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ENHANCING LARGE UNDERGROUND EXCAVATION RISK ASSESSMENT: OPTIMIZATION THROUGH INFORMATION SYSTEMS

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ABSTRACT

This article endeavours to introduce a thorough risk management framework tailored for the assessment of underground facilities situated within rock formations. Drawing insights from the data analysis gathered from two notable underground cavern projects in India, the framework undergoes development and refinement. It revisits the setbacks encountered in these projects alongside the corresponding strategies for mitigation. By leveraging empirical data, the article explores risk assessment using a Decision Tree model grounded on entropy. This risk assessment model integrates various factors concerning geological conditions such as rock mass classification, Q value, joint set orientation, and shear zones, which are correlated with diverse sources of failure. The outcomes of this model underscore the significance of prioritizing resource allocation and costs based on the importance of parent attributes and the associated levels of child attributes. Thus present method is expected to optimize the construction of underground structures.
Keywords: *Decision Tree, Risk Management, Geological Uncertainties, Tunnelling.*

1. INTRODUCTION

The high demand for infrastructure facilities motivates engineering innovation to explore novel technologies, concepts, materials, and spatial possibilities, aiming to deliver safer and more dependable infrastructure. Meeting such demand typically involves underground excavation technology, which is associated with comparatively large investments, relatively long construction phases, various combinations, and the coordination of multiple contractors. Despite detailed geological investigations, most underground excavations face geological and hydrological surprises in actual ground conditions. These surprises, combined with inappropriate excavation methods and unfavorable surface and sub-surface conditions such as busy traffic, existing facilities, and a lack of efficient construction management, can lead to accidents or hazards [1]. Consequently, owners and contractors incur significant losses, making the management and minimization of risks in underground excavation a critical factor in tunnel or cavern construction work.

Since the 1970s, the recognition of underground excavation risks has led to subsequent research, with a focus on qualitative measurement and reliability analysis [2, 3]. However, the majority of research has centered on reliability analysis of geotechnical risks, presenting inherent difficulties. Geotechnical risk management has become challenging due to the increased use of underground space. According to Michael Latham, "No construction project is devoid of risk. Risk can be managed, reduced, shared, transferred, or acknowledged. It cannot be disregarded." [4].

Over the years, a variety of risk analysis techniques have evolved, including the Influence Diagram Method, Monte Carlo Simulation Method, Expected Value Method, Decision Tree Method, and Fault Tree Method, as well as their combinations [5]. Each method has its merits and demerits, making them suitable for specific civil construction processes. In the context of underground excavation, risk is primarily related to geological surprises, and entropy serves as a measure of the uncertainty of the excavation process. Therefore, risk in underground excavation is defined as the probability of the occurrence of a hazard. A decision tree, a simple and powerful method for inferring classification rules, provides an advantage over the neural network method due to its easy-to-follow sequence of decisions [6]. However, developing a decision tree with the minimum number of leaves poses challenges [6].

Elmi and Attar (2021) delve into the optimization of tunnel construction methods through multicriteria decision analysis, showcasing innovative approaches to enhance construction efficiency and performance. Feng, et al. (2020) introduce a novel risk assessment framework for underground utility tunnel construction, grounded in the theory of complex networks, providing a holistic perspective on risk management in underground infrastructure projects.

In the Indian context, underground structures play a pivotal role, given the anticipated land use density of 403 persons/km², surpassing that of even the most populous country, China, by 2.5 times [7]. The urban population concentration in towns and cities, where tall buildings are commonplace, necessitates an expanded network of mass transit systems and various facilities. However, this urban growth and densification pose substantial challenges to the uncertainties linked to intricate geological conditions and rock mass reactions within the Earth's crust. These uncertainties manifest as potential risks of rock mass instabilities, underscoring the imperative for risk management measures encompassing elimination, mitigation, acceptance, or transfer. Nonetheless, a standardized method for quantifying underground engineering risk analysis is currently lacking. Therefore, the quantification of risk emerges as a critical component of risk management [8]. This paper introduces an interval entropy measurement method rooted in expert investigation, built upon the principles of entropy and its generalization and extension.

