and safe range.
Add an assumption	Wind speed	The wind speed itself cannot determine the ventilation status; instead, the quantity of air indicates the required air volume to dilute the flammable gases. However, considering that this study takes place in a specific location in the mine and assuming a constant roadway geometry, the wind speed can be considered to represent the quantity of air.
Add a variable	Inflow quality	In addition to the air quantity, the level of methane in the incoming air also affects the ventilation conditions. This methane level can be measured using sensors installed in the main gate.
Add a relationship	Preventive Measures; Ignition	Preventive measures can be used not only to reduce the methane concentration in the atmosphere but also to eliminate or mitigate the ignition sources.
Combine variables	Methane emission from goaf; Leakage of methane drainage pipe; Methane discharge from coal seam	Since the final methane concentration in the tailgate is determined using sensors, it is not necessary to break it down into its emission sources.

conditions. Key locations requiring continuous monitoring in underground environments include the working face, ventilation gates, and roadways. The data collection interval varies, ranging from seconds to hours, depending on the specific hazards being investigated, the environmental factors under consideration, regulatory requirements, the type of underground environment, and its inherent characteristics. Careful planning of the deployment strategy is essential to accommodate these factors.

The collected data must be transmitted to a designated data storage system for subsequent use in the following modules of the proposed framework. In coal mining applications, industry standards and common practices recommend Wi-Fi as the primary wireless technology for data transmission, followed by LTE and 5 G [35]. Therefore, when selecting data transmission tools, careful consideration should be given

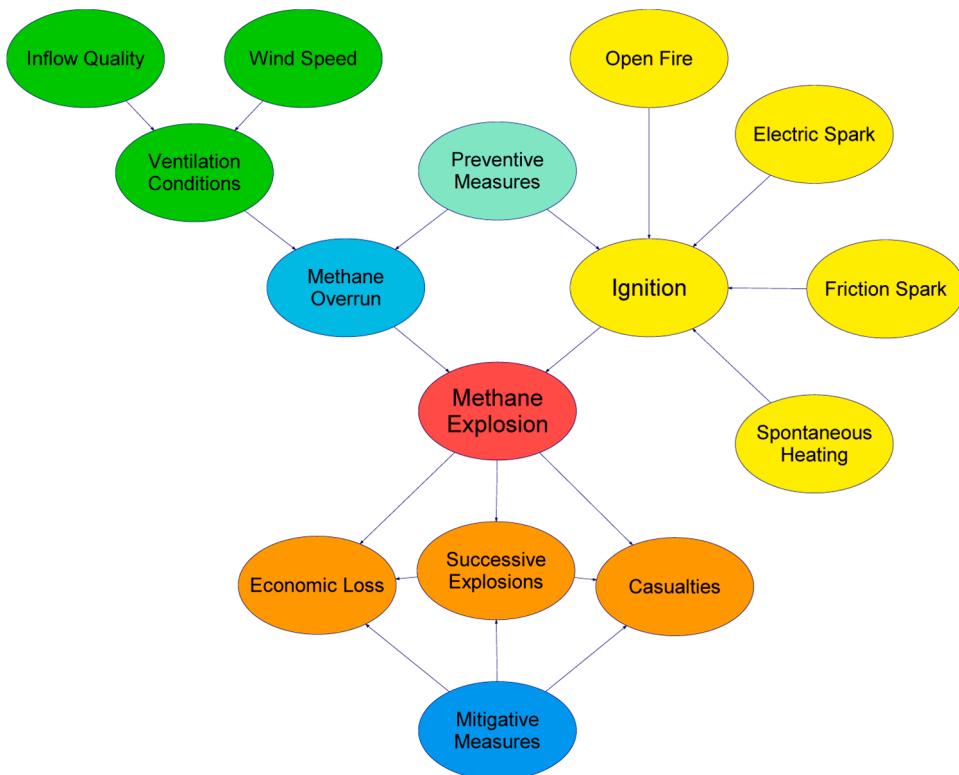


Fig. 3. Final BN for methane explosions in underground coal mines.

to these wireless technologies based on their suitability for the underground environment. Further insights into the use of communication technologies in underground settings can be found in the study by Li and Saydam [36].

3.2. Data preparation

The likelihood of generating flawed data is minimized when sensors are accurately installed and calibrated. However, since IoT data is collected and transmitted in real-time, missing data may still occur in the collected dataset. Several factors contribute to missing data in industrial monitoring systems like IoT sensors, including sensor inactivity, data transmission dropouts, and data storage failures [37]. These issues can create gaps in data collection, complicating accurate real-time risk analysis. Addressing missing data is essential for maintaining the reliability and effectiveness of the proposed risk monitoring system. For real-time series data, one effective method for handling missing data is to fill gaps using the most recent meaningful data [38].

The data collected from IoT sensors initially exists as numerical time-series data, while the BN requires categorical data as input. Therefore, a crucial data cleaning and thresholding process is necessary to transform the raw data into a suitable format for the BN. The cleaned data must undergo thresholding based on the specific requirements of the BN. At this stage, a review of existing regulations and relevant documents is needed to establish appropriate thresholds for categorizing the data generated by each type of sensor. For example, if methane concentration exceeds one percent in certain locations within a coal mine, it can disrupt mining operations and cause concern among workers [39]. As a result, the one percent threshold can be defined to classify methane concentration levels as serious or slight. Concentrations below this threshold are labeled as slight, while values exceeding it are classified as serious. These discrete categories then serve as evidence within the BN model to update the risk assessment of other nodes in the network. This logical approach can also be applied to raw environmental data generated by other sensor types.

3.3. Bayesian network development

The proposed framework incorporates BNs as robust tools for risk assessment. BNs are DAGs that effectively represent probabilistic relationships among variables. A DAG does not contain cycles, meaning there is no way to start at one node and follow the directed edges back to the same node. This structure is essential for modeling causal relationships, as it prevents circular dependencies. The acyclic nature of a DAG ensures that relationships can be analyzed clearly, enabling efficient probability computations and a better understanding of complex systems [40]. In a BN, nodes represent random variables, and directed edges indicate probabilistic dependencies or causal relationships between these variables. Each node can take values from a finite set of mutually exclusive and collectively exhaustive states [41]. An edge from node X_j to node X_i indicates that X_j has a direct influence on X_i . This relationship is often interpreted as X_j being a parent of X_i , and X_i being a child of X_j . Each node X_i has an associated conditional probability distribution $P(X_i|Parents(X_i))$, which quantifies the effect of the parent nodes on the child node. If a node has no parents, its distribution is simply $P(X_i)$ [42].

To begin BN modeling, the network structure must be established. This involves specifying the directed edges to represent dependencies and conditional independence among the input variables. The structure is typically determined using domain knowledge or data-driven learning. In the context of safety and disaster risk management, each node in the BN can represent a potential cause or consequence of accidents [43]. Following this approach, the proposed framework adopts a similar method for determining the structure of the BN. Fig. 2 provides an example of a cause-consequence relationship selected for investigating environmental safety accidents in this study.

Once the BN structure is defined, it is essential to quantify the strength of the relationships among variables using CPTs. CPTs specify the conditional probabilities for each variable, given its parent variables in the network [44]. Fig. 2 shows sample CPTs for three nodes in the network. Since the preventive measures node has no parent nodes, its

Table 3
An overview of the final BN variables.

