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Ming Huang, Liankui Zhao, Fan Yang* and Yueling Jing

School of Civil and Hydraulic Engineering, Hefei University of Technology, Hefei, 230009, China

INFORMATION

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ABSTRACT

During the construction of diversion tunnels, different support schemes exhibit varying stability conditions and entail distinct economic costs. To enhance the cost-effectiveness of tunnel support while ensuring its safety, a multi-objective optimization model has been developed for deeply buried diversion tunnels with bad geological conditions, enabling the execution of multi-objective optimization calculations regarding construction safety and economy. By considering the settlement of the vault and the cost of supporting materials as the objective function, a set of solution sets is computed using the multi-objective multi-verse algorithm (MOMVO), and subsequently, an optimal solution is obtained by integrating the entropy weight-technique for order preference by similarity to an ideal solution (TOPSIS) decision. The Luzhi River Tunnel of the Central Yunnan Water Diversion Project was selected as the subject of analysis to conduct support optimization calculations. The results demonstrate that, compared to the original design, there is an 8.16% reduction in the cost of support materials per linear meter. Although there is a 0.76% increase in settlement at the tunnel vault, it remains significantly below the safety critical value and aligns with project safety requirements. The proposed optimization method for tunnel support demonstrates remarkable efficacy, effectively reducing the cost of support materials while ensuring engineering safety. Moreover, it provides valuable technical support for optimizing the support system in water diversion tunnels.

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1 Introduction

Water diversion tunnels are crucial for constructing water conservancy projects in China. In recent years, there has been a trend towards longer, larger, and deeper diversion tunnels. The stability during the construction phase of deeply buried tunnels is closely linked to overall project safety. To ensure tunnel safety, it is often necessary to provide rock support around the excavation [1]. Excessively conservative design parameters for support can lead to inefficiencies in resource allocation, resulting in economic waste problems. Conversely, it will give rise to safety problems. Optimizing the support parameters of tunnels while striking a balance between safety and economy constitutes a crucial research focus in contemporary tunnel engineering. The optimization approaches for tunnel support

*Correspondence: Fan Yang (fyang@hfut.edu.cn).

can be categorized into conventional optimization methods and intelligent optimization methods. Traditional optimization methods encompass the finite element method, orthogonal test method, strength reduction method, similar simulation method, etc. [2]. Intelligent optimization methods seamlessly integrate optimization theory with computer technology, showcasing not only rapid convergence speed and high computational accuracy but also remarkable versatility [3,4]. Prominent examples encompass multi-objective genetic algorithms, particle swarm optimization algorithms, and multi-verse optimization algorithms. The multi-objective multi-verse optimization algorithm (MOMVO), among others, exhibits a concise structure and offers advantages such as high robustness, rapid convergence speed, and superior computational accuracy. Mirjalili et al. [5] tested the performance of the MOMVO algorithm by using an unconstrained multi-objective test function, a constrained multi-objective test function, and an engineering design multi-objective problem, and the results clearly show that the MOMVO algorithm performs very competitively. Consequently, it enables faster attainment of improved solutions for complex problems and finds wider applicability in solving optimization problems within the engineering domain.

Currently, the majority of research on tunnel support optimization predominantly employs single-objective optimization techniques or approaches that consolidate multiple objectives into a singular objective. However, there is a relatively limited body of literature focusing on the concurrent optimization of multiple objectives. Wen et al. [6] considered the optimization objective function to be the total support resistance of the tunnel. Su et al. [7] optimized the support by formulating the objective function as minimizing the cost of the initial support per linear meter. Zhao et al. [8] employed the particle swarm optimization algorithm to optimize the support parameters by considering the crown settlement as the objective function and integrating it with numerical simulation. Niu et al. [9] employed the particle swarm optimization algorithm and adopted the method of expert weighting to transform the multi-objective issue into a single-objective one for the optimization of the tunnel support structure. If the simultaneous optimization of multiple objectives is considered, the objective function can be more comprehensive, leading to enhanced accuracy in the optimization results. When conducting multi-objective optimization computations, it is common to employ multi-objective optimization algorithms and calculate the Pareto solution set in conjunction with the principles of Pareto theory [10], the optimal solution from the Pareto solution set can be determined by employing various methods, such as the entropy weight method, the analytic hierarchy process, and the technique for order preference by similarity to ideal solution (TOPSIS), among others [11].