Each underground construction endeavor entails a unique level of risk contingent upon its site-specific conditions. This paper systematizes the procedure for risk identification and consequence assessment, culminating in the formulation of a predictive model grounded in suitable strategies [9]. A systematic methodology entails scrutinizing and comprehending the risks associated with buildings or constructions under analogous conditions and functional specifications to devise a predictive model adept at recognizing risks in forthcoming projects. This research introduces a straightforward approach for crafting a risk assessment-driven predictive model, leveraging data from two completed projects and implementing this model to forecast outcomes for a prospective project.

The demand for infrastructure facilities drives continuous innovation in engineering, necessitating the exploration of novel technologies and methods to ensure the delivery of safer and more dependable infrastructure. Underground excavation technology, crucial for meeting this demand, involves substantial investments and coordination efforts but is often plagued by unforeseen geological and hydrological challenges. These challenges, combined with inappropriate excavation methods and unfavorable surface conditions, pose significant risks to project owners and contractors, resulting in substantial losses. Despite decades of research on underground excavation risks, current methodologies primarily focus on qualitative measurements and reliability analysis, lacking a standardized approach for quantifying risks. This critical gap underscores the importance of developing robust risk management frameworks specific to underground construction. This paper addresses this need by introducing an interval entropy measurement method, providing a systematic approach for identifying and assessing risks in underground construction projects.

2. METHODS UTILIZED FOR RISK EVALUATION

Risk assessment plays a pivotal role in providing a platform to identify and measure risks accurately, enabling the evaluation of their magnitude [10]. A range of tools for analyzing and assessing risks, including fault tree analysis, event tree analysis, cause-consequence analysis, bowtie diagrams, decision tree analysis, probabilistic risk analysis, Bayesian networks, analytic hierarchy process, fuzzy logic, and artificial intelligence, have been gathered for quantification purposes.

The selection of suitable tools hinges on the specific nature of the problem at hand. In this study, particular attention is given to the entropy of attributes, which plays a pivotal role in shaping the decision tree. At the core of this decision tree lies the quantification of rock mass instability occurrences, determining whether the rock mass remains stable or becomes unstable.

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A decision tree serves to evaluate the level of risk associated with different courses of action within the realm of risk-based decision-making. This research employs quantitative diagrams featuring nodes and branches that depict various potential decision paths and chance events. The confidence in the decision tree stems from the identification of potential attribute nodes and an assessment of their likelihood of occurrence. This structured approach delineates decisions and chance events in a sequential manner, resulting in a tree structure with branches indicating events and their probabilities, with decisions appended to each node. The most consistent and prominent attribute serves as the focal point, with entropy serving as one of the tools used to gauge homogeneity at the node level. Entropy acts as a metric for evaluating the uniformity of a node.

$$M_i = Entropy(N_i) = -\sum_j p(j/N_i)\log_2(j/N_i)$$

Here, P(j/Ni) denotes the relative frequency of class j at node Ni.

The highest entropy value arises when records are evenly distributed among all classes, indicating maximum impurity. Conversely, the lowest entropy value indicates maximum homogeneity. To construct the decision tree framework, the subsequent sections delve into the analysis of two underground cavern projects. The study is segmented into three parts:

a. Formulation of a prediction model based on Project-1.
b. Validation of the model using data from Project-2.
c. Projection for Project-3's future outcomes.

3. SYNOPSIS OF PROJECTS

Presently, under examination are two significant underground cavern projects, namely Project-1 and Project-2, located in the southern region of India. Project-1 comprises five underground chambers, varying in length from 380m to 800m, excavated in gneiss rock. The quality of the rock mass varies from poor in shear zones to good [12]. Similarly, Project-2 boasts comparable dimensions, featuring a chamber length of 700m excavated in granitic gneiss [13]. The standard dimensions of these caverns measure 20m in height and 30m in width. The data collected from these projects primarily focuses on instability zones near excavations/structures or areas where significant instability has been observed.