Type	Variable	Description	States	Mode
Cause	Ignition	Presence of an ignition source.	Yes/No	Dependent
	Open fire	Presence of open fire sources such as smoke, cutting or welding, or blasting flame.	Yes/No	Offline
	Electric spark	Presence of electric spark sources such as static electricity or electrical failure.	Yes/No	Offline
	Spontaneous heating	Presence of spontaneous heating sources such as coal spontaneous combustion or self-ignition of macromolecular materials.	Yes/No	Offline
	Friction spark	Presence of friction spark sources such as friction between metal and rock.	Yes/No	Offline
	Methane overrun	Exceedance of methane concentration in the tailgate, which may result from gas leakage from drainage pipes, emissions from goaf, and discharge from the coal seam.	Serious/Negligible	Online/Dependent
	Ventilation conditions	Performance of the ventilation system.	Poor/Acceptable	Dependent
	Wind speed	Speed of the airflow within the tailgate.	Inadequate/Adequate	Offline/Online
	Inflow quality	Methane concentration in the maingate.	Poor/Acceptable	Offline/Online
	Methane explosion	Risk of methane explosion.	Yes/No	Dependent
Consequence	Casualties	The severity of the methane explosion's casualties.	Severe/Slight/None	Dependent
	Economic loss	The severity of the methane explosion's economic loss.	Severe/Slight/None	Dependent
	Successive explosions	The severity of the methane explosion's successive explosions.	Severe/Slight/None	Dependent
Preventive measures	Preventive measures	Control measures for causes like shearer slowdown, power cut off, or water barriers.	Poor/Effective	Offline
Mitigative measures	Mitigative measures	Control measures for consequences such as post-drainage or emergency responses.	Poor/Effective	Offline

CPT defines the prior probability of these measures. The causes node represents factors that can lead to an accident, such as equipment failures or unsafe conditions, and it depends on the preventive measures node. Its CPT shows the probability of causes occurring, given that preventive measures are in place. The accidents node depends on the causes node, and its CPT indicates the probability of an accident occurring, given the presence of causes. Assuming the BN consists of n nodes, the joint probability distribution over all variables in the network is expressed by Eq. (1).

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

where X_i denotes the i^{th} random variable, and $\pi(X_i)$ represents the set of parent nodes of X_i .

In an ideal scenario, acquiring a BN's structure and conditional probabilities can be facilitated by the availability of historical data. However, in the case of environmental safety accidents, particularly those in underground environments, comprehensive and reliable historical datasets are often limited. As a result, alternative methods must be employed to construct the BN. A practical approach is to consult various resources, such as standards, regulations, technical and accident reports, and scholarly publications, to obtain the structure and conditional probabilities needed for the BN when such datasets are lacking. In these cases, it is crucial to involve domain experts to validate the structure and conditional probabilities of the BN and ensure the accuracy of its inference outcomes [25,45].

3.4. Real-Time risk assessment and monitoring

After constructing the BN, the next step is to introduce real-time IoT data as new evidence into the network. This dynamic process triggers the belief updating mechanism within the BN. Belief updating recalculates the probabilities of the nodes (variables) in the BN when new evidence or data is introduced. This involves adjusting the network's CPTs to reflect the impact of the new information, ensuring that the posterior distributions of the variables accurately represent the current state of knowledge. Essentially, belief updating enables the network to dynamically incorporate observations from sources like inspection measurements or continuous monitoring systems, refining the risk assessment or prediction based on the most recent data [46]. As new data streams into the network, the probabilities associated with the accident node are recalculated considering the latest information. For a variable A dependent on a variable B , the updated probability is computed using Bayes' Theorem as shown in Eq. (2):

$$P(a_i|b) = \frac{P(b|a_i)P(a_i)}{P(b)} \quad (2)$$

where a_i denotes the i^{th} state of variable A , b is a state of variable B observed as evidence, $P(a_i|b)$ is the posterior probability of a_i given the evidence b , $P(a_i)$ is the prior probability of a_i , $P(b|a_i)$ is the likelihood of observing evidence b given a_i , and $P(b)$ is the marginal probability of the evidence b . Inference in BNs involves computing the posterior distribution of a subset of variables given evidence about other variables [42]. Additionally, the probabilities associated with the various causes and consequences linked to the accident node are also updated. This process is repeated whenever additional evidence is observed. This continuous refinement of probabilities allows the BN to provide real-time insights, adapting to changing conditions and enhancing the accuracy of risk assessments and predictions.

Based on the risk assessment results obtained from the BN developed in the previous module, a real-time risk progression chart is generated for the target nodes, providing decision-makers and safety managers with valuable insights. This chart helps anticipate safety accidents, identify probable causes, and implement preventive measures to

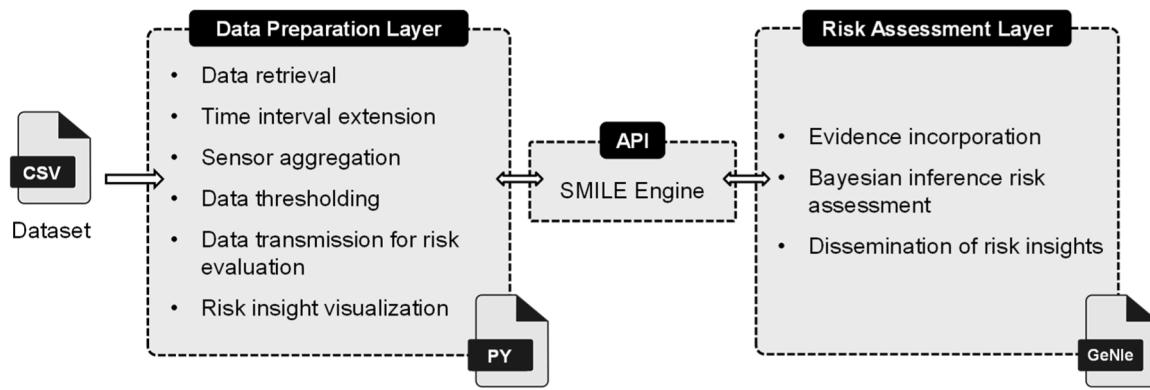


Fig. 4. IoT-Bayes fusion system architecture.

Table 4
An overview of the characteristics of the utilized sensors from the Polish mine.

Sensor Type	Unit	Code	Min	Max	Mean	SD
Methane meter MM-2PWk	% CH ₄	MM261	0	30	0.049	0.125
		MM262	-0.2	30	0.051	0.136
		MM263	-2	30	0.248	0.197
		MM264	-2	40	0.327	0.206
		MM256	0	30	0.43	0.204
Anemometer [-5, 5]	m/s	AN422	0	2.4	1.655	0.128

manage and mitigate the impact of accidents and their outcomes. Safety managers responsible for underground environments can adjust the BN variables to simulate various scenarios and promptly observe how these changes affect the dynamic risk progression charts.

4. Case studies on underground coal mines

Coal mining generates methane as a by-product, with the gas being trapped under pressure within coal seams and gradually released into the mining site as coal extraction progresses [47]. Beyond its flammability, even at low concentrations, methane levels ranging from 5 % to 15 % are considered explosive [48]. Methane explosions have consistently been a major hazard in underground coal mines worldwide [49]. Despite recent technological advancements, methane explosions remain

the leading cause of fatal accidents in the mining industry [50]. Additionally, these explosions damage mining machinery and equipment, resulting in significant economic and productivity losses for mining companies. Methane explosions also make existing coal dust flammable, leading to subsequent explosions [24]. To mitigate these hazards, mine operators typically shut down all mining activities when methane concentrations exceed 1 % in designated areas. This precaution significantly slows down mining activities and imposes substantial financial losses, amounting to millions of dollars, on affected companies [50]. Given the critical importance of addressing methane explosions and the complexity of such incidents, further research is crucial to improve the prediction of methane explosions and implement effective preventive and mitigative measures. To demonstrate the applicability of the proposed framework, two case studies were conducted to predict the real-time progression of methane explosion risk in underground coal mines in Poland and China. The following sections provide a detailed breakdown of the framework implementation for these proof-of-concept cases.