In conclusion, this study integrates the MOMVO algorithm with support vector machine (SVM) to establish a multi-objective optimization model for tunnel support, aiming to leverage the benefits of a more comprehensive objective function and achieve more accurate optimization results. Additionally, entropy weight and TOPSIS are combined to determine the optimal solution, providing a complete set of methods for optimizing support parameters. By applying these methods to the Luzhi River Tunnel of the Central Yunnan Water Diversion Project as an illustrative example for calculation and analysis, our goal of ensuring tunnel safety while significantly reducing the cost of support materials has been successfully accomplished.

2 Principle of the MOMVO Algorithm

The MOMVO [5] algorithm was proposed by Seyedali Mirjalili and evolved into an algorithm for multi-objective optimization based on the multi-verse optimizer (MVO) [12]. The algorithm is based on theoretical knowledge, including the concepts of the Big Bang and the multiverse. It is postulated that the multiverse originated from a primordial event known as the Big Bang, giving rise to various phenomena such as black holes, white holes, and wormholes within its framework. Black holes possess immense gravitational pull capable of engulfing all matter in their vicinity, while white holes are speculated to expel matter energetically. Wormholes serve as conduits connecting distinct universes and facilitating inter-universal transportation. The universe is considered a potential solution for the problem, with its expansion rate serving as the fitness value of this candidate solution. In this study, the support optimization parameters to be solved in the optimization problem are represented by candidate solutions, while their corresponding fitness values represent the target values of the support optimization to be solved. The specific procedure is outlined as follows:

(1) Initialization

The initialization of the multiverse is depicted as follows:

$$U = \begin{bmatrix} P_{1,1} & \cdots & P_{1,d} \\ \vdots & \ddots & \vdots \\ P_{n,1} & \cdots & P_{n,d} \end{bmatrix} \tag{1}$$

where a multiverse depicted by the variable U, the variable n represents the number of parallel universes contained within the multiverse U, the variable d represents the cardinality of substances within each universe.

(2) Iteration and Renewal

Where $P_{i,j}$ is processed in two ways: one utilizes the roulette wheel mechanism, while the other preserves the original value, as illustrated by the following formula.

$$P_{i,j} = \begin{cases} P_{k,j}, & rand_1 < Norm\left(U_i\right) \\ P_{i,j}, & rand_1 \geq Norm\left(U_i\right) \end{cases} \tag{2}$$

where $P_{i,j}$ is the jth object of the ith universe, $P_{k,j}$ signifies the jth object of kth universe opted by the roulette wheel, U_i reveals the ith universe, $Norm\left(U_i\right)$ shows normalized inflation rate of the ith universe and $rand_1$ denotes a random number in the interval [0, 1].

The white hole will conduct a spiral search based on the standardized expansion rate of the universe, whereby objects with a higher expansion rate are more likely to be transported via the white hole, while those with a lower expansion rate are more likely to be transported through the black hole.

The hypothesis posits that object exchange can potentially occur between any solution and the current optimal solution through a wormhole, with the corresponding formula for updating solutions being as follows:

$$P_{i,j} = \begin{cases} P_{i,j} + r_{TDR} \times \left(\left(b_{u,j} - b_{l,j}\right) \times rand_4 + b_{l,j}\right), & rand_3 < 0.5, rand_2 < P_{WEP} \\ P_{i,j} - r_{TDR} + \left(\left(b_{u,j} - b_{l,j}\right) \times rand_4 + b_{l,j}\right), & rand_3 \geq 0.5, rand_2 < P_{WEP} \\ P_{i,j} & rand_2 \geq P_{WEP} \end{cases} \tag{3}$$

where $b_{u,j}$ and $b_{l,j}$ are upper bound and lower bound of the jth object, respectively, and $rand_2$, $rand_3$, and $rand_4$ are random numbers between the interval [0, 1]. The variable P_{WEP} represents the probability of a wormhole model's existence within the search space. As the iterations progress, P_{WEP} incrementally increases to enhance the algorithm's exploitation ability, thereby preventing convergence failure. The variable r_{TDR} represents the rate of travel distance, which gradually decreases during the iterative process to facilitate a more precise local search around the obtained optimal solution. The formulae for updating P_{WEP} and r_{TDR} are as follows:

$$P_{WEP} = P_{WEP_{\min}} + I_{cu}\left(\frac{P_{WEP\max} - P_{WEP_{\min}}}{I_{\max}}\right) \tag{4}$$

$$r_{TDR} = 1 - \frac{{I_{cu}}^{1/Pe}}{{I_{\max}}^{1/Pe}} \tag{5}$$

where $P_{WEP_{\min}}$ and $P_{WEP_{\max}}$ represent the lower and upper bounds of P_{WEP} in the given equation, the variable I_{cu} represents the current count of iterations, the symbol $I_{\max}$ represents the total number of iterations, the variable P_e represents the algorithm's exploitation degree during its operation. A higher value indicates a greater level of exploitation, resulting in more accurate iterative results. The flowchart is shown in Fig. 1.

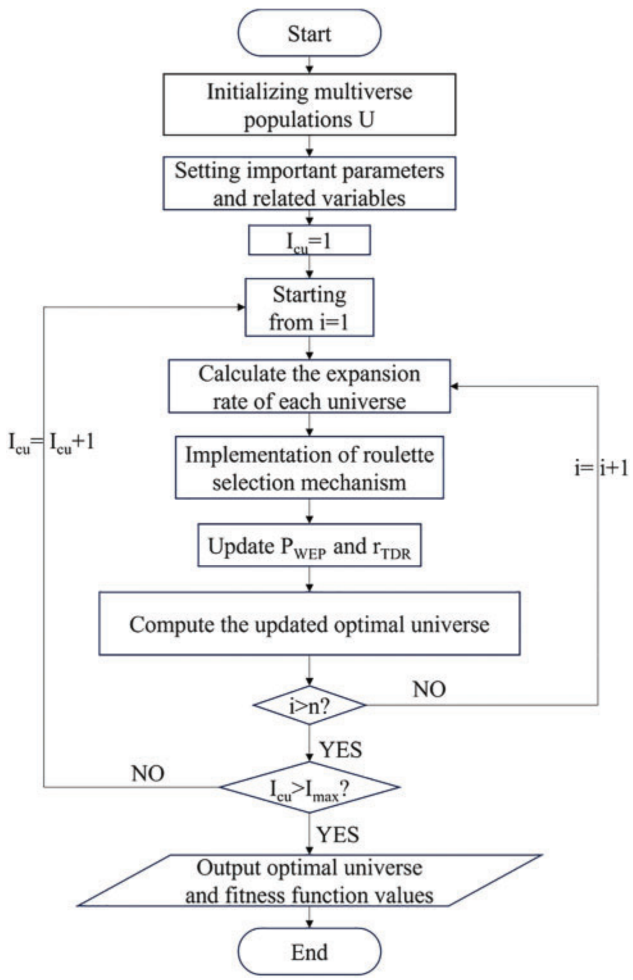

Figure 1: Flowchart of MOMVO algorithm

3 Optimization Model for Support

3.1 Objective Function

In the optimization of tunnel support, ensuring safety and reducing costs are often the primary objectives. Therefore, this paper aims to optimize the original support design by considering both crown settlement G [8] and the cost of tunnel support materials per meter J [13,14] as objective functions, with a focus on guaranteeing tunnel safety while minimizing material expenses. The accurate selection of support parameters is crucial for the rationality of the optimization scheme. Based on previous research findings [14,15], it has been observed that when the anchor bolt length reaches 2.0 m, any variations in its length have a negligible impact on displacement changes [16]. Consequently, optimizing this parameter can be disregarded under these circumstances. The design variables for support optimization in this paper include the longitudinal spacing of anchor bolts, the circumferential spacing of anchor bolts, the spacing of steel supports, and the thickness of the concrete spray layer. The vector representing these design variables is as follows:

$$X = [x_1, x_2, x_3, x_4]^T = [s_a, s_b, s_c, s_d]^T \tag{6}$$

where s_a represents the longitudinal spacing of anchor bolts (m), s_b denotes the circumferential spacing of anchor bolts (m), s_c indicates the spacing of steel supports (m), s_d signifies the thickness of the concrete spray layer (cm).

