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Improved TOPSIS Model Applied to Water Reservoir Multi-Attribute Decision-Making

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Abstract:

In light of the increasing demand for water resources, the construction of large hydraulic projects has revealed challenges related to power supply, as well as flood and drainage control. As investments rise, construction cycles become longer, and the external ecological costs increase, making project management more intricate. The main goal of water conservancy project management is to complete projects on schedule while ensuring sustainable quality standards and expenditures to maximize project value. Given the clear relationship between attribute indices in water conservancy and hydropower project management, along with the shortcomings of the traditional Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method based on Euclidean distance, this paper introduces the concept of weighted generalized Mahalanobis distance and applies it to the traditional TOPSIS method. The traditional TOPSIS method, enhanced by weighted generalized Mahalanobis distance, can serve as a more effective intelligent decision-making tool for evaluating and optimizing decision-making strategies for hydraulic construction projects. Following this, the improved TOPSIS model is applied to real reservoir project decisions, facilitating the scheduling and optimization of operational schemes, which can provide a reference for establishing an objective management framework for reservoir managers and decision-making consultations, while also playing a significant guiding role in ensuring reservoir safety and economic operations.

Keywords: water resources; water conservancy project management; large hydraulic projects; improved TOPSIS model; decision-making strategies; generalized Mahalanobis distance

Introduction

Water conservation construction project planning involves balancing conflicting goals of time, cost, and quality. Effective planning is essential to enhance project quality while controlling expenses and maximizing benefits. Developing a hydraulic project

planning strategy requires addressing multi-objective and multi-attribute, resulting in complex decision-making. Quantifying expert opinions is complicated due to the interrelatedness and constraints of each attribute, introducing subjectivity. Traditional decision-making methods may fail to yield reliable insights, compromising the credibility of the outcomes. (Borole, et al., 2022; Kaveh & Kamran, 2022; Mendomo Meye, et al., 2022).

Large-scale water conservation projects are complex, involving multi-objective, multi-input, multi-variable, multi-interference, and multi-output. A key challenge is to find ways to assess and manage this extensive system effectively for good results. The water management project aims to balance duration, cost, and quality in construction. These interconnected objectives can theoretically be optimized through mathematical programming, but increasing variable dimensions lead to exponential calculations, creating an unsolvable "disaster of dimension" problem. The theoretical challenges in water conservancy construction management involve optimizing project goals, selecting satisfactory solutions from optimization results, and exploring effective optimization methods and decision-making mechanisms. Studying the balance of construction period, cost, and quality in hydraulic construction projects holds significant theoretical value. The main decision-making techniques in water conservancy construction project operations include the evidence reasoning method (Ning, et al., 2021), fuzzy optimization method (Mousavi, et al., 2005; Panigrahi & Mujumdar, 2000; Russell & Campbell, 1996; Fu, 2008; Mendomo Meye, et al., 2022), grey correlation analysis (Zhang, et al., 2018), Promethee-II (Majid, et al., 2010), TOPSIS (Elham , et al., 2021), and set pair analysis (Pan, et al., 2017).

TOPSIS is favored in multi-attribute decision-making for its simple principle, intuitive geometric meaning, and ability to objectively highlight decision-making gaps (Dutta, et al., 2021; Subrata, 2022). Due to the varying degrees of correlation among the attribute indexes concerning the construction period, cost, and quality of hydraulic projects—such as the reduction of construction time, increased costs, and quality fluctuations—the information in the indexes overlaps. However, the traditional TOPSIS method, based on Euclidean distance, is greatly impacted by the dimensions of the attribute indicators and neglects the correlation and differences in importance among these indicators, resulting in the covariance matrix problem remaining unsolved (Vahedberdi, et al., 2019). In light of this, it is important to enhance the traditional TOPSIS method for its application to the various characteristics of attribute indexes in hydraulic engineering construction projects.