4.1. BN instantiation for methane explosions

As a key part of the case study implementation, a BN was developed to assess the risk of methane explosion incidents in underground coal mines. Due to the lack of a reliable dataset on historical methane explosions, an extensive review of relevant literature was conducted to

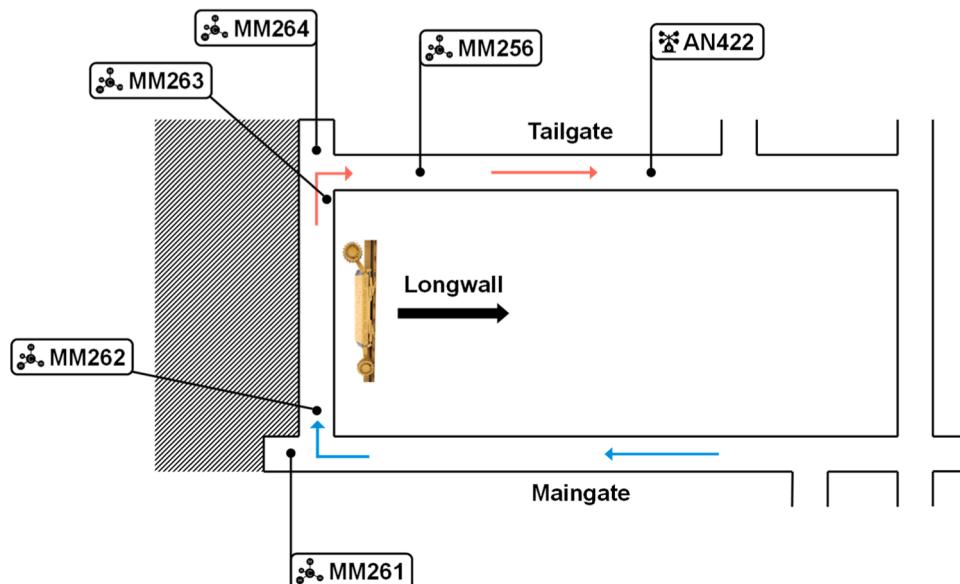


Fig. 5. Spatial distribution of the utilized sensors within the Polish coal mine area map.

Table 5

Description of the prepared inputs for the developed BN for the Polish mine.

Associated BN Node	Value Derivation	Threshold	Min	Max	Mean	SD
Inflow Quality (%)	Avg (MM261, MM262)	Poor: > 1 Acceptable: < 1	-0.10	4.05	0.050	0.075
		Inadequate: < 0.15 Adequate: > 0.15	0.09	2.22	1.655	0.114
Wind Speed (m/s)	AN422	Serious: > 2 Negligible: < 2	0	2.29	0.335	0.135
Methane Overrun (%)	Avg (MM263, MM264, MM256)					

Table 6

A summary of the developed scenarios for the Polish mine.

No.	Input Evidence	Time Point/Interval	Rationale for Scenario Development
1	Methane Overrun [Online]	At each time step	This serves as a baseline to assess the system's ability to monitor methane overrun in real time under normal operating conditions. The aim is to provide a standard risk progression with minimal intervention.
2	Wind Speed [Online]	At each time step	Focuses on testing how well the system can predict explosion risks when ventilation parameters (wind speed and inflow quality) change in real time. Ventilation is a critical aspect in maintaining safe methane levels underground, making this scenario relevant for assessing environmental changes.
	Inflow Quality [Online]	At each time step	
3	Methane Overrun [Online]	At each time step	Introduces a period of preventive failure, simulating real-life situations where preventive measures might be insufficient or poorly implemented. This scenario is designed to assess how the system manages multiple risk factors and sudden spikes in danger, especially when combined with ignition sources (open fire).
4	Preventive Measures = Poor	Time step < 0.7E+5	
	Open Fire = Yes	0.3E+5 < Time step < 0.9E+5	
	Preventive Measures = Effective	Time step > 0.7E+5	
	Methane Overrun [Online]	At each time step	A scenario designed to showcase the system's capability in managing mitigative measures post-failure.
	Preventive Measures = Poor	At each time step	Here, the focus shifts to how mitigative efforts (like firefighting or ventilation adjustments) can reduce the severity of consequences, even when preventive measures fail.
	Open Fire = Yes	0.3E+5 < Time step < 0.9E+5	
	Mitigative Measures = Poor	Time step < 0.7E+5	
	Mitigative Measures = Effective	Time step > 0.7E+5	

construct the preliminary network structure and determine the prior probabilities for each root node. The conditional probabilities for intermediate nodes were then estimated based on reasonable assumptions and established relationships documented in the literature. A detailed literature-based BN is presented in the paper by Mousavi, et al. [51]. Table 1 provides a summary of the most significant causes and consequences of methane explosions in underground coal mines, derived from a review of similar studies. The variables listed in Table 1 were collected from studies by He, et al. [3], Li, et al. [11], You, et al. [15], Muduli, et al. [17], Tong, et al. [24], Mottahedi, et al. [52]. In selecting the variables for Table 1, the focus was on those most likely to change over time during operation. Consequently, factors such as the quality of the ventilation system design or the type of coal seam being exploited, which are likely to remain constant, were excluded from this study.

Three experts were consulted to verify the constructed structure and validate the reliability of the BN outcomes. First, two experienced academics, renowned for their expertise in underground mine ventilation systems, mine explosives, and gas management, were individually approached to review the network's structure and the causal relationships between nodes. Their input helped refine the network's structure, ensuring that the identified causes and consequences were accurately connected. Next, a ventilation officer with substantial experience in underground coal mines was invited to validate the final structure and confirm the reliability of the risk assessment results. Drawing on years of practical experience with ventilation systems, this expert provided a valuable practical perspective and validation of the model.

The consultations were conducted in one- to two-hour sessions using a semi-structured format. The interviews began with an overview of existing methane concentration datasets and an introduction to the available sensors and their locations in the coal mine cases. The experts were then asked to evaluate the overall structure of the preliminary network, focusing on identifying any potential redundancies or missing factors. They assessed the structure and conditional probabilities of each section of the BN, providing detailed analysis and recommending improvements based on their expertise and experience. The research team carefully considered the experts' recommendations and incorporated the necessary adjustments into the network to refine the model. The insights and feedback provided by the experts were compiled and summarized in Table 2.

Fig. 3 displays the updated BN, which includes eight distinct node categories: methane overrun, ignition, ventilation, accident, consequences, preventive measures, and mitigative measures. Each category is visually differentiated by a distinct color scheme. Table 3 provides a comprehensive explanation of the variables present in the updated BN. The BN was constructed using BayesFusion's GeNIE Modeler [53].

The mode assigned to each variable is specified in the last column of Table 3. Variables are categorized as offline, online, or dependent. Offline variables serve as root nodes, where users directly input evidence. These variables do not receive real-time data from IoT sensors. For example, if ignition sources are detected at a specified location, users must set the state to "yes," and the model will then adjust the risk assessment for all other nodes accordingly. Online variables, in contrast, automatically receive real-time values without user intervention. These nodes represent dynamic variables that change over time. Dependent variables do not receive direct input from users or real-time data; instead, their values are computed based on evidence from root nodes and the probabilistic relationships defined within the BN. Bayesian inference is used to propagate probabilities throughout the network and calculate the posterior probabilities of these dependent nodes. Both inflow quality and wind speed can either receive real-time data or be directly adjusted by users. Methane overrun is the only node in the network that can function both as an online node and a dependent node, depending on user preferences.

4.2. IoT-Bayes fusion

The next phase of the case implementation involved developing a system to link IoT data streams with the constructed BN. Fig. 4 illustrates the architecture of the IoT-Bayes fusion system created for this purpose. The system consists of two layers: data preparation and risk assessment. In the data preparation layer, the dataset is retrieved and processed according to the procedures outlined in Section 3.2, ensuring it is properly formatted for input into the BN described in Section 4.1. To integrate these layers seamlessly, the Python wrapper for the SMILE Engine [54] was used. The SMILE library includes a set of C++ classes for managing the GeNIE Modeler through an Application Programming Interface (API). The prepared data is then entered into the BN's online nodes as evidence within the risk assessment layer. Bayesian inference procedures are employed to propagate risk and generate insights as specified by the user. These insights are then fed back to the data

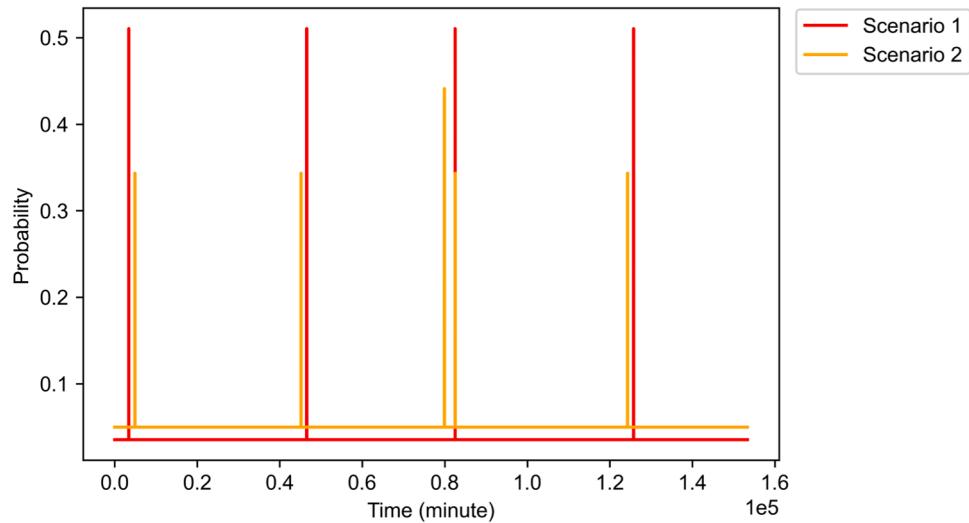


Fig. 6. Methane explosion risk progression in Scenarios 1 and 2 for the Polish mine.