The formula for calculating the cost of support materials per meter is presented in Eq. (7).

$$J = \left[\mathrm{a} \left(\frac{Q}{s_b} \times X_1 \times \frac{\pi}{4} (X_2)^2 \times \rho \times \frac{1}{s_a} \right) + s_d \times b \right] + \frac{764}{s_c} \times c \tag{7}$$

where a represents the unit cost of anchor bolts per unit mass, b represents the unit cost of concrete per unit thickness, c represents the unit cost of steel support per unit mass, Q represents the perimeter length of the cave, X_1 represents the anchor bolt length, X_2 represents the anchor bolt diameter, ρ represents the material density of the anchor bolt.

The relationship between the vault settlement of the tunnel and the support parameters is highly complex, making it challenging to establish an objective function due to the nonlinear nature of their connection, which cannot be accurately represented by a specific explicit mathematical model. Therefore, in this paper, we employ SVM machine learning to establish a nonlinear relationship between the vault settlement and the support parameters. The process of machine learning involves training and processing a predetermined dataset to determine the model, enabling accurate predictions for the target being tested. Therefore, in this paper, finite element calculations were initially conducted on the 25 training samples of the orthogonal experimental design to acquire the sample dataset. Subsequently, machine learning was employed using the sample dataset to establish a fitting model for capturing the nonlinear relationship between vault settlement G and support parameters. The obtained fitted values for vault settlement G and cost J of support materials per meter were then integrated into the MOMVO algorithm to solve the Pareto solution set.

3.2 Constraints

The establishment of the optimization model for support parameters relies heavily on setting reasonable constraints for design variables. It is crucial to select a value range for these constraints that aligns with relevant norms and engineering characteristics. Drawing upon relevant engineering experience [8] and considering the model's applicability, this paper presents the fundamental ranges of each variable, referred to as constraint conditions, as illustrated in Table 1.

Table 1: Aggregation of constraint conditions

Design variable	Constraints
Longitudinal spacing of anchor bolts/m	$0.5 \leq s_a \leq 2.5$
Circumferential spacing of anchor bolts/m	$0.5 \leq s_b \leq 2.5$
Spacing of steel supports/m	$1.0 \leq s_c \leq 1.4$
Thickness of the concrete spray layer/cm	$10 \leq s_d \leq 30$

3.3 The Process of Decision-Making

After obtaining the Pareto solution set through the multi-objective optimization algorithm, we employ the entropy weight-TOPSIS method to determine the optimal scheme.

A decision matrix $F = [f_{ij}]$ is constructed based on the Pareto solution set obtained through the MOMVO algorithm, the value of the jth objective function corresponding to the ith Pareto solution, denoted as f_{ij}, is standardized as follows:

$$Y_{ij} = \frac{f_{ij}}{\sqrt{\sum_{i=1}^{I} f_{ij}^2}} \tag{8}$$

where Y_{ij} denotes the standardized value of the jth objective function corresponding to the ith Pareto solution, I represents the cardinality of Pareto solution sets.

Determine the negative ideal solution Y^- and the positive ideal solution Y^+.

$$\begin{cases} Y^- = \min\left(Y_{i1}, Y_{i2}, \cdots, Y_{ij}\right) \\ Y^+ = \max\left(Y_{i1}, Y_{i2}, \cdots, Y_{ij}\right) \end{cases} \tag{9}$$

The weights ω for each optimization objective are calculated using the entropy weight method.

$$\begin{cases} H_j = -\dfrac{1}{\ln I} \sum_{i=1}^{I} Y_{ij} \ln Y_{ij} \\ d_j = 1 - H_j \\ \omega_j = \dfrac{d_j}{\sum_{j=1}^{M} d_j} \end{cases} \tag{10}$$

where H_j represents the entropy value associated with the jth optimization objective, the variable I represents the cardinality of Pareto solution sets. The variable d_j denotes the redundancy of information entropy for the jth optimization objective, the variable ω_j denotes the weight assigned to the jth optimization objective, the symbol M denotes the quantity of optimization objectives.

The weighted euclidean distances R_i^+ and R_i^- of each scheme from the positive and negative ideal solutions are computed.

$$\begin{cases} R_i^+ = \sqrt{\sum_{j=1}^{J} \omega_j \left(Y_j^+ - Y_{ij}\right)^2} \\ R_i^- = \sqrt{\sum_{j=1}^{J} \omega_j \left(Y_j^- - Y_{ij}\right)^2} \end{cases} \tag{11}$$

Compute the ranking score Z_i for the ith scheme.

$$Z_i = \frac{R_i^-}{R_i^- + R_i^+} \tag{12}$$

Arrange the different solutions based on their Z_i scores in descending order and select the one with the highest score as the optimal support scheme.

