A Research on Evaluating General Design of Ultra-long Tunnel Based on Pareto-optimal Weight

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Abstract. In tunnel engineering, the choice of general design scheme critically impacts safety, economy, and sustainability. To optimize this for ultra-long tunnels, a Pareto optimal weight-based evaluation system was developed. It encompasses design elements, construction conditions, operation risks, and economic impacts. A multi-expert decision matrix using binary language structure was built, and a three-objective Pareto model determined optimal weights. Evaluation cloud maps were generated to compare schemes, revealing the K scheme as optimal for the Tianshan Shengli Tunnel. This system offers a scientific method for tunnel design decisions, improving decision-making efficiency and quality, with significance for complex engineering problems. The application of this system helps to improve the efficiency and quality of engineering decision-making and promotes the development and innovation of tunnel engineering technology.

Keywords. Tunnel engineering; general design evaluation; Pareto-optimal weight; ultra-long tunnel; consensus reaching process; binary language structure; 2D cloud model

1. Introduction

As China's highway network expands into western mountains, ultra-long highway tunnels become vital for strategic corridors. These projects face challenges like complex terrain, unstable geology, tough construction, and high operational risks, raising project uncertainty and demanding better tunnel design, construction, and operation. Developing a scientific evaluation system for their general design is crucial to optimize schemes, reduce risks, and enhance project benefits.

Currently, evaluation studies on long tunnels prioritize geological hazards and construction risks. Wang et al. explored water ingress risks in karst tunnel construction [1], while Liang et al. developed a risk assessment system for tunnel boring.[2] Li et al. (2022) introduced a comprehensive risk evaluation system for ultra-long tunnels, evaluating construction risks through case studies [3]. However, existing evaluations of ultra-long tunnels overlook the cumulative dangers across their lifecycle, often focusing on a single disaster or construction phase. Given their vast scale, distance, terrain complexity, and geological variability, a holistic approach considering multiple factors is crucial in their design. Furthermore, the intricate evaluation systems suffer from ambiguity and randomness among factors [4], hindering effective qualitative and quantitative analysis. This limitation impedes practical guidance for tunnel construction.

Currently, engineering practices for ultra-long tunnels heavily rely on expert decision-making for general design, yet academic research has laid a foundation for quantitative weight-based comprehensive evaluation methods. These models encompass weight calculation and scheme evaluation techniques. Weighting methods include AHP [5], CRITIC [6], and combined methods [7],while evaluation approaches span TOPSIS[8], fuzzy evaluations[9], and innovative cloud modeling[10]. For instance, Li et al. (2022) utilized cloud modeling and AHP to assess risks from water surges, deformations, rockbursts, and landslides in China's Chizhou-Qimen Expressway tunnel [3]. Xue et al. (2021) employed AHP and extension theory to quantitatively evaluate routing options for an undersea tunnel [5]. However, AHP's subjective weighting process is complex and demands consistency, while combined methods, blending subjective and objective criteria, may over-process or distort data during fusion, impacting scientificity and reliability [11].

Study establishes a comprehensive evaluation system for optimizing ultra-long tunnel designs, integrating CRP (consensus reaching process) [13,14], Pareto optimization and cloud model theory [12] for quantitative analysis and visual comparison, guiding rational choices and assessing optimization effects.

2 Materials and Methods

2.1 Evaluation Methods

Fig. 1 outlines an eval method where experts rate using binary terms, iteratively compute weights via CRP, select Pareto optimal weights, & apply them to 1D & 2D cloud gens to generate final tunnel design eval results. This study establishes an eval index system for ultra-long tunnels, grounded in project experience, research, & ultra-long tunnel eval references, as in Fig. 2.