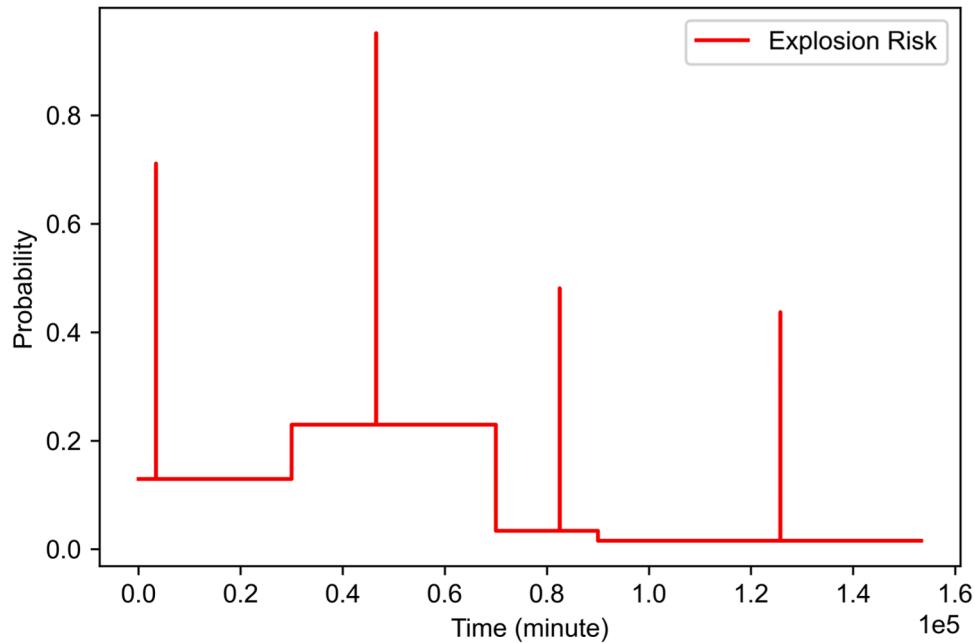


Fig. 7. Methane explosion risk progression in Scenario 3 for the Polish mine.

preparation layer for visualization and presentation, aiding in decision-making.

4.3. Case study on open-access data from a coal mine in Poland

This case study simulated real-time IoT data streams using an open-source dataset from an underground coal mine in the Upper Silesian Coal Basin in Poland. The dataset is publicly accessible in the Mendeley data repository, as referenced by Sikora and Wróbel [55]. It includes data from 28 sensors strategically placed throughout the mine from March 2, 2014, to June 16, 2014. The dataset covers environmental data from the mine and the operational status of a longwall shear, comprising a total of 9199,930 time-sensitive readings taken at one-second intervals, complete with timestamps and measurements. Notably, the dataset contains no missing values, ensuring its completeness and reliability. A detailed overview of the sensor types used in the dataset can be found in Kozielski, et al. [56]. Table 4 lists the sensors used in this case

study, while Fig. 5 shows their spatial distribution within the coal mine.

The data collected from environmental sensors was gathered using the SMP-NT safety system, designed for monitoring conditions in underground environments with risks of methane and coal dust explosions. The SMP-NT system facilitated near-continuous communication with underground sensors. This data was then transmitted to a central dispatching system called THOR, which served as a hub for storing and visualizing the environmental data in real-time. The THOR dispatching system was used in the control room to ensure continuous monitoring of underground conditions [56].

The dataset had no missing values. Initial measurements were recorded at one-second intervals. However, these intervals were deemed impractical for the study, as significant changes within each second were not expected. Additionally, short intervals could exacerbate the impact of outliers, potentially resulting in false alarms. Therefore, the authors decided to extend the time steps to 60 s (1 min). This adjustment involved averaging the measurements collected within each 60-second

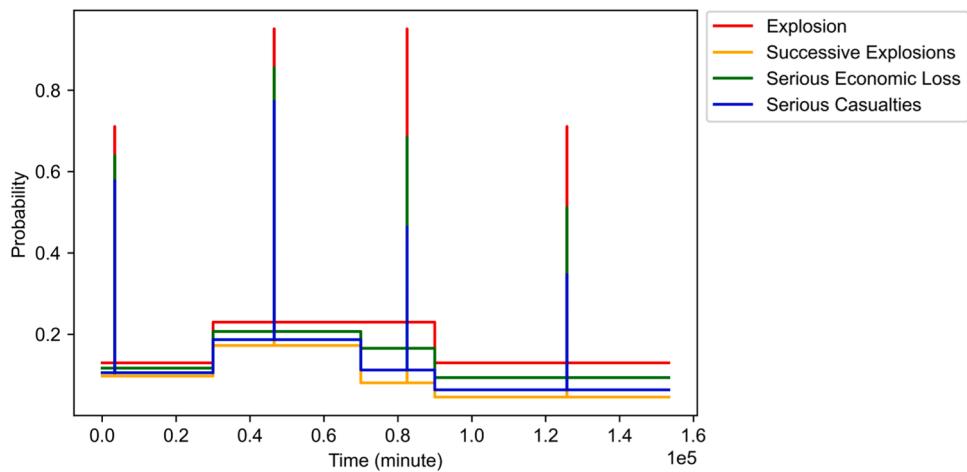


Fig. 8. Impact of mitigative measures on explosion consequences in Scenario 4 for the Polish mine.

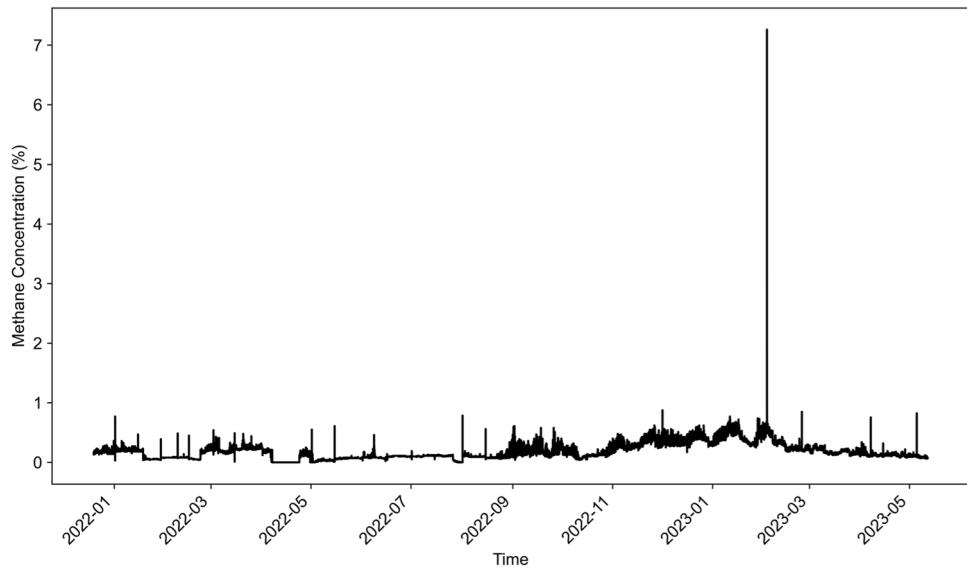


Fig. 9. Cleaned sensor data trend in the Chinese dataset.

interval to represent each time step. This approach aimed to reduce the influence of outliers while giving mine safety managers and personnel a sufficient timeframe to implement necessary preventive measures. As a result, the dataset was reduced to 153,333 data samples for each sensor used in the study.