In light of the connection between construction timelines, costs, and quality attribute indicators, as well as the drawbacks of the standard TOPSIS method that fails to account for the correlation between indicators during distance calculations (Mendomo Meye, et al., 2022), the weighted generalized Mahalanobis distance is applied to the distance calculation within the traditional TOPSIS framework. The enhanced TOPSIS method considers the correlation among attribute indexes, the impact of both subjective and objective weights of decision information on outcomes, and the irreversibility of the covariance matrix. A specific example involving a rockfill dam project illustrates how this method can derive the optimal non-inferior equilibrium scheme based on

construction duration, cost, and quality, yielding reasonable evaluation results. The rationality and effectiveness of the proposed method are confirmed through comparisons with existing methods in the literature. Ultimately, for practical application in reservoir engineering, the TOPSIS method-optimized scheme, which is based on weighted generalized Mahalanobis distance, aligns with the comprehensive assessment of decision-making objectives in real-world scenarios and can offer technical assistance to reservoir project managers in developing project scheduling plans and executing systematic project control.

Methods and materials

Weighted Mahalanobis distance for TOPSIS

In this research, the TOPSIS method is applied to analyze multi-attribute decision-making in the management of real reservoir construction projects.

Traditional TOPSIS method

The TOPSIS method, which is also called the ideal point method, is a sorting technique designed to approximate the ideal solution. The primary idea is to view the multi-attribute decision-making problem, which includes *m* alternatives and *n* attributes, as a geometric system formed by *m* points in *n*-dimensional space. This requires the creation of positive and negative ideal points, followed by the calculation of the Euclidean distance between each alternative and these ideal points. The ultimate criterion is the degree of closeness of each alternative to the positive ideal point and its distance from the negative ideal point.

Traditional TOPSIS involves specific steps.

Step 1: create the original decision matrix A with n attributes of m alternatives.

$$A=\left(a_{ij}\right)_{m\times n}=\begin{matrix}A_1\\A_2\\\vdots\\A_m\end{matrix}\begin{bmatrix}a_{11} & a_{12} & \cdots & a_{1n}\\a_{21} & a_{22} & \cdots & a_{2n}\\\vdots & \vdots & \ddots & \vdots\\a_{m1} & a_{m2} & \cdots & a_{mn}\end{bmatrix}=\begin{bmatrix}A_1 & A_2 & \cdots & A_m\end{bmatrix}^T, \quad (1)$$

in the formula, a_{ij} represents the original evaluation value of the j^{th} attribute of the i^{th} scheme (i =1, 2, ..., m; j =1, 2, ..., n).

Step 2: to solve the problem of dimension and order of magnitude inconsistency, a normalized decision matrix B is constructed.

There are three types of processing methods: benefit-type attributes, cost-type attributes, and fixed-type attributes.

Eq. (2) shows the transformation formula.

$$b_{ij}=\begin{cases}\dfrac{a_{ij}-\min\limits_{1\le i\le m}a_{ij}}{\max\limits_{1\le i\le m}a_{ij}-\min\limits_{1\le i\le m}a_{ij}}, & j\in J^{+}\\ \dfrac{\max\limits_{1\le i\le m}a_{ij}-a_{ij}}{\max\limits_{1\le i\le m}a_{ij}-\min\limits_{1\le i\le m}a_{ij}}, & j\in J^{-}\\ 1-\dfrac{a_{ij}-\max\limits_{1\le i\le m}a_{ij}}{\max\limits_{1\le i\le m}\left|a_{ij}-\max\limits_{1\le i\le m}a_{ij}\right|}, & j\in J^{*}\end{cases} \tag{2}$$

in the formula, J^{+} is the benefit attribute set, J^{-} denotes the cost attribute set, and J^{*} is the fixed attribute set.

Step 3: create a weighted normalized decision matrix C.

$$\begin{aligned}C&=\left(c_{ij}\right)_{m\times n}=B?W=\left(b_{ij}\times W_j\right)_{m\times n}\\&=\begin{bmatrix}b_{11}&b_{12}&\cdots&b_{1n}\\b_{21}&b_{22}&\cdots&b_{2n}\\\vdots&\vdots&\ddots&\vdots\\b_{m1}&b_{m2}&\cdots&b_{mn}\end{bmatrix}\begin{bmatrix}\omega_1&0&\cdots&0\\0&\omega_2&\cdots&0\\\vdots&\vdots&\ddots&\vdots\\0&0&\cdots&\omega_n\end{bmatrix}\\&=\begin{bmatrix}b_{11}\omega_1&b_{12}\omega_2&\cdots&b_{1n}\omega_n\\b_{21}\omega_1&b_{22}\omega_2&\cdots&b_{2n}\omega_n\\\vdots&\vdots&\ddots&\vdots\\b_{m1}\omega_1&b_{m2}\omega_2&\cdots&b_{mn}\omega_n\end{bmatrix}=\begin{bmatrix}c_{11}&c_{12}&\cdots&c_{1n}\\c_{21}&c_{22}&\cdots&c_{2n}\\\vdots&\vdots&\ddots&\vdots\\c_{m1}&c_{m2}&\cdots&c_{mn}\end{bmatrix}\end{aligned} \tag{3}$$