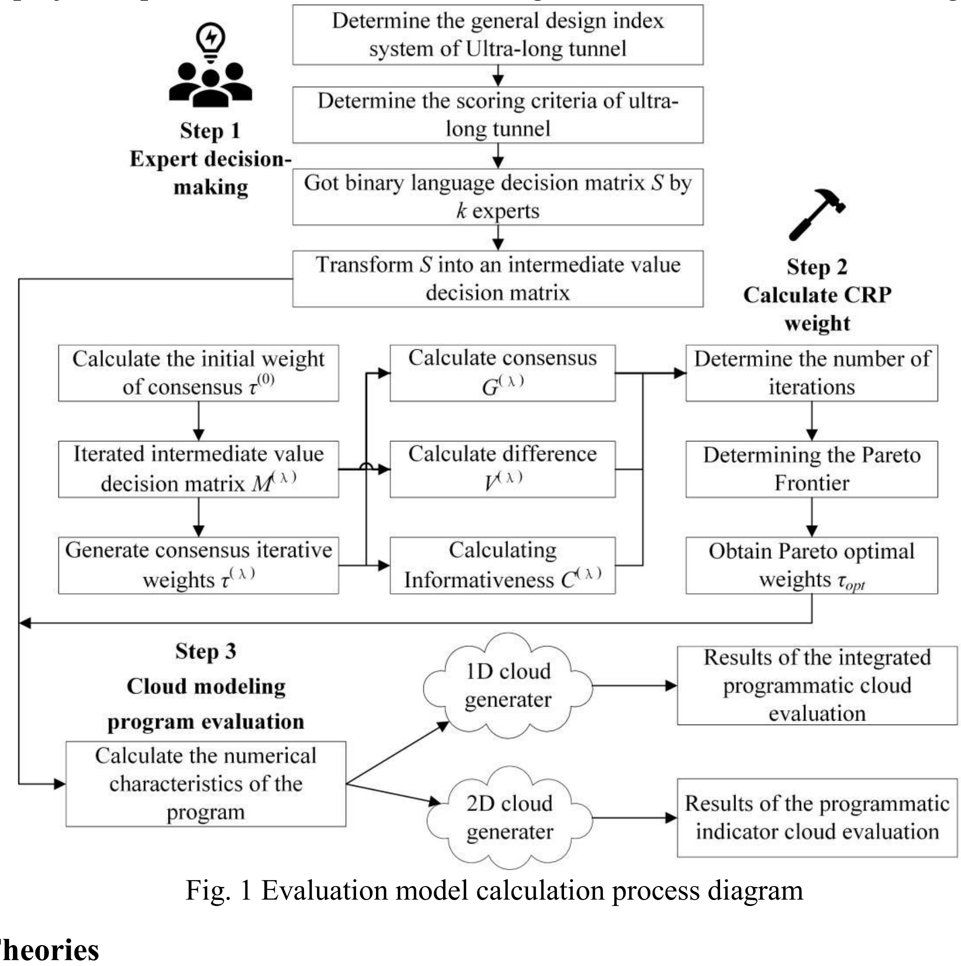

Fig. 1 Evaluation model calculation process diagram

2.2 Basic Theories

2.2.1 Binary language structure

The binary language structure used in this study [15] expands the original two terms to 4 intervals,