In Project-1, various instances of failure were observed, as depicted in Fig. 1(a). These incidents encompass the displacement of a substantial wedge within the sidewall, attributed to the unfavorable alignment of a shear zone (oriented parallel to the chamber axis) intersecting with another unidentified shear zone. Furthermore, significant deformations arose from stress relaxation within weak shear zones formed as a result of dyke intrusions, leading to the cracking and spalling of shotcrete. Fig. 1(b) illustrates the structural geological map of the project, illustrating shear zones and dyke intrusions. Notably, notable seepage issues were absent in this project due to clay-filled joints. The failure of the large wedge led to a one-year delay in that specific area for muck removal and the implementation of stabilization measures (including rock bolts and concreting) to prevent further failure, resulting in additional costs. Instances of shotcrete cracking and spalling were observed near the crown region, necessitating the construction of access ramps due to sequential excavation in that area to address these issues [14-18].

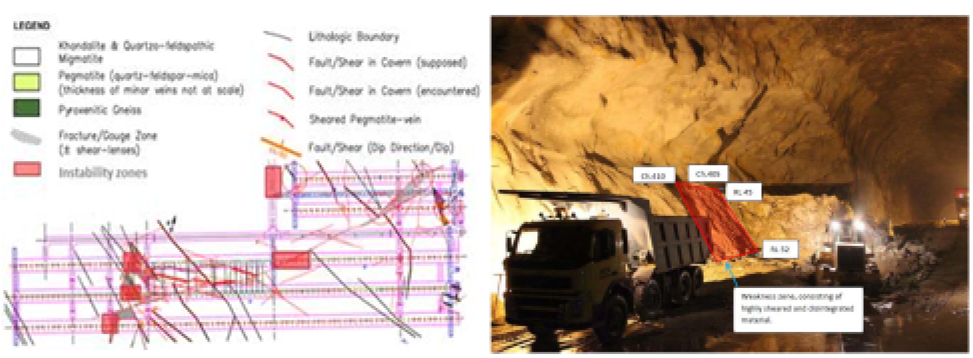

Figure 1. Project 1 (a) Structural geological map with layout (b) Wedge failure in the cavern

Figure 2 illustrates the structural geological map of Project-2, highlighting dyke intrusions, shear zones, and sub-horizontal joints. Failures in this project were primarily attributed to significant seepage caused by the open configuration of the sub-horizontal joint set and its connection to a water source. The encounter with high-pressure seepage was exacerbated by the project's depth, prompting post-grouting interventions that resulted in time delays and increased costs. Furthermore, notable deformations occurred in weak shear zones formed due to dyke intrusions.

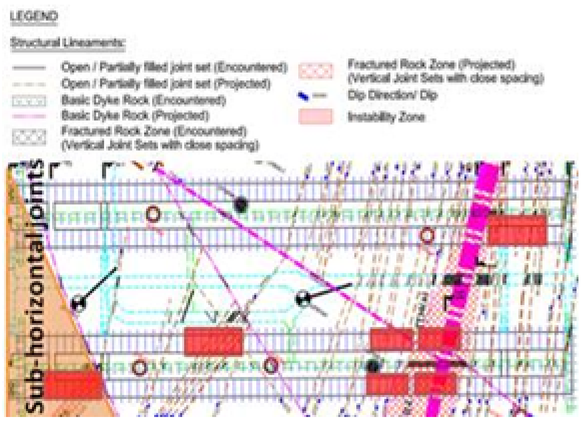

Figure 2. Structural geological map of Project 2.

The factors identified as contributing to failures encompassed rock class (Q value), joint set orientation, and shear zones. Field observations were employed to delineate these attributes across the entire span of both caverns. The circumstances precipitating failure or rock mass instability were broadly classified into deformation and seepage failures. Extensive data pertaining to real failures that transpired during the construction of the caverns were also gathered. A direct correlation between the mapped attribute data and the failure type was established to construct the prediction model.