4 Research on Applications

4.1 Engineering Profile

Central Yunnan, located in Yunnan Province, stands as the most economically developed region within the province and also faces severe aridity and water scarcity issues within the Yangtze River basin. The Central Yunnan Water Diversion Project, a colossal undertaking sanctioned by the State Council, aims to address the pressing water shortage problem in this area. Drawing water from the Jinsha River, precisely 1.5 km upstream of Shigu Town in Yulong County, Lijiang City, this project commences at Wangcheng Slope in Shigu Town and traverses through Lijiang City, Dali Prefecture, Chuxiong Prefecture, Kunming City, and Yuxi City before culminating at Xinpobei in Honghe Prefecture. Spanning an extensive length of 661.07 km for its water transmission line alone, with karst terrain constituting approximately 21% of its total distance covered, it encompasses a remarkable number of 129 conveyance structures, including 63 tunnels that collectively span across a length of 607.23 km, accounting for an impressive proportion of 91.86%. Based on the Luzhi River Tunnel of the Central Yunnan Water Diversion Project, we conducted research utilizing the MOMVO algorithm to optimize tunnel support. By integrating advanced geological prediction and exploration findings from the Luzhi River Tunnel, it was determined that the LZH0+104-LZH0+174 section exhibits type IV surrounding rock conditions, which informed our subsequent support design: The side-top arch is coated with a 20 cm thick layer of C20 coarse-fiber concrete. φ25 hollow grouting bolts are utilized, with a bolt length of 6 m, a circumferential spacing of 1.5 m, and a longitudinal spacing of 1.5 m. I20a steel supports are installed in the tunnel section at intervals of 1.1 m. This support measure exemplifies the construction process for bad geological conditions encountered in the Luzhi River Tunnel.

4.2 The Establishment of Finite Element Model

Based on the engineering data of the Luzhi River Tunnel, the finite element model of the tunnel was established using ANSYS software to achieve dynamic simulation of tunnel construction. In accordance with the Saint-Venant theory, the numerical calculation model presented in this study is defined with a range that is five times the diameter of the tunnel. Specifically, the left, right, and lower boundaries of the model are positioned 50 m from the axis of the tunnel section, while the upper boundary extends to ground level. Furthermore, along its axial direction, the length of the tunnel is set at 70 m. The Burgers model is employed to calculate the surrounding rock, while solid elements are used to simulate the surrounding rock mass, shell elements represent the concrete spray layer, link elements depict the anchor bolts, and beam elements represent the steel support. The model is subjected to displacement constraints, and during the calculation, the self-weight stress field induced by the overlying rock mass is taken into account. The schematic representation of the established calculation model is presented in Fig. 2.

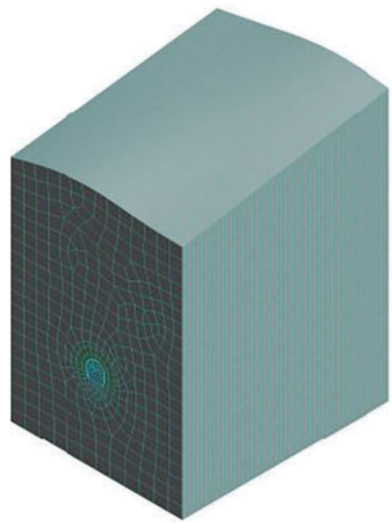

Figure 2: The finite element calculation model diagram

Fig. 3 shows the established pre-optimization support model.