in the formula, $(W=W_1, W_2,\ldots, W_j,\ldots W_n)$, $W_j=(0,\ldots,0, \omega_j, 0,\ldots, 0)^T$, the weights satisfy $\omega_j\in[0, 1]$, then $\sum_{j=1}^{n}\omega_j=1$

Step 4: Determine the positive ideal solution C^{+} and the negative ideal solution C^{-}.

$$\begin{aligned}C^{+}&=\left\{\left(\max_{1\le i\le m}c_{ij}\,\middle|\,j\in J^{+}\right),\left(\min_{1\le i\le m}c_{ij}\,\middle|\,j\in J^{-}\right)\right\}=\left\{c_1^{+},c_2^{+},\ldots,c_j^{+},\ldots,c_n^{+}\right\}\\C^{-}&=\left\{\left(\min_{1\le i\le m}c_{ij}\,\middle|\,j\in J^{+}\right),\left(\max_{1\le i\le m}c_{ij}\,\middle|\,j\in J^{-}\right)\right\}=\left\{c_1^{-},c_2^{-},\ldots,c_j^{-},\ldots,c_n^{-}\right\}\end{aligned} \tag{4}$$

Step 5: calculate the Euclidean distances D_i^{+} and D_i^{-} from A_i of each alternative scheme to positive and negative ideal solutions.

$$\begin{aligned}D_i^{+}&=\sqrt{\sum_{j=1}^{n}\left(c_{ij}-c_j^{+}\right)^2}\\D_i^{-}&=\sqrt{\sum_{j=1}^{n}\left(c_{ij}-c_j^{-}\right)^2}\end{aligned} \tag{5}$$

Step 6: Calculate the closeness of each alternative to the ideal solution.

$$e_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{6}$$

Step 7: Program sorting.

As $e \in [0,1]$, sorting is carried out according to the size of the e value. The larger the e value, the better the scheme.

The following are the three drawbacks of the Euclidean distance:

(1) Euclidean distance value depends on index dimensions and is greatly influenced by them.
(2) Euclidean distance treats all indicators equally, ignoring importance variations.
(3) Euclidean distance ignores correlation between indicators.

The indicators reveal intertwined data due to correlations among construction period, cost, and quality of water conservancy projects, highlighting issues like shorter construction times, increasing cost, and fluctuating quality. Consequently, the conventional TOPSIS method based on Euclidean distance is inadequate for sorting, selecting, and evaluating schemes, requiring improvements in dimensional consistency, index importance, and distance calculation in linear correlation scenarios.

Proposed weighted generalized Mahalanobis distance

Mahalanobis distance

The Mahalanobis distance, proposed by Indian statistician Mahalanobis (1936), is a measure that is independent of measurement scale and dimensionality. It uses covariance to remove correlation among attribute indices (Brereton, 2014). The TOPSIS method effectively uses Mahalanobis distance instead of Euclidean distance to solve correlation issues among attributes, as outlined in the calculation formula provided in Equation (7).

$$d(X,Y) = \sqrt{(X-Y)^T \Sigma^{-1} (X-Y)} \tag{7}$$

Σ represents the covariance matrix of attribute indicators, which remains unchanged under linear transformations. Normalization of the original decision matrix is unnecessary, and attribute indicators' correlations can be eliminated.