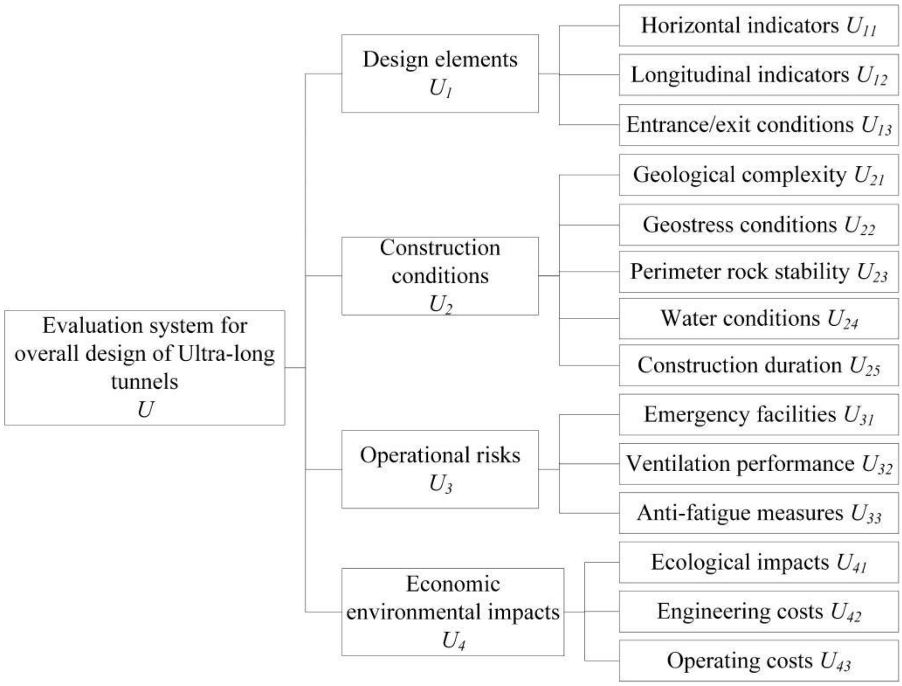

Fig. 2 Evaluation index system for general design of ultra-long tunnels

forming 5 variables, as shown in Fig. 3. Experts' evaluations on a program form a binary language decision matrix, and equations are used to represent and calculate intermediate values.

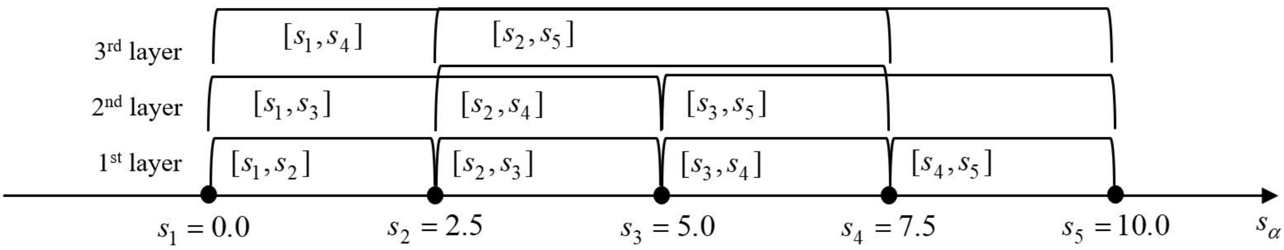

Fig. 3 Correspondence diagram of binary language terms

$$\tilde{s} = [s_L, s_R], s_L, s_R \in S, s_L \le s_R,\quad \mathrm{m}(\tilde{s}) = (I(s_L) + I(s_R))/2 \tag{1}$$

2.2.2 Consensus reaching process

This paper introduces an iterative consensus model $G^{(\lambda)}$, to calculate weights in program decision-making [13]. For detailed calculation steps refer to Ref. [13,14].

2.2.3 Objective function

(1) The consensus function $G^{(\lambda)}$ iteratively optimizes consensus by adjusting the median matrix and replacing experts' decisions based on minimum consensus levels. Iterations continue until λ weights and consensus degrees are obtained.

(2) The variance function $V^{(\lambda)}$ assesses the total weight distribution, measuring the degree of discrepancy from the average weight. A larger discrepancy indicates more uneven weights.

(3) The informativeness function $C^{(\lambda)}$ reflects the data value and information carrying capacity of weights. It uses the CRITIC method's idea to calculate the information degree, considering contrast and contradiction. Larger values indicate higher information degree.

$$V^{(\lambda)} = \left|\tau^{(\lambda)} - \overline{\tau}^{(\lambda)}\right| \tag{2}$$

$$C^{(\lambda)} = \sum\nolimits_{j=1}^{n} \sqrt{\frac{1}{km-1}\sum_{i=1}^{km}(m_{ij} - \overline{m_{ij}})^2} \cdot \left(\sum\nolimits_{i=1}^{i=km}\left(1 - \frac{\mathrm{cov}(M_{ij}^{(\lambda)})}{std(M_{ij}^{(\lambda)}) \cdot std(M_{ij}^{(\lambda)})^T}\right)\right) \tag{3}$$