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3.1 SELECTION OF ATTRIBUTES FROM DATA DURING DECISION TREE AANALYSIS

The comprehensive risk management system heavily relied on the process of data collection. Information obtained during the construction phase was crucial in establishing a dependable decision-making framework. The specific details of the chosen attributes and instability criteria addressed in this study are elaborated in subsequent sections [19-22].

If shear zones measure less than 1m in thickness, their influence on stress and deformation in the adjacent rock mass following excavation is relatively negligible and may be disregarded. Similarly, faults that do not intersect the cavern excavation and are located farther away than the cavern's span have minimal effect on the stress and deformation of the surrounding rock mass. Moreover, if a shear zone is situated near the cavern floor, its impact on cavern stability is marginal [23-27]. However, if the shear zone is located near the crown within the cavern's span and close to the sidewalls within half the cavern's span, it significantly affects tunnel stability. Hence, including the shear zone in the analysis depends on its thickness being more than 1m and falling within the cavern's span at the crown and half the cavern's span at the sidewall of the excavation.

Rock mass classification by Q- system, mainly applied in medium to hard rock tunnelling, serves as a crucial parameter for evaluating the strength of the rock mass. Three classes of Q values are considered in this analysis to characterize the rock mass.

$Q < 1$, indicating very poor rock mass (TYPE 1)

$1 < Q < 4$, indicative of poor rock mass (TYPE 2)

$Q > 4$, representing fair to good rock mass (TYPE 3)

Joints play a pivotal role in cavern stability, particularly when their orientation is unfavorable to the cavern's alignment. If, for example, the cavern's alignment parallels the strike of the joint set and dips toward the cavern axis, it poses a risk to cavern stability. Thus, joint sets opposing the cavern's alignment are identified as contributors to instability in this analysis.

This study examines various instability parameters, including significant deformation (defined as deformation exceeding 1 percent), the formation or failure of wedges, and sagging or falling of shotcrete. Excessive seepage is flagged if the Lugeons value surpasses 2. Data from Project-1 are consolidated, detailing joint orientation, Q value, and shear zone attributes in Table 1. The predictive model is validated using data from Project-2, with synthesized data outlining representative parameters for Project-2 also presented in Table 1.

3.2 RISK ASSESSMENT ANALYSIS MODEL

The construction of a prediction model, focused on identifying potential risk zones contributing to instability within the cavern, involves the application of decision tree analysis. Additionally, the utilization of the concept of entropy is employed to determine the optimal split as a branch of the tree among various attributes. In this framework, the parent node is indicated by the lowest entropy value among different attributes, serving as the starting point for splitting into child nodes. Figure 3a outlines the methodology adopted in this study for the development, verification, and validation of the prediction model based on data from Project-1 and Project-2 under analogous conditions. It also illustrates the application of the model to a proposed project.