Generalized Mahalanobis distance

If the covariance matrix's determinant is 0, Σ^{-1} is non-existent, preventing Mahalanobis distance calculation. To address this, substitute the inverse with the Moore-Penrose pseudo-inverse matrix of Σ using singular value decomposition, enabling the use of generalized Mahalanobis distance, as defined in Equation (8).

$$d(X,Y) = \sqrt{(X-Y)^T \Sigma^{+} (X-Y)} \tag{8}$$

The construction method of Σ^+: The singular value decomposition form of Σ is $\Sigma = USV'$, then $\Sigma^+ = VTU'$, where $S = diag\left(a_1, a_2, ..., a_r\right)$, $a_r > 0$; r denotes the rank of the matrix Σ, and U and V stand for the orthogonal matrices. If $S\left(i,j\right) \neq 0$, then $T\left(i,j\right) = 1/S\left(i,j\right)$; if $S\left(i,j\right) = 0$, then $T\left(i,j\right) = 0$.

The pseudo-inverse matrix Σ^+ has basic properties similar to the inverse matrix Σ^{-1}.

(1) $\left(\Sigma^+\right)^+ = \Sigma$

(2) $\Sigma\Sigma^+\Sigma = \Sigma$

(3) $\Sigma^+\Sigma\Sigma^+ = \Sigma^+$

(4) $\Sigma\Sigma^+ = E$

(5) $\Sigma^+\Sigma = E$

(6) $\left(\Sigma^T\right)^+ = \left(\Sigma^+\right)^T$

(7) $\Sigma^+ = \left(\Sigma^T\Sigma\right)^+\Sigma^T = \Sigma^T\left(\Sigma\Sigma^T\right)^+$

(8) $\left(\Sigma^T\Sigma\right)^+ = \Sigma^+\left(\Sigma^T\right)^+$

Weighted generalized Mahalanobis distance

The generalized Mahalanobis distance addresses attribute correlation and dimension influence but neglects the varying importance of attribute indexes. This article introduces a weighted generalized Mahalanobis distance calculation formula, detailed in Equation (9), complementing the earlier weighted Mahalanobis distance.

$$d\left(X,Y\right) = \sqrt{\left(X-Y\right)^T\Omega^T\Sigma^+\Omega\left(X-Y\right)}, \tag{9}$$

in the formula $\Omega = diag\left(\sqrt{\omega_1}, \sqrt{\omega_2}, ..., \sqrt{\omega_j}\right)$, $\omega_j = \dfrac{\alpha_j^{1-\lambda}\beta_j^{\lambda}}{\sum_{j=1}^{n}\alpha_j^{1-\lambda}\beta_j^{\lambda}}$; α is the subjective weight of the decision-maker; β denotes the objective weight of decision information; λ represents the preference index, $\lambda \in \left[0,1\right]$; ω_j stands for the combined weight of the subjective weight of the comprehensive decision-maker and the objective weight of the decision information.

The weighted generalized Mahalanobis distance satisfies three fundamental distance properties:

(1) The symmetry

$$d(X,Y)=\sqrt{(X-Y)^T\Omega^T\Sigma^+\Omega(X-Y)}$$
$$=\sqrt{\left[-(Y-X)\right]^T\Omega^T\Sigma^+\Omega\left[-(Y-X)\right]}$$
$$=\sqrt{\left[-(Y-X)\right]^T\Omega^T\Sigma^+\Omega\left[-(Y-X)\right]}$$
$$=\sqrt{(Y-X)^T\Omega^T\Sigma^+\Omega(Y-X)}=d(Y,X)$$

(2) The non-negativity

The covariance matrix Σ is a symmetric matrix $\Rightarrow$ singular value decomposition matrix $U=V\Rightarrow\Sigma^+=VTU^T=VTV^T\Rightarrow\Sigma^+$ contracts with T. Diagonal matrix with T≥0 $\Rightarrow$ T positive semi-definite $\Rightarrow$ Σ^+ positive semi-definite $\Rightarrow$ $d^2(X,Y)=(X-Y)^T\Omega^T\Sigma^+\Omega(X-Y)\geq 0$. $d(X,Y)=0$ if and only if X=Y.