A strategy was implemented to address erroneous sensor measurements. Instead of relying solely on individual sensor values, the average measurements from closely situated sensors were aggregated and used as inputs for their respective nodes in the developed BN. Specifically, the mean values from three sensors—MM263, MM264, and MM256—located near the junction of the mine face and tailgate, were used to trigger the methane overrun node. This location is crucial for gas monitoring due to high-intensity activities such as digging, blasting, coal dropping, and transportation [57]. Similarly, the average readings from MM261 and MM262 were used to activate the inflow quality node, as these methane meters were positioned close to each other in the main-gate. The readings from AN422 were directly used to provide evidence for the wind speed node, as it was the only sensor in the tailgate measuring air velocity.

The next step in data preparation involved translating the numerical sensor measurements into states that the BN could interpret. Each input was thresholded based on predefined criteria to achieve this. Acceptable

methane levels in underground coal mines can vary worldwide due to differing regulations in various countries. Additionally, different sections of a mine may have varying maximum threshold limits even within a single location. For this case study, the coal mine was located in Poland. Therefore, the regulatory standards of Poland were used to determine the permissible maximum methane concentrations. Specifically, methane concentrations exceeding 2 % and 1 % were classified as serious or poor for the air exiting and entering the mine face, respectively, as stated by Tutak, et al. [58]. For wind speed, any recorded measurements below 0.15 m/s were considered inadequate, while those exceeding this threshold were deemed adequate [3]. Table 5 describes the three distinct inputs prepared for integration into the developed BN.

To demonstrate the practicality of the proposed framework, four hypothetical scenarios were created to represent various situations that could potentially arise during the operation of an underground coal mine. These scenarios were designed to showcase the framework's specific capabilities. Table 6 summarizes the details of these scenarios, the input evidence provided to the model at designated times, and the reasoning behind their selection.

In Scenario 1, the variables within the developed BN were kept in their initial states. Meanwhile, the methane overrun node received real-time input from the simulated IoT data stream at each time step. As a

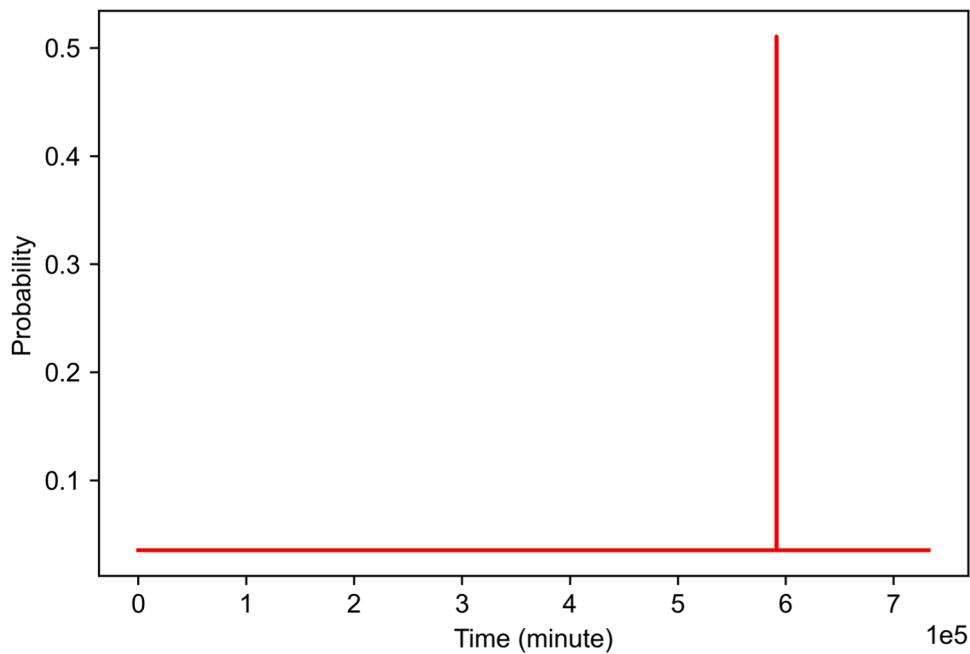


Fig. 10. Predicted risk of explosion based on methane concentration in Chinese mine data.

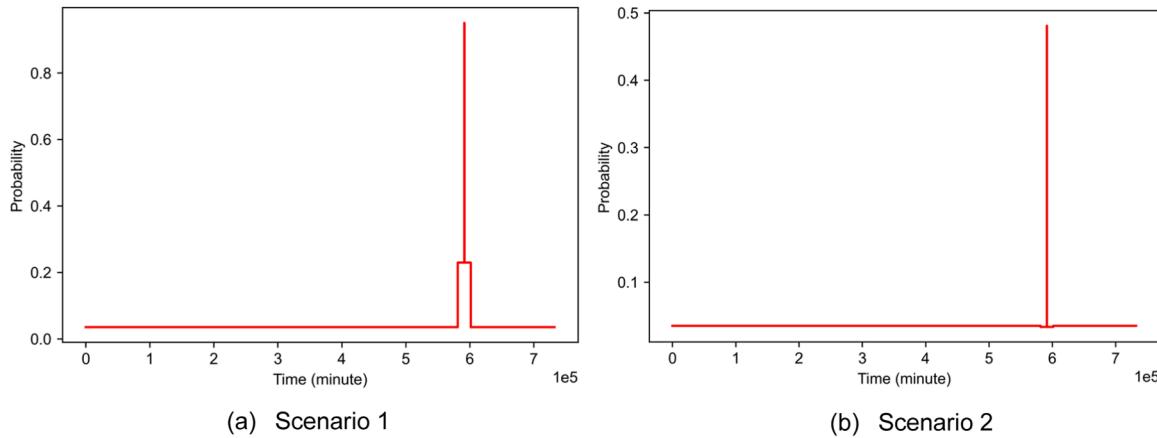


Fig. 11. Predicted risk of explosion Chinese mine data for Scenarios 1 and 2.

result, the value of the methane overrun node at each time step could be classified as either negligible or serious based on predefined thresholds described in Section 4.1. After incorporating the real-time data into the network, the probabilities of all other variables were updated iteratively. Fig. 6 visually presents the progression of methane explosion risk over the data collection period. Notably, distinct spikes in explosion probability appear at regular intervals, which may be due to periodic sensor performance tests or specific activities causing immediate methane releases in the roadways. However, the peak predicted explosion risk during these spikes only marginally exceeded 0.5. This result can be attributed to the assumption in this scenario that all network variables remained in their prior states (e.g., preventive measures were assumed to be 80 % effective at all times), with no observable evidence suggesting any changes.

Fig. 6 also shows the outcomes of Scenario 2. In this scenario, it was assumed that real-time data for methane overrun was unavailable, but the inflow quality and wind speed nodes received online evidence from IoT sensors. In the developed BN, the methane overrun node was influenced by ventilation conditions, which depended on the inflow quality and wind speed (see Fig. 3). Consequently, it was expected that

assuming all other nodes remained in their initial states, the outcomes of Scenario 2 would resemble those of Scenario 1. Fig. 6 confirms this expectation, with nearly consistent spikes in predicted explosion risk observed in both scenarios. In most cases, the spike appeared earlier in Scenario 2, possibly due to the spatial distance between the sensors triggering the first scenario and those used in the second scenario.

In Scenario 3, real-time evidence continuously informed the methane overrun node at each time step. It was assumed that some evidence existed before time step 0.7E+5, indicating a potential failure in the coal miner's efforts to prevent methane accumulation or eliminate ignition sources. However, it later became clear that effective preventive measures were implemented after this time step. Additionally, a welding activity was assumed to have occurred between time steps 0.3E+5 and 0.9E+5 near the end of the coal face. Due to the high risk associated with this activity, users designated the open fire status as "yes" within this time interval. Fig. 7 visually represents the explosion risk progression in Scenario 3. As shown, the time steps before 0.7E+5 exhibited an increased explosion risk of 0.13 due to the lack of effective preventive measures, compared to Scenario 1's risk of only 0.04. While this risk level isn't concerning without an apparent ignition source, the

introduction of an open fire source raised the risk to a probability of 0.23. The most critical point occurred at time step 46,563, marked by the simultaneous presence of an open fire ignition source, a brief spike in methane concentration, and ineffective preventive measures. This situation resulted in a high explosion risk probability of 0.95. After time step 0.7E+5, when effective preventive measures were in place, the explosion risk dropped to 0.5, even with an ignition source and a sudden release of methane. This scenario highlights the proposed framework's ability to account for the cascading effects of influencing factors, thereby capturing the dynamic nature of environmental risks in underground environments.