Table 1. Attribute Data From Project

Project-1				Project-2				Project-3			
Joint orientation	Q	Shear zones	Instability occurs?	Joint orientation	Q	Shear zones	Instability occurs?	Joint orientation	Q	Shear zones	Instability occurs?
Favourable	TYPE 1	NO	NO	Favourable	TYPE 2	NO	NO	Unfavourable	TYPE 2	NO	Stable
Favourable	TYPE 1	NO	NO	Favourable	TYPE 1	NO	NO	Unfavourable	TYPE 3	YES	Instable
Favourable	TYPE 2	NO	NO	Favourable	TYPE 2	YES	NO	Unfavourable	TYPE 1	NO	Stable
Favourable	TYPE 2	NO	NO	Favourable	TYPE 2	YES	NO	Unfavourable	TYPE 3	NO	Stable
Favourable	TYPE 1	NO	NO	Favourable	TYPE 1	NO	NO	Unfavourable	TYPE 2	NO	Stable
Favourable	TYPE 3	YES	NO	Favourable	TYPE 1	NO	NO	Unfavourable	TYPE 3	NO	Stable
Favourable	TYPE 1	YES	NO	Favourable	TYPE 2	NO	NO	Unfavourable	TYPE 1	YES	Instable
Favourable	TYPE 2	NO	NO	Favourable	TYPE 1	NO	NO	Favourable	TYPE 2	NO	Stable
Favourable	TYPE 2	NO	NO	Favourable	TYPE 2	YES	NO	Favourable	TYPE 2	NO	Stable
Favourable	TYPE 2	YES	NO	Favourable	TYPE 1	NO	NO	Favourable	TYPE 3	YES	Stable
Favourable	TYPE 1	NO	NO	Unfavourable	TYPE 1	YES	YES	Favourable	TYPE 1	NO	Stable
Favourable	TYPE 2	NO	NO	Favourable	TYPE 2	NO	NO	Favourable	TYPE 3	NO	Stable
Favourable	TYPE 3	NO	NO	Favourable	TYPE 1	NO	NO	Favourable	TYPE 1	NO	Stable
Favourable	TYPE 2	YES	NO	Unfavourable	TYPE 1	YES	YES	Unfavourable	TYPE 3	YES	Instable
Favourable	TYPE 1	YES	NO	Unfavourable	TYPE 2	YES	YES	Unfavourable	TYPE 1	NO	Stable
Favourable	TYPE 3	YES	NO	Unfavourable	TYPE 2	YES	YES				
Favourable	TYPE 2	YES	NO	Favourable	TYPE 1	NO	NO				
Favourable	TYPE 3	YES	NO	Unfavourable	TYPE 1	YES	YES				
Unfavourable	TYPE 3	YES	YES	Favourable	TYPE 2	YES	NO				
Unfavourable	TYPE 3	YES	YES	Favourable	TYPE 1	NO	NO				
Unfavourable	TYPE 3	YES	NO	Unfavourable	TYPE 1	YES	YES				
Unfavourable	TYPE 1	YES	YES	Unfavourable	TYPE 2	YES	Yes				
Unfavourable	TYPE 1	YES	YES	Favourable	TYPE 1	NO	NO				

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The attribute data from Project-1 is synthesized into frequency distributions for each attribute and its respective class at the initial node of the decision tree. Entropy is calculated for each attribute, and homogeneity is assessed; specifically, the attribute with the lowest entropy value signifies the optimal split. Table 2 presents the entropy calculation at the initial node. Notably, the attribute "joint set orientation" exhibits the lowest entropy value of 0.4, thus being designated as the first node, with subsequent attribute splitting conducted using entropy in subsequent calculations to formulate the decision tree.

The outcome of constructing a prediction model using decision tree analysis is depicted in Figure 3b. The accuracy assessment of the prediction model for Project-1 data is provided in Table 1. The accuracy of this prediction model for Project-1 data stands at 90%.