(3) The trigonometric inequality

Let $M=(\Sigma^+)^{\frac{1}{2}}\left[\Omega(X-Y)\right]$, $N=(\Sigma^+)^{\frac{1}{2}}\left[\Omega(Y-Z)\right]$, $W=(\Sigma^+)^{\frac{1}{2}}\left[\Omega(X-Z)\right]$, then

$$W=(\Sigma^+)^{\frac{1}{2}}\left[\Omega(X-Z)\right]=(\Sigma^+)^{\frac{1}{2}}\left[\Omega(X-Y+Y-Z)\right]=(\Sigma^+)^{\frac{1}{2}}\left[\Omega(X-Y)\right]+(\Sigma^+)^{\frac{1}{2}}\left[\Omega(Y-Z)\right]=M+N.$$

According to Minkowski's inequality,

$$d(X,Z)=\sqrt{W^TW}\leq\sqrt{M^TM}+\sqrt{N^TN}=d(X,Y)+d(Y,Z)$$

The TOPSIS method addresses importance differences between attributes, dimensional influences, correlations on decisions, and covariance matrix irreversibility by employing weighted generalized Mahalanobis distance instead of Euclidean distance.

Weighted Mahalanobis distance TOPSIS method

Information entropy-based weight determination method

Information entropy indicates the disorder of information; lower entropy suggests greater order and higher utility value. The entropy weight method establishes objective weights based solely on decision matrix data, involving specific calculation steps to determine attribute weight effectively.

(1) The standardization processing of attribute data

The decision matrix $X=\left[x_{ij}\right]_{m\times n}$ is normalized and its normalized value is $r_{ij}=\dfrac{x_{ij}}{\sum_{i=1}^{m}x_{ij}}$

(2) The calculation of the entropy value of each attribute

$$H_j = -\frac{1}{\ln m}\sum_{i=1}^{m} r_{ij} \ln r_{ij}, \quad j = 1, 2, ..., n, \tag{10}$$

m is the number of schemes, and n is the number of attributes.

(3) The calculation of the entropy weight of each attribute

$$\omega_j = \frac{1 - H_j}{\sum_{j=1}^{n}\left(1 - H_j\right)} and \quad \sum_{j=1}^{n} \omega_j = 1, \tag{11}$$

The entropy weight, as indicated in Equation (11), possesses several defects: particularly, when H_j tends toward 1, the entropy weight will vary exponentially as the entropy value changes. To counteract this issue, the revised entropy weight formula depicted in Equation (12) may be applied.

$$\omega_{hj} = \frac{\sum_{k=1}^{n} H_k + 1 - 2H_j}{\sum_{l=1}^{n}\left(\sum_{k=1}^{n} H_k + 1 - 2H_j\right)}. \tag{12}$$

However, there is a flaw in this formula. When H_j=1, ω_{ij}>0 is obtained, which is unreasonable. An improved formula shown in Equation (13) may be useful in solving this problem.

$$\beta_j = \begin{cases} H_s \omega_{hsj} + \left(1 - H_s\right) \omega_{hkj}, & if \quad H_j < 1 \\ 0, & if \quad H_j = 1 \end{cases} \tag{13}$$

$\omega_{hsj} = \frac{1 - H_s}{\sum_{k=1, H_k \neq 1}^{m}\left(1 - H_s\right)}$, $\omega_{hkj} = \frac{1 - H_s}{\sum_{k=1, H_k \neq 1}^{m}\left(1 - H_s\right)}$, H_s is the same part of attribute entropy from the first decimal point. For example, when the attribute entropy value is (0.998, 0.997, 0.996), H_s is 0.99; When the attribute entropy value is (0.9, 0.7, 0.6), H_s is 0. It can be seen from the entropy weight Equation (13) that when H_j<1, 0< ω_{ij}<1; when H_j=1, ω_{ij}=0.

TOPSIS steps using Mahalanobis distance

Step 1: an original decision matrix A containing m alternatives and n attributes is constructed. $A = \left[A_1, A_2, ..., A_M\right]^T$.

Step 2: the positive ideal solution A^+ and the negative ideal solution A^- are determined.

$$A^+ = \left\{\left(\max_{1\le i\le m} a_{ij} \,\middle|\, j \in J^+\right), \left(\min_{1\le i\le m} a_{ij} \,\middle|\, j \in J^-\right)\right\}, \quad (1 \le i \le m)$$
$$A^- = \left\{\left(\min_{1\le i\le m} a_{ij} \,\middle|\, j \in J^+\right), \left(\max_{1\le i\le m} a_{ij} \,\middle|\, j \in J^-\right)\right\}, \quad (1 \le i \le n) \tag{14}$$

J^+ is the benefit attribute set and J^- is the cost attribute set.