Scenario 4 was designed to demonstrate the prediction of explosion-related consequences and the effectiveness of mitigative measures in managing them. The configuration of Scenario 4 closely resembles that of Scenario 3. In this case, preventive measures were assumed to be ineffective at each time step, and mitigative measures were improved from poor to effective at time step 0.7E+5. The outcomes are shown in Fig. 8. As observed, an increase in explosion risk was associated with a rise in consequences. This correlation was expected, given that the methane explosion node influences all consequences in the network. Another observation in Fig. 8 occurs at time step 0.7E+5 when the mitigative measures became effective. At this point, the risk associated with all consequences decreased, while the risk of the explosion itself remained constant. This difference arises from the distinction between preventive measures, which address the causes of the explosion, and mitigative measures, which focus on minimizing the severity of consequences, in the developed BN.

4.4. Case study on real data from an underground mine in China

The second case study was conducted at an underground coal mine in China. Although this was a longwall mine, the dataset provided to the research team was collected during the excavation of access tunnels using a roadheader. The dataset recorded methane gas concentration from a sensor near the excavation site, covering the period from December 19, 2021, to May 12, 2023, for a total of 509 days. The sensor reported the maximum, minimum, and average methane concentration every minute, resulting in a total of 732,451 data points.

Since this data was collected under real-world conditions, it included some missing values. These values, recorded as *Nan* in the dataset, were identified and replaced with the last available data. Additionally, the sensor had been regularly tested with controlled amounts of methane gas at set intervals, hence these periodic tests resulted in some methane concentration values being recorded that did not reflect the actual environmental conditions of the mine. These values were removed from the dataset with the help of mine managers by matching them with the test dates and were replaced with the last meaningful available value. Fig. 9 shows the trend of the sensor data after cleaning. The data ranges from 0 to 7.26 %, with an average of 0.17 %.

The maximum methane concentration recorded each minute was used as input evidence for the methane overrun node in the BN shown in Fig. 3, while the other nodes remained in their prior states. Mine experts set a concentration threshold of 1 % for this node. Therefore, concentrations above 1 % were labeled as serious, and those below 1 % were labeled as negligible. After feeding the BN with these labels, Fig. 10 shows the predicted risk of explosion in the examined mine. The risk of explosion was predicted to be very minimal throughout most of the data collection period, which aligns with the actual mine conditions. Only once, on February 3, 2023, at 3:23am, did the risk suddenly spike to 0.51. This spike was due to a sharp and sudden increase in methane concentration in the mine, which rose to 7.26 %. The high concentration was attributed to a sudden release of a large volume of methane from the upper coal seam after mining, combined with initially high methane levels and the occurrence of soft stratification.

To examine the conditions that might have occurred following this incident, two additional scenarios were analyzed. In the first scenario, it

was assumed that an open fire source was located near the sensor for one week before and after the incident and that preventive measures were not effectively in place during that time. In the second scenario, it was assumed that while an open fire source was present during the same period, effective preventive measures were in place to control gas accumulation. Figs. 11a and 11b show the model's predicted results for explosion risk for Scenario 1 and Scenario 2, respectively.

According to Fig. 11a, in the absence of effective preventive measures and with a negligible methane concentration, a single open fire source increased the explosion risk to 0.23. When a high methane concentration of 7.26 % was introduced into the mine, the explosion risk peaked at 0.951. This high probability suggests that the lack of effective preventive measures allows gas accumulation to reach dangerous levels, which, combined with the presence of an open fire source, leads to a significant explosion risk. The sharp spike also indicates that the explosion risk is time-sensitive and could potentially occur within a short time frame, highlighting the need for timely and effective preventive actions to mitigate such risks. Fig. 11b shows a much lower probability of explosion, with the peak reaching a significantly lower level of 0.481. This reduced peak probability indicates that effective preventive measures successfully mitigate the risk of gas accumulation, thereby lowering the explosion risk. It underscores the importance of having robust safety protocols and measures in place to control potential hazards and prevent catastrophic events such as explosions.

4.5. Results and discussion

The implementation of the proposed IoT-Bayes fusion system in the selected case studies provided significant insights into the risk assessment and management of methane explosions in underground coal mines. The findings from the two case studies highlight the system's effectiveness in dynamic risk prediction and its potential implications for real-time risk management.

In the first case study, the BN model was applied to an open-source dataset from a Polish coal mine, where real-time sensor measurements were integrated into the BN through the IoT-Bayes fusion system. The results showed that the BN effectively processed the dynamic inputs, allowing it to update the risk levels of a potential methane explosion as new data became available. For example, when an increase in methane concentration was detected by the sensors, the BN model responded by immediately raising the predicted risk of an explosion, enabling timely preventive actions. This case study also underscored the critical role of ventilation conditions in controlling methane levels, as poor ventilation consistently correlated with higher methane concentrations. The model's ability to predict risk dynamically, adjusting to real-time data, was validated by its close alignment with historical incident reports. This capability is particularly valuable in the context of underground coal mining, where conditions can change rapidly and unpredictably.

The second case study focused on a proprietary dataset from a Chinese coal mine, which included instances of serious methane concentrations. The dataset allowed for a more in-depth examination of the BN's predictive accuracy and robustness under different scenarios. In a real-time risk assessment scenario, the BN provided accurate risk levels corresponding to the observed methane concentrations, effectively predicting the potential for an explosion. When a scenario was simulated where an open fire occurred alongside high methane concentrations, the BN's risk assessment reflected a significant increase in the explosion risk, demonstrating the model's sensitivity to cascading hazard scenarios. Furthermore, when effective preventive measures, such as improved ventilation and the elimination of ignition sources, were assumed, the BN indicated a substantial reduction in the risk of an explosion. This finding illustrates the model's utility in evaluating the potential impact of various safety interventions.

The comparative analysis of these two case studies reveals several innovative implications for the practical application of the IoT-Bayes fusion system in underground operations. Integrating IoT data streams

into the BN enables real-time data analytics to monitor and manage cascading risks as they occur. The system's ability to capture and analyze data in real-time allows for immediate identification and evaluation of potential hazards, leading to timely decision-making and proactive risk mitigation. In this way, instead of merely monitoring raw data, underground managers can track analyzed risks in real time. By performing what-if analyses, the system provides a robust platform for simulating different risk conditions and their impacts, enhancing the ability to foresee and respond to emerging threats in real time. This real-time feedback loop also allows for immediate adjustments to risk management strategies based on new data and evolving conditions. Additionally, the BN framework captures tacit knowledge by modeling complex interdependencies and risk factors, translating expert insights into actionable data.

5. Conclusions

This paper introduces a real-time framework for evaluating safety risks in underground settings. The framework leverages IoT sensors to generate real-time environmental data and uses BNs as a reliable risk assessment tool. To validate the effectiveness of the proposed framework, two case studies were conducted using two datasets focusing on methane levels in coal mines in Poland and China. The findings highlight the potential of the framework to assist safety managers in continuously monitoring safety hazards in underground environments, enabling prompt interventions when needed.

The proposed framework offers two significant benefits for enhancing safety in underground settings. First, the creation of a BN facilitates the encapsulation and preservation of tacit knowledge from safety experts in the underground environment. This type of knowledge is often difficult to communicate but capturing it in BN models can preserve it as a valuable organizational asset. Second, the semi-automatic fusion of IoT data with the BN establishes a real-time risk assessment and monitoring platform. This enables underground operators and safety managers to observe how complex and dynamic factors interact and affect risks in real-time. The platform also allows managers to adjust variables and see immediate changes, which is useful for evaluating various risks and making safety decisions. Through this system, ongoing evaluation and improvement of safety measures become feasible, along with the early identification and mitigation of potential risks before they escalate into more severe incidents.