2.2.4 Pareto optimization algorithm

The Pareto-optimal algorithm optimizes weights by balancing three parallel objectives: consensus, variance, and informativeness. It identifies non-dominated solutions, sorts them based on dominance, selects frontier-plane solutions, measures their crowding distance, and finally determines the Pareto-optimal weights with the maximum crowding distance on the frontier surface.

$$d(\tau_F^{(i)},\tau_F^{(j)})=\sqrt{(G(\tau_F^{(i)})-G(\tau_F^{(j)}))^2+(V(\tau_F^{(i)})-V(\tau_F^{(j)}))^2+(C(\tau_F^{(i)})-C(\tau_F^{(j)}))^2} \tag{4}$$

2.2.5 Cloud model

Exploring the qualitative-quantitative link, the cloud model utilizes Ex, En, He to depict qualitative ambiguity & uncertainty. The 1D model characterizes a concept, while the 2D model extends to connections & impacts of two concepts. Both are founded on scoring criteria & expert matrices, yielding criterion & evaluation clouds for multi-dimensional conceptual analysis.

According to the detailed elaboration in the literature [16], the specific calculation of cloud model parameters involves the combined use of sample cloud eigenvalues and indicator weights. The comprehensive cloud eigenvalues derived from the calculation can further construct a programmed indicator cloud to provide quantitative support for qualitative analysis. In particular, the cloud generator sets the He to 0.1[1] during its operation, whether it generates a one-dimensional comprehensive evaluation cloud or a two-dimensional indicator evaluation cloud map, a setting that aims to maintain the stability and consistency of the model in specific application scenarios.

3 Case Study

3.1 Project Summary

The Wuyu Expressway in Xinjiang features a crucial project, the Tianshan Shengli Tunnel, spanning 22.105km in alpine, high-altitude terrain. Designed for 100km/h, it's a 2-way, 4-lane tunnel constructed using TBM methods. 6 design options exist, differing in length, construction difficulty, environmental impact, and cost. A comprehensive evaluation is needed to select the best option.

3.2 Calculation of Numerical Characteristic

The binary linguistic matrix is iteratively transformed, consensus measured, weights computed, & decision matrix optimized for consensus & decision-making. Optimal weights, stabilized by iterations (Fig. 4), are found at 15th iteration via Matlab's Pareto search, which τ_{opt} = [4.75, 6.06, 6.86, 8.20, 7.06, 8.16, 3.89, 7.33, 6.17, 7.09, 7.64, 10.02, 8.97, 7.54] $*10^{-2}$. 1D & 2D eval clouds are generated from parameters, visualized by Matlab's cloud gens (Fig. 5-6), enabling direct scheme comparison & performance understanding.

3.3 Results and Discussion

The binary linguistic structure enhances linguistic accuracy and simplifies weight & cloud model calculations, outperforming traditional AHP. However, the number of experts should not be less than 3 for the consideration of the accuracy of weight calculation.

1001 weight vectors are initialized via CRP, with Pareto optimal model selecting the most congested frontier solution as optimal. This represents the optimal weights under three objectives.

According to the one-dimensional comprehensive evaluation cloud results, the order of the advantages and disadvantages of the six schemes is as follows: K > A11 > A15 > A12 > A14 > A13, and the Scheme K solution is optimal.