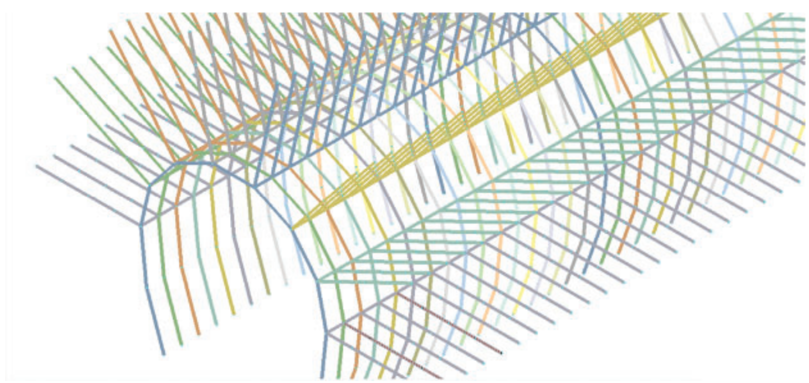

Figure 3: Support model diagram before optimization

The values of surrounding rock parameters were determined as follows, based on the geological exploration report of the Luzhi River Tunnel and the results of parameter inversion studies conducted for similar engineering projects [17]: an elastic modulus of 2.4 GPa, a Poisson's ratio of 0.33, a Kelvin modulus of 8.6 GPa, a Kelvin viscosity coefficient of 13.6 × 10^3 Pa·S, a Maxwell modulus of 0.3 GPa, and a Maxwell viscosity coefficient of 1223.5 × 10^3 Pa·S.

4.3 Support Parameter Optimization and Decision Analysis

4.3.1 Establishment of the SVM Model

The SVM algorithm was implemented using MATLAB to establish the SVM model of vault settlement G by incorporating 25 groups of learning samples from the orthogonal experiment. This model will be utilized for MOMVO optimization calculations in subsequent sections. The algorithm randomly selected 20 groups of training set samples (accounting for 80%) and 5 groups of test set samples (accounting for 20%) [18]. The learning effects are illustrated in Figs. 4 and 5.

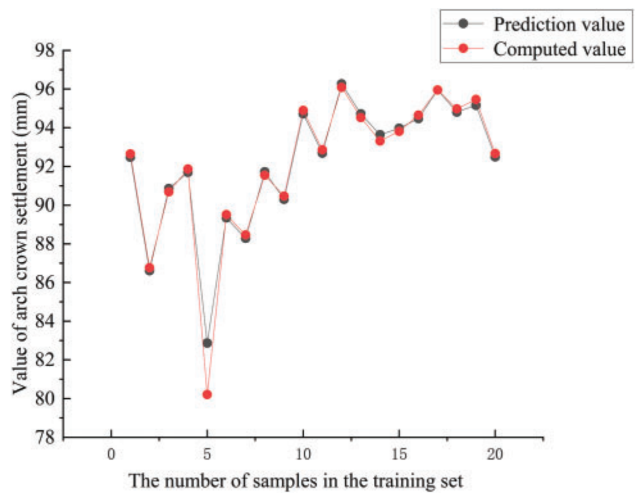

Figure 4: The training effect of the SVM training set

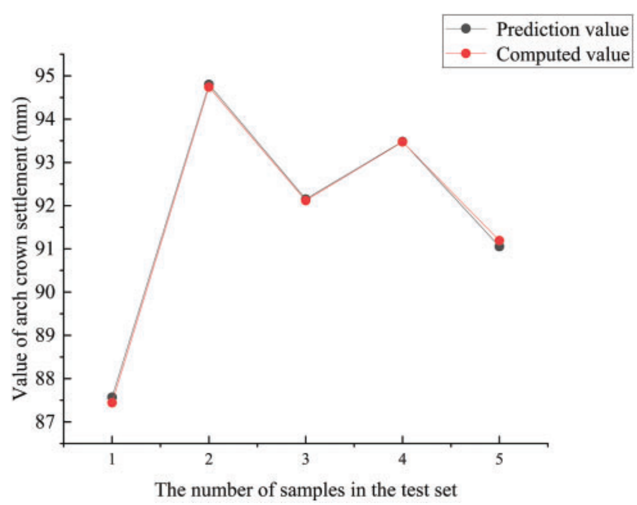

Figure 5: The testing effect of the SVM test set

To assess the fitting effect, in this paper, the average absolute percentage error and root mean square error are adopted as the evaluation metrics of the model performance [19]. The calculation formulas are:

$$E_{\text{MAPE}} = \frac{1}{\lambda} \sum_{i=1}^{\lambda} \left| \frac{y_i - \hat{y}}{y_i} \right| \times 100\% \tag{13}$$

$$E_{\text{RMSE}} = \sqrt{\frac{1}{\lambda} \sum_{i=1}^{\lambda} \left(y_i - \hat{y} \right)^2} \tag{14}$$

where E_{MAPE} represents the average absolute percentage error, E_{RMSE} denotes the root mean square error, λ signifies the sample size, $\hat{y}$ stands for the model output value, and y_i refers to the calculated value.