Step 3: the weighted generalized Mahalanobis distances B_i^+ and B_i^- from A_i of each alternative scheme to positive and negative ideal solutions are calculated.

$$B_i^+ = \sqrt{\left(A_i - A^+\right)^T \Omega^T \Sigma^+ \Omega \left(A_i - A^+\right)}$$
$$B_i^- = \sqrt{\left(A_i - A^-\right)^T \Omega^T \Sigma^+ \Omega \left(A_i - A^-\right)}, \tag{15}$$

$\Omega = diag\left(\sqrt{\omega_1}, \sqrt{\omega_2}, ..., \sqrt{\omega_j}, ..., \sqrt{\omega_n}\right)$, $\omega_j = \dfrac{\alpha_j^{1-\lambda} \beta_j^{\lambda}}{\sum_{j=1}^{n} \alpha_j^{1-\lambda} \beta_j^{\lambda}}$; α is the subjective weight of decision-makers obtained by the Delphi method (Mendomo Meye, et al., 2022); β stands for the objective weight of entropy value; λ is the preference index, $0 \le \lambda \le 1$, the smaller the λ, the more preferred α; the larger the λ, the more preferred β; ω_j means the combined weight of the comprehensive subjective weight and the objective weight.

Step 4: the closeness of each alternative to the ideal solution is calculated.

$$c_i = \frac{B_i^-}{B_i^+ + B_i^-}. \tag{16}$$

Step 5: Sort the plans. The larger the closeness value, the better the plan.

Application to the real reservoir project

The expansion of hydraulic structure projects in emerging economies has accelerated notably in recent years. A real-world reservoir project serves as a case study in this paper to showcase the soundness and viability of the construction period-cost-quality balance optimization model and decision-making methodology introduced in this work.

Overview of the reservoir project

The reservoir project focuses on flood control, water supply, irrigation, power generation, ecological improvement, and facilitating water and sediment transfer in the river's mainstream.

The total investment for the project is $420,454,545, with a 60-month construction period. Construction of the concrete face rockfill dam's main body started in September 2011, reached 232 m elevation by August 2013, and was completed in July 2014. The project was accepted in May 2015. Relevant data on costs, quality, and construction

modes are detailed in Table 1. Figure 1 shows the reservoir network plan.

Operation 1 demonstrates the basis of data value through a preparation project involving the construction of 12 approach roads, preparation of materials, concrete mixing, and construction facilities for air, water, and power supply, with two schemes: implementation mode 2 and implementation mode 3. The construction period of one scheme is (9, 10, 11), the direct construction cost ($) is determined as (29,545,454； 31,818,181； 34,090,909) accounting for the engineering quantity, and the project quality is evaluated by experts as (0.90, 0.93, 0.96). The construction period of the other scheme is (11, 12, 13), the direct construction cost ($) is (26,515,151； 27,272,727； 29,545,454), and the engineering quality is (0.85, 0.87, 0.89). The critical path is 1-2-3-4-5-9. This paper assumes the critical path remains unchanged with different execution modes, with a maximum construction period of 60 months and a project cost cap of $277,787,878, as detailed in Table 1.