During the development of the BN, challenges in implementation led to consolidating various preventive and mitigative measures into single nodes. This simplification does not account for potential variations in the effects of different measures. Future research could address this by incorporating the diverse impacts of individual measures into the model. Another area of interest for further research might involve integrating this system with visualization technologies. This could lead to the creation of an environmental digital twin for underground construction and mining environments, enhancing the monitoring and management of environmental safety.

CRediT authorship contribution statement

Milad Mousavi: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Software, Validation. **Xuesong Shen:** Writing – review & editing, Supervision, Funding acquisition. **Zhigang Zhang:** Data curation. **Khalegh Barati:** Supervision. **Binghao Li:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The 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.

Acknowledgments

This research is supported by funding from the Australian Research Council (ARC) Research Hub for Resilient and Intelligent Infrastructure Systems (IH210100048). The authors would like to thank Mr. Duncan Chalmers and A/Prof. Guangyao Si at the School of Minerals and Energy Resources at the University of New South Wales (UNSW Sydney), and Mr. Flynn Malnic, Ventilation Officer at Anglo American, for their invaluable contributions to this research. Their guidance, insights, and assistance were crucial in enhancing the quality of this study. We also extend our gratitude to BayesFusion, LLC for providing us with free access to GeNIE Modeler and SMILE Engine software, which greatly aided our research.

Data availability

The authors do not have permission to share data.

References

- [1] Jang H, Topal E. Transformation of the Australian mining industry and future prospects. *Mining Technol* 2020;129(3):120–34. <https://doi.org/10.1080/2526668.2020.1786298>.
- [2] Dong L, Tong X, Li X, Zhou J, Wang S, Liu B. Some developments and new insights of environmental problems and deep mining strategy for cleaner production in mines. *J Clean Prod* 2019;210:1562–78. <https://doi.org/10.1016/j.jclepro.2018.10.291>.
- [3] He S, Lu Y, Li M. Probabilistic risk analysis for coal mine gas overrun based on FAHP and BN: a case study. *Environ Sci Pollut Res* 2022;29(19):28458–68. <https://doi.org/10.1007/s11356-021-18474-3>.
- [4] Wu Y, Chen M, Wang K, Fu G. A dynamic information platform for underground coal mine safety based on internet of things. *Saf Sci* 2019;113:9–18. <https://doi.org/10.1016/j.ssci.2018.11.003>.
- [5] Qiao W. Analysis and measurement of multifactor risk in underground coal mine accidents based on coupling theory. *Reliab Eng Syst Saf* 2021;208:107433. <https://doi.org/10.1016/j.ress.2021.107433>.
- [6] Liang Y, Liu Q. Early warning and real-time control of construction safety risk of underground engineering based on building information modeling and internet of things. *Neural Comput Appl* 2022;34(5):3433–42. <https://doi.org/10.1007/s00521-021-05755-8>.
- [7] Tariq S, Loy-Benitez J, Nam K, Kim S, Kim M, Yoo C. Deep-AI soft sensor for sustainable health risk monitoring and control of fine particulate matter at sensor devoid underground spaces: a zero-shot transfer learning approach. *Tunnel Underground Space Technol* 2023;131:104843. <https://doi.org/10.1016/j.tust.2022.104843>.
- [8] Xue G, Liu S, Ren L, Gong D. Risk assessment of utility tunnels through risk interaction-based deep learning. *Reliab Eng Syst Saf* 2024;241:109626. <https://doi.org/10.1016/j.ress.2023.109626>.
- [9] Slezak D, Grzegorowski M, Janusz A, Kozielski M, Nguyen SH, Sikora M, et al. A framework for learning and embedding multi-sensor forecasting models into a decision support system: a case study of methane concentration in coal mines. *Inf Sci* 2018;451–452:112–33. <https://doi.org/10.1016/j.ins.2018.04.026>.
- [10] Janusz A, Grzegorowski M, Michałak M, Wróbel Ł, Sikora M, Ślęzak D. Predicting seismic events in coal mines based on underground sensor measurements. *Eng Appl Artif Intell* 2017;64:83–94. <https://doi.org/10.1016/j.engappai.2017.06.002>.
- [11] Li M, Wang H, Wang D, Shao Z, He S. Risk assessment of gas explosion in coal mines based on fuzzy AHP and bayesian network. *Process Saf Environ Protect* 2020;135:207–18. <https://doi.org/10.1016/j.psep.2020.01.003>.
- [12] Janusz A, Sikora M, Wróbel Ł, Stawicki S, Grzegorowski M, Wojtas P, et al. Mining data from coal mines: IJCRS'15 data challenge. Rough sets, fuzzy sets, data mining, and granular computing 2015:429–38. https://doi.org/10.1007/978-3-319-25783-9_38.
- [13] Cham, Y., Yao, Q., Hu, H., Yu, J. W. Grzymala-Busse2015//.
- [14] Huang MQ, Ninić J, Zhang QB. BIM, machine learning and computer vision techniques in underground construction: current status and future perspectives. *Tunnel Underground Space Technol* 2021;108:103677. <https://doi.org/10.1016/j.tust.2020.103677>.
- [15] Moradi R, Cofre-Martel S, Lopez Drogue E, Modarres M, Groth KM. Integration of deep learning and Bayesian networks for condition and operation risk monitoring of complex engineering systems. *Reliab Eng Syst Saf* 2022;222:108433. <https://doi.org/10.1016/j.ress.2022.108433>.
- [16] You M, Li S, Li D, Xu S. Applications of artificial intelligence for coal mine gas risk assessment. *Saf Sci* 2021;143:105420. <https://doi.org/10.1016/j.ssci.2021.105420>.
- [17] Muduli L, Mishra DP, Jana PK. Application of wireless sensor network for environmental monitoring in underground coal mines: a systematic review.