Upon calculation, for the training set, E_{MAPE} was 0.8119% and E_{RMSE} was 0.6224 mm, for the test set, E_{MAPE} was 0.4046% and E_{RMSE} was 0.4182 mm. The results demonstrate that the SVM model established for vault settlement exhibits high accuracy and exceptional learning performance. Therefore, in this study, SVM is utilized to compute the safety index, denoted as G, for subsequent multi-objective optimization analysis of the support structure aimed at obtaining optimal support parameters.

4.3.2 Optimization of Supporting Parameters

The objective of multi-objective optimization for support parameters is to ensure the safety of the surrounding rock in tunnels, namely, while meeting the requirements of vault settlement G specified reducing the cost of support materials J. The optimization model can be represented by a set of objective functions and associated constraints. To sum up, the mathematical expression of the multi-objective optimization model of support parameters can be generalized as follows:

$$\min F(x) = [G(x), J(x)]^T, x = [s_a, s_b, s_c, s_d]^T \in R^4$$
$$\begin{Bmatrix} 0.5m \le s_a \le 2.5m \\ 0.5m \le s_b \le 2.5m \\ 0.5m \le s_c \le 0.9m \\ 10cm \le s_d \le 30cm \end{Bmatrix} \tag{15}$$

where $G(x)$ is the established SVM calculation model for the vault settlement, $J(x)$ is the calculation formula for the cost of support materials, as shown in Eq. (7).

The optimization problem at hand is a 2 objective and 4 variable optimization problem, which is effectively addressed using the MOMVO algorithm. MATLAB programming language is employed for implementation, with the initial parameters of the algorithm set as presented in Table 2.

Table 2: The initial parameter settings of the MOMVO algorithm

Population size	Number of iterations	The size of the archive set	Dimensionality	The quantity of targets
200	500	50	4	2

By incorporating $G(x)$ and $J(x)$ into the MOMVO algorithm, the iterative update and calculation yield a Pareto solution set, as illustrated in Fig. 6. It is evident that the optimization effect of the MOMVO algorithm is favorable, with a uniformly and orderly distributed Pareto solution set demonstrating clear convergence.

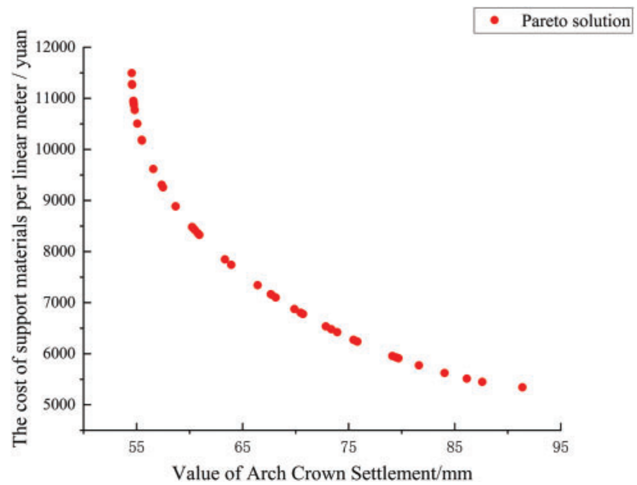

Figure 6: The pareto solution set of the MOMVO algorithm

4.3.3 Analysis of Decision Results

The Pareto solution set is obtained, and then entropy weight-TOPSIS is employed to assign weights and rank the vault settlement G and the cost of support materials per meter J, respectively. This process helps select a subset of solutions that meet the given requirements. Finally, the optimal solution is determined. According to the entropy weighting method described in Section 3.3, the weight of G is calculated to be 30.02%, and the weight of J is 69.98%. TOPSIS is used to rank the solutions according to Eqs. (8) and (9), Eqs. (11) and (12), and the first-ranked solution is selected as the optimal solution for this optimization. The comparative results are presented in Tables 3 and 4. The optimized support model is shown in Fig. 7.