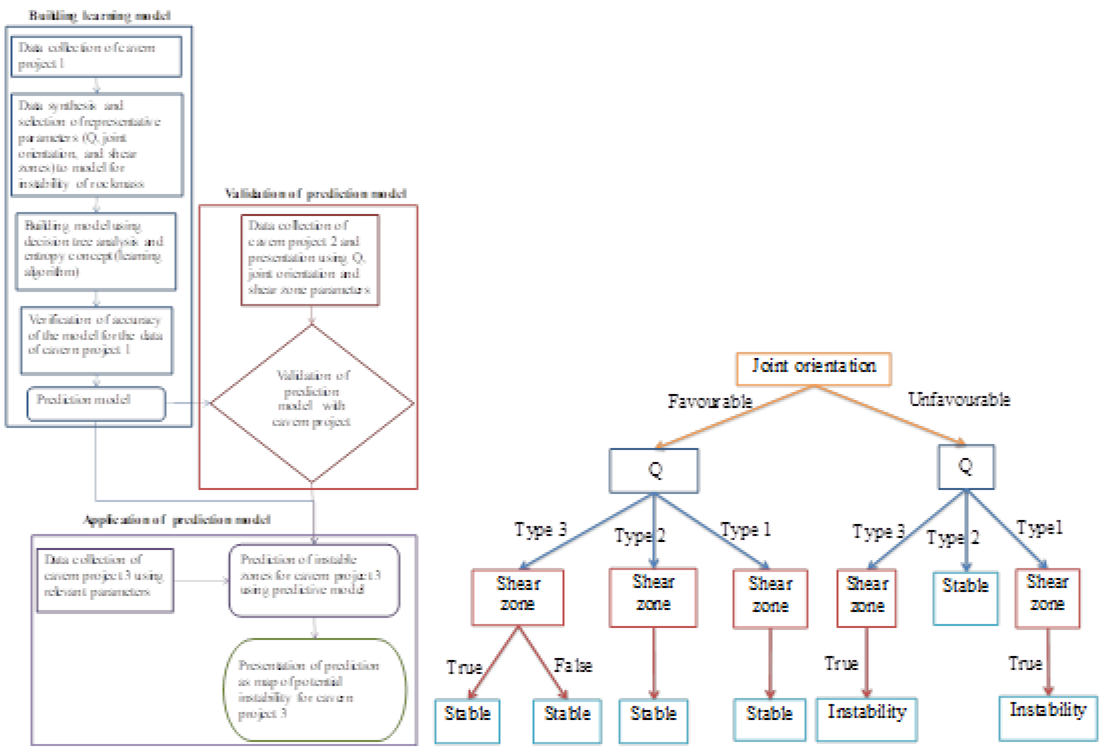

Figure 2. Methodology of risk assessment analysis

3.3 Validation of the Prediction Mmodel

Table 3 presents the validation outcomes of the prediction model utilizing the Project-2 dataset. The predictive accuracy achieved for this dataset stands at a commendable 78%. This accuracy metric underscores the robustness and efficacy of the model in extrapolating insights from the provided data.

Beyond merely achieving a high accuracy rate, the validation outcomes showcased in Table 3 signify the model's proficiency in handling the unique characteristics and complexities embedded within the Project-2 dataset. Through rigorous analysis and iterative refinement, the model has demonstrated its capability to discern patterns, extract relevant features, and make accurate predictions.

Moreover, the validation process serves as a critical checkpoint, ensuring that the model's performance remains consistent and reliable across diverse datasets. By scrutinizing the predictive outcomes against ground truth labels, stakeholders can ascertain the model's generalization capacity and its ability to yield actionable insights in real-world scenarios.

The 78% accuracy attained in this validation exercise underscores the model's potential to serve as a valuable decision-support tool across various domains. Whether applied in financial forecasting, healthcare diagnostics, or resource optimization, the predictive capabilities showcased by the model offer tangible benefits, empowering stakeholders to make informed decisions and drive meaningful outcomes.

In summary, the validation outcomes presented in Table 3 not only affirm the model's predictive accuracy but also highlight its adaptability and utility in diverse applications. Moving forward, continued validation and refinement will be essential to ensure the model's relevance and effectiveness in addressing evolving challenges and opportunities.

Table 1. *Sample calculation of entropy at the first node of decision tree analysis for the prediction model*

Q	Frequency			M_1 = Entropy (Q, instability)
	Unstable	Stable	Total	
Type 3	3	4	7	0.30
Type 2	0	8	8	0.00
Type 1	2	6	8	0.28
Total				0.58
Shear zones	Frequency			M_2 = Entropy (Shear zones, instability)
	Instable	Stable	Total	
TRUE	5	8	13	0.54
FALSE	0	10	10	0.00
Total				0.54
Joint orientation	Frequency			M_3 = Entropy (Joint orient, instability)
	Instable	Stable	Total	
Unfavourable	4	1	5	0.16
Favourable	1	17	18	0.24
Total				**0.40**

3.4 Application of prediction model

The existing forecasting model has been expanded to predict potential risk areas for a proposed Project-3 located in the eastern region of India. This project shares similar geological conditions and functional requirements with Project-1 and Project-2. By analyzing borehole and surface geological mapping data, it is expected that Project-3 will face two shear zones along the cavern axis and an unfavorably dipping foliation plan along the same axis. The projection of the potential risk zone for Project-3 is determined using the extended prediction model, as illustrated in Figure 4. The summarized prediction results can be found in Table 1.