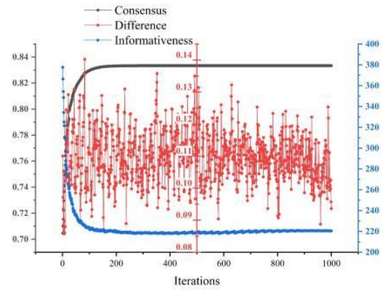

Fig. 4 Variation of objective function with iterations

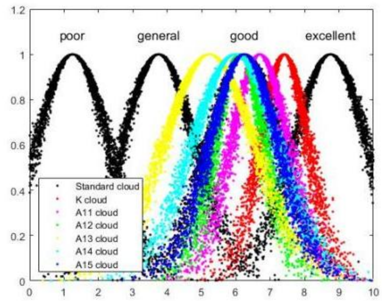

Fig. 5 1D comprehensive evaluation cloud chart

U1&U2's 2D cloud diagram exemplifies a scheme centered on "good" design & construction. Scheme K excels in design but lags slightly behind A11 in construction. Minor design disparities exist, yet A13 & A14 suffer from poor alignment, impacting their ratings. Construction disparities are pronounced, influenced by factors like proximity to Tianshan No. 1 glacier.

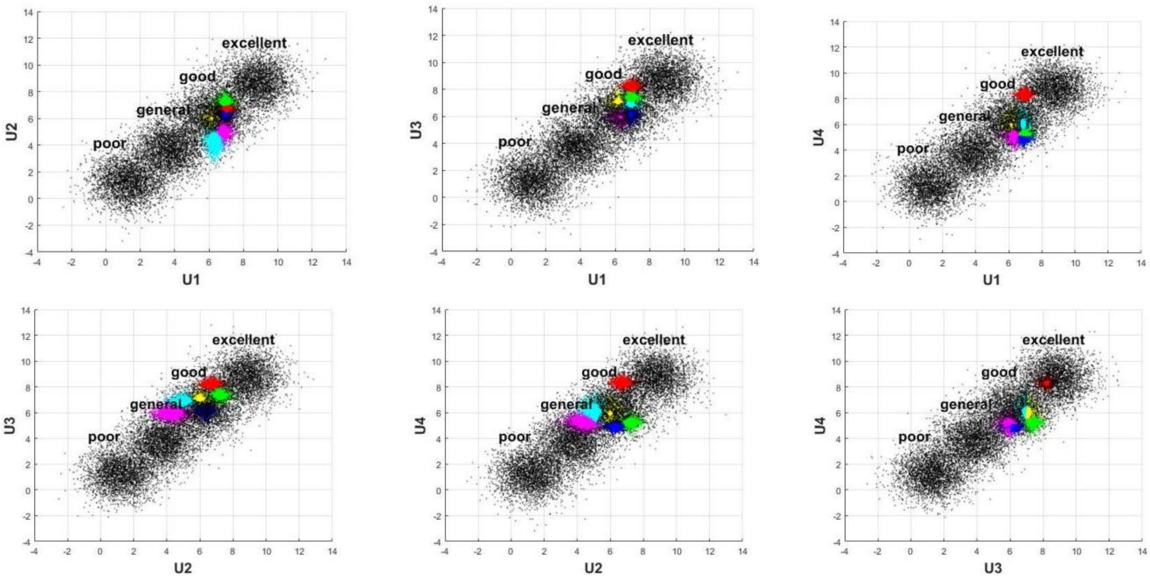

Fig. 6 2D indicator evaluation cloud charts

4 Conclusions

1. The first comprehensive design index system for ultra-long tunnels proposes 14 secondary indexes across design elements, construction conditions, operation risks, and economic environmental impacts, addressing gaps in existing research.
2. The Pareto optimal solution model utilizes binary language structure, CRP, and Pareto algorithm to determine optimal weights considering consensus, difference, and information degrees.
3. Combining Pareto optimal weights with 1/2D cloud concepts, a Matlab generator creates 2D cloud diagrams for indicator evaluation, addressing uncertainty and randomness.
4. Applying this system to the TianShan Shengli Tunnel, the optimal K scheme aligns with 2D analysis and actual project needs.

Acknowledgements

The authors are profoundly grateful for the financial support received from the Science and Technology R&D Project of CCCC Second Highway Survey and Design Institute Co., Ltd., under the grant number KJFZ-2021-005 (construction of high-cold and high-altitude highway long tunnels).

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