Table 3: The comparative results between the initial design parameters and the optimized parameters

Supporting parameters	The initial design parameter	The value of optimization
Longitudinal spacing of anchor bolts/m	1.5	1.6
Circumferential spacing of anchor bolts/m	1.5	1.7
Spacing of steel supports/m	1.1	1.2
Thickness of the concrete spray layer/cm	20	19

Table 4: The comparative outcomes of design objectives and optimization objectives

Objective function	The original scheme	Optimization scheme
Vault settlement/mm	91.6	92.3
Cost of support materials per linear meter/Yuan	5536.3	5084.1

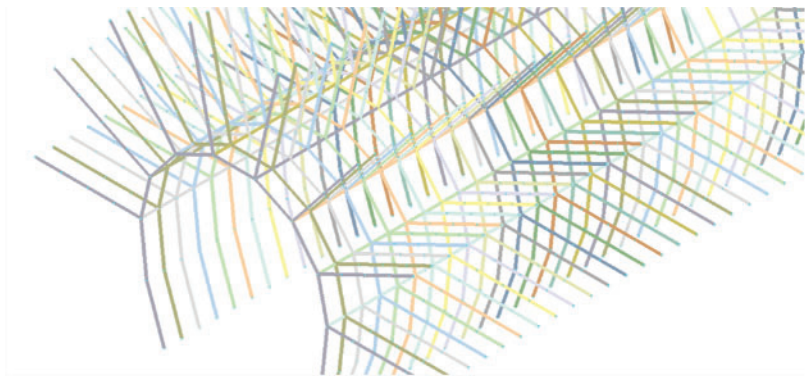

Figure 7: Support model diagram after optimization

To assess compliance with safety requirements regarding crown subsidence, this study applies the Technical Code for Rock Anchoring and Shotcrete Support Engineering (GB50086-2015) [20] in conjunction with project-specific geological conditions. The relative contraction value around the cave is considered as 1.2% [8], and Eq. (16) is employed to calculate the permissible maximum tunnel subsidence, resulting in a value of 118.3 mm.

$$\partial = \frac{\delta}{B} \tag{16}$$

where ∂ denotes the permissible relative convergence value of the excavation, δ represents the maximum allowable settlement at the crown, and B signifies the initial width of the tunnel section.

According to Table 4, the settlement of the tunnel vault increased from 91.6 to 92.3 mm after optimization, with a slight increase of only 0.7 mm and an increase rate of 0.76%. Furthermore, this increase is significantly lower than the allowable maximum settlement of 118.3 mm, indicating a sufficient safety margin. The cost of support materials per linear meter decreased from 5536.3 yuan to 5084.1 yuan, resulting in a savings of 452 yuan per linear meter, representing a reduction rate of 8.16%. The support cost per linear meter can evidently be significantly reduced while simultaneously ensuring the safety of the surrounding rock in the Luzhi River Tunnel. This optimization method demonstrates remarkable economic effects for long-distance diversion tunnels.

5 Conclusions

This paper presents an optimization model for tunnel support, addressing the multi-objective nature of safety and economy requirements. The proposed approach integrates the MOMVO algorithm with the entropy weight-TOPSIS method to establish a comprehensive framework for tunnel support optimization. By applying this methodology to the Luzhi River Tunnel as a case study, several key research findings are obtained.

(1) The original support design was optimized by considering the vault settlement G and the material cost J per linear meter of tunnel support as the objective functions. The nonlinear relationship between the vault settlement G and the support parameters was accurately modeled using SVM, leading to the establishment of an SVM model for predicting the vault settlement G. Finally, the MOMVO algorithm was employed to integrate these two objectives.

(2) The MOMVO algorithm is employed to solve the Pareto solution set of the multi-objective problem in conjunction with the proposed support parameter optimization model in this paper. Subsequently, an evaluation and ranking of solutions within the Pareto solution set is conducted using the entropy weight-TOPSIS method. Finally, by obtaining the optimal solution for the support parameters, a comprehensive optimization process for water diversion tunnel support is established.

(3) A comparative analysis was conducted between the original support scheme and the optimized one in terms of crown settlement and material cost. The crown settlement of the tunnel after optimization was 92.3 mm, representing a marginal increase of only 0.76%, which falls well below the allowable maximum settlement of 118.3 mm, indicating a significant safety margin. Additionally, there was an 8.16% reduction in support material costs observed as a result of this optimization process. Consequently, while ensuring tunnel safety remains paramount, this project effectively achieved a cost reduction.

In summary, this paper proposes a comprehensive set of optimization methodologies for determining support parameters of deep-buried water diversion tunnels in bad geological conditions. By analyzing practical engineering examples, this approach demonstrates high applicability and offers scientific and technological assurances for resolving support optimization challenges in similar projects.

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Availability of Data and Materials: Data is available upon request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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