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Table 2. Validation of prediction model for Project-2 data via accuracy calculation

Joint orientation	Q	Shear zones	Instability occurs?	Prediction result
Favourable	TYPE 2	NO	NO	Pass
Favourable	TYPE 1	NO	NO	Pass
Favourable	TYPE 2	YES	NO	Fail
Favourable	TYPE 2	YES	NO	Pass
Favourable	TYPE 1	NO	NO	Pass
Favourable	TYPE 1	NO	NO	Pass
Favourable	TYPE 2	NO	NO	Pass
Favourable	TYPE 1	NO	NO	Pass
Favourable	TYPE 2	YES	NO	Fail
Favourable	TYPE 1	NO	NO	Pass
Unfavourable	TYPE 1	YES	YES	Pass
Favourable	TYPE 2	NO	NO	Pass
Favourable	TYPE 1	NO	NO	Pass
Unfavourable	TYPE 1	YES	YES	Pass
Unfavourable	TYPE 2	YES	YES	Fail
Unfavourable	TYPE 2	YES	YES	Fail
Favourable	TYPE 1	NO	NO	Pass
Unfavourable	TYPE 1	YES	YES	Pass
Favourable	TYPE 2	YES	NO	Pass
Favourable	TYPE 1	NO	NO	Pass
Unfavourable	TYPE 1	YES	YES	Pass
Unfavourable	TYPE 2	YES	Yes	Fail
Favourable	TYPE 1	NO	NO	Pass

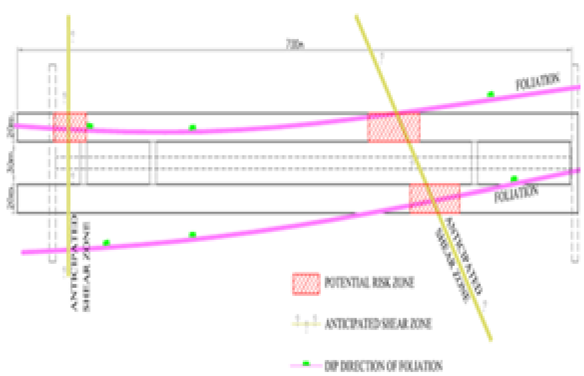

Figure 3. Predicted structural geological map of Project 3

4 CONCLUSIONS

This study incorporates an entropy-based model to predict potential instability in underground tunneling and cavern projects. An extensive analysis was carried out on data related to risks in three distinct underground projects. The data were thoroughly examined using various criteria to identify attributes and potential causes of

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instability. Subsequently, a decision tree analysis based on entropy was applied to these attributes.

The decision tree was specifically tailored for Project-1, comprising parent and child attributes. In the event of instability, this decision tree aids in resource allocation. The initial analysis of the parent attribute allows for the avoidance or mitigation of the risk. Typically, the parent attribute acts as the root cause, requiring a significant allocation of resources for risk mitigation measures. However, if the root cause persists, the decision tree provides a prioritized list of child attributes.

The investigation expands to encompass the validation process employed in Project-2 and offers a forward-looking projection for structures encountering analogous geological conditions and functional demands, as illustrated in Project-3. Thus, the model established in this research is rooted in fundamental characteristics and instances of failure. The findings underscore substantial potential for enhancing risk management, with the possibility of further refinement through the incorporation of additional case studies and a wider spectrum of attributes.

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