- J Network Comput Appl 2018;106:48–67. <https://doi.org/10.1016/j.jnca.2017.12.022>.
- [18] Tubis A, Werbińska-Wojciechowska S, Wroblewski A. Risk assessment methods in mining industry—a systematic review. Appl Sci 2020;10(15). <https://doi.org/10.3390/app10155172>.
- [19] Zhang P, Zhang Z-J, Gong D-Q. An improved failure mode and effect analysis method for group decision-making in utility tunnels construction project risk evaluation. Reliab Eng Syst Saf 2024;244:109943. <https://doi.org/10.1016/j.ress.2024.109943>.
- [20] Bai Y, Wu J, Liu K, Sun Y, Shen S, Cao J, et al. Energy-based coupling risk assessment (CRA) model for urban underground utility tunnels. Reliab Eng Syst Saf 2024;250:110255. <https://doi.org/10.1016/j.ress.2024.110255>.
- [21] Hai N, Gong D, Liu S, Dai Z. Dynamic coupling risk assessment model of utility tunnels based on multimethod fusion. Reliab Eng Syst Saf 2022;228:108773. <https://doi.org/10.1016/j.ress.2022.108773>.
- [22] Li N, Feng X, Jimenez R. Predicting rock burst hazard with incomplete data using Bayesian networks. Tunnel Underground Space Technol 2017;61:61–70. <https://doi.org/10.1016/j.tust.2016.09.010>.
- [23] Wu J, Bai Y, Fang W, Zhou R, Reniers G, Khakzad N. An integrated quantitative risk assessment method for urban underground utility tunnels. Reliab Eng Syst Saf 2021;213:107792. <https://doi.org/10.1016/j.ress.2021.107792>.
- [24] Tong X, Fang W, Yuan S, Ma J, Bai Y. Application of Bayesian approach to the assessment of mine gas explosion. J Loss Prev Process Ind 2018;54:238–45. <https://doi.org/10.1016/j.jlp.2018.04.003>.
- [25] Wu X, Liu H, Zhang L, Skibniewski MJ, Deng Q, Teng J. A dynamic Bayesian network based approach to safety decision support in tunnel construction. Reliab Eng Syst Saf 2015;134:157–68. <https://doi.org/10.1016/j.ress.2014.10.021>.
- [26] Marcot BG, Penman TD. Advances in Bayesian network modelling: integration of modelling technologies. Environ Model Softw 2019;111:386–93. <https://doi.org/10.1016/j.envsoft.2018.09.016>.
- [27] Zhou C, Ding LY. Safety barrier warning system for underground construction sites using Internet-of-Things technologies. Autom Constr 2017;83:372–89. <https://doi.org/10.1016/j.autcon.2017.07.005>.
- [28] Zhang P, Chen R-P, Dai T, Wang Z-T, Wu K. An AloT-based system for real-time monitoring of tunnel construction. Tunnel Underground Space Technol 2021;109:103766. <https://doi.org/10.1016/j.tust.2020.103766>.
- [29] Ye Z, Ye Y, Zhang C, Zhang Z, Li W, Wang X, et al. A digital twin approach for tunnel construction safety early warning and management. Comput Ind 2023;144:103783. <https://doi.org/10.1016/j.compind.2022.103783>.
- [30] Liu Q, He R, Zhang L. Simulation-based multi-objective optimization for enhanced safety of fire emergency response in metro stations. Reliab Eng Syst Saf 2022;228:108820. <https://doi.org/10.1016/j.ress.2022.108820>.
- [31] Zhou J, Zhang Y, Li C, He H, Li X. Rockburst prediction and prevention in underground space excavation. Underground Space 2024;14:70–98. <https://doi.org/10.1016/j.udsp.2023.05.009>.
- [32] Zhang H, Li B, Karimi M, Saydam S, Hassan M. Recent advancements in IoT implementation for environmental, safety, and production monitoring in underground mines. IEEE Internet Things J 2023;1. <https://doi.org/10.1109/JIOT.2023.3267828>.
- [33] Wang N, Xiao Y, Tian T, Yang J. The optimal 5G base station location of the wireless sensor network considering timely reliability. Reliab Eng Syst Saf 2023;236:109310. <https://doi.org/10.1016/j.ress.2023.109310>.
- [34] Feng JR, Zhao M-k, Lu S-x. Accident spread and risk propagation mechanism in complex industrial system network. Reliab Eng Syst Saf 2024;244:109940. <https://doi.org/10.1016/j.ress.2024.109940>.
- [35] Global Mining Guidelines Group. Underground Mine Communications Infrastructure Guidelines Part III: general Guidelines. Underground mine communications infrastructure guideline suite. Global Mining Guidelines Group (GMG); 2019.
- [36] Li B, Saydam S. Communication, Monitoring, and Control. SME underground mining handbook. Society for Mining, Metallurgy & Exploration (SME); 2023. p. 635–64. P. Darling Ed.ch. 27.
- [37] Yang J, Yue Z, Yuan Y. Deep probabilistic graphical modeling for robust multivariate time series anomaly detection with missing data. Reliab Eng Syst Saf 2023;238:109410. <https://doi.org/10.1016/j.ress.2023.109410>.
- [38] Jia-Qi L, Yun-Wen F, Da T, Jun-Yu C, Cheng L. Operational reliability evaluation and analysis framework of civil aircraft complex system based on intelligent extremum machine learning model. Reliab Eng Syst Saf 2023;235:109218. <https://doi.org/10.1016/j.ress.2023.109218>.
- [39] Lyu P, Chen N, Mao S, Li M. LSTM based encoder-decoder for short-term predictions of gas concentration using multi-sensor fusion. Process Saf Environ Protect 2020;137:93–105. <https://doi.org/10.1016/j.psep.2020.02.021>.
- [40] Byun J-E, Song J. A general framework of Bayesian network for system reliability analysis using junction tree. Reliab Eng Syst Saf 2021;216:107952. <https://doi.org/10.1016/j.ress.2021.107952>.
- [41] Kamounah O, Gardoni P, Cimellarino GP. Probabilistic framework to evaluate the resilience of engineering systems using Bayesian and dynamic Bayesian networks. Reliab Eng Syst Saf 2020;198:106813. <https://doi.org/10.1016/j.ress.2020.106813>.
- [42] Iamsuamang C, Mosleh A, Modarres M. Monitoring and learning algorithms for dynamic hybrid Bayesian network in on-line system health management applications. Reliab Eng Syst Saf 2018;178:118–29. <https://doi.org/10.1016/j.ress.2018.05.016>.
- [43] Tohidifar A, Mousavi M, Alvanchi A. A hybrid BIM and BN-based model to improve the resiliency of hospitals' utility systems in disasters. Int J Dis Risk Reduct 2021;57:102176. <https://doi.org/10.1016/j.ijdr.2021.102176>.
- [44] Zhang X, Mahadevan S. Bayesian network modeling of accident investigation reports for aviation safety assessment. Reliab Eng Syst Saf 2021;209:107371. <https://doi.org/10.1016/j.ress.2020.107371>.
- [45] Ademujimi T, Prabhu V. Digital twin for training bayesian networks for fault diagnostics of manufacturing systems. Sensors 2022;22(4). <https://doi.org/10.3390/s22041430>.
- [46] Adedipe T, Shafee M, Zio E. Bayesian network modelling for the wind energy industry: an overview. Reliab Eng Syst Saf 2020;202:107053. <https://doi.org/10.1016/j.ress.2020.107053>.
- [47] Meng X, Chang H, Wang X. Methane concentration prediction method based on deep learning and classical time series analysis. Energies 2022;15(6). <https://doi.org/10.3390/en15062262>.
- [48] Brodny J, Felka D, Tutak M. The use of the neuro-fuzzy model to predict the methane hazard during the underground coal mining production process. J Clean Prod 2022;368:133258. <https://doi.org/10.1016/j.jclepro.2022.133258>.
- [49] Meng X, Liu Q, Luo X, Zhou X. Risk assessment of the unsafe behaviours of humans in fatal gas explosion accidents in China's underground coal mines. J Clean Prod 2019;210:970–6. <https://doi.org/10.1016/j.jclepro.2018.11.067>.
- [50] Rahimi S, Ataei-pour M, Madani H, Aminossadati SM. Investigating the impact of gas emission uncertainty on airflow distribution in an auxiliary ventilation system using CFD and Monte-Carlo simulation. Build Environ 2021;204:108165. <https://doi.org/10.1016/j.buildenv.2021.108165>.
- [51] Mousavi M, Shen X, Li B. Online safety risk management for underground mining and construction based on IoT and Bayesian networks. In: presented at the Proceedings of the 40th International Symposium on Automation and Robotics in Construction; 2023. <https://doi.org/10.22260/ISARC2023/0067>. 2023/07/07.
- [52] Mottahedi A, Sereshki F, Ataei M, Qarahasanlu AN, Barabadi A. Resilience estimation of critical infrastructure systems: application of expert judgment. Reliab Eng Syst Saf 2021;215:107849. <https://doi.org/10.1016/j.ress.2021.107849>.
- [53] BayesFusion. "GeNe Modeler: complete Modeling Freedom." <https://www.bayesfusion.com/genie/>; 2024 (accessed 20 July 2022).
- [54] BayesFusion. "SMILE: structural Modeling, Inference, and Learning Engine." <https://www.bayesfusion.com/smile/>; 2024 (accessed 20 July 2022).
- [55] M. Sikora and L. Wróbel. Methane, Mendeley Data, V1, 2021, doi: [10.17632/yd7vw4c5mk.1](https://doi.org/10.17632/yd7vw4c5mk.1).
- [56] Kozielski M, Sikora M, Wróbel L. Data on methane concentration collected by underground coal mine sensors. Data Brief 2021;39:107457. <https://doi.org/10.1016/j.dib.2021.107457>.
- [57] Chang H, Meng X, Wang X, Hu Z. Research on coal mine longwall face gas state analysis and safety warning strategy based on multi-sensor forecasting models. Sci Rep 2024;14(1):13795. <https://doi.org/10.1038/s41598-024-64181-7>.
- [58] M. Tutak, J. Brodny, D. Szurgacz, L. Sobik, and S. Zhironkin, "The Impact of the Ventilation System on the Methane Release Hazard and Spontaneous Combustion of Coal in the Area of Exploitation—A Case Study," Energies, vol. 13, no. 18, <https://doi.org/10.3390/en13184891>.