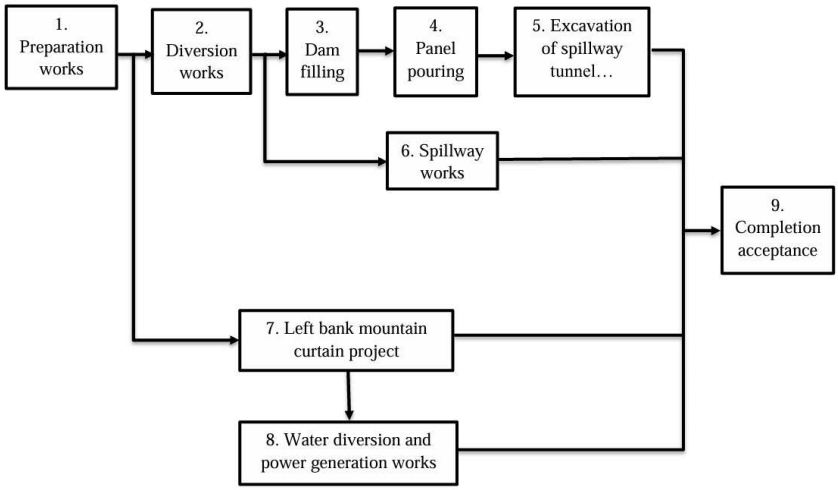


Figure 1: Reservoir project network design

Table 1 Relevant parameters and data of the reservoir project

Work number	Schemes	$\tilde{d}_i/month$	$\tilde{c}_i/us\$$	$\tilde{q}$
1	1	(9, 10, 11)	(29,545,454； 31,818,181； 34,090,909)	(0.90, 0.93, 0.96)
	2	(11, 12, 13)	(26,515,151； 27,272,727； 29,545,454)	(0.85, 0.87, 0.89)

	1	(7, 8, 9)	(15,454,545；16,515,151；17,575,757)	(0.80, 0.82, 0.84)
2	2	(8, 9, 10)	(13,636,363；15,000,000；16,363,636)	(0.73, 0.75, 0.77)
	3	(9, 10, 11)	(12,263,636；13,624,242；14,984,848)	(0.67, 0.70, 0.73)
	1	(14, 16, 18)	(68,181,818；74,242,424；80,303,030)	(0.77, 0.80, 0.83)
3	2	(17, 18, 19)	(65,151,515；68,181,818；71,212,121)	(0.76, 0.78, 0.80)
	3	(18, 20, 22)	(56,060,606；62,121,212；68,181,818)	(0.75, 0.76, 0.77)
	1	(2, 3, 4)	(12,424,242；15,454,545；18,484,848)	(0.80, 0.82, 0.84)
4	2	(3, 4, 5)	(9,381,818；12,418,181；15,454,545)	(0.74, 0.75, 0.76)
	1	(6, 7, 8)	(24,242,424；27,272,727；30,303,030)	(0.87, 0.89, 0.91)
5	2	(7, 8, 9)	(21,284,848；24,278,787；27,272,727)	(0.85, 0.87, 0.89)
	1	(21, 23, 25)	(19,696,969；21,363,636；23,030,303)	(0.86, 0.87, 0.88)
6	2	(23, 25, 27)	(18,484,848；19,848,484；21,212,121)	(0.84, 0.85, 0.86)
	3	(25, 27, 29)	(17,087,878；18,468,181；19,848,484)	(0.78, 0.80, 0.82)
	1	(23, 25, 27)	(4,924,242；5,227,272；5,530,303)	(0.77, 0.78, 0.79)
7	2	(25, 27, 29)	(4,696,969；5,000,000；5,303,030)	(0.71, 0.73, 0.75)
	3	(27, 29, 31)	(4,645,454；4,822,727；5,000,000)	(0.67, 0.70, 0.73)
	1	(25, 27, 29)	(6,666,666；6,969,696；7,272,727)	(0.84, 0.85, 0.86)
8	2	(28, 30, 32)	(6,212,121；6,515,151；6,818,181)	(0.80, 0.82, 0.84)
	3	(30, 33, 36)	(5,500,000；6,007,575；6,515,151)	(0.77, 0.78, 0.79)
	1	(4, 5, 6)	(7,272,727；8,484,848；9,696,969)	(0.90, 0.92, 0.94)
9	2	(5, 6, 7)	(6,060,606；7,272,727；8,484,848)	(0.88, 0.90, 0.92)

Optimizing reservoir project: period-cost-quality balance

A comprehensive equilibrium optimization model for the reservoir project construction period is developed using Mendomo Meye et al.'s second method (Mendomo Meye, et al., 2022). Key parameters include λ=0.5 (no preference), delay penalty coefficient α as \$1,212,121/month, early completion reward coefficient β as \$757,575/month, indirect

cost coefficient IC as $1,515,151/month, a planned construction period D of 60 months, and a cost budget B of $278,787,878 with required project quality of good or better.

The construction period-cost-quality balance optimization model of the reservoir project is as follows:

$$\min T = \sum_{i \in cp} \sum_{k=1}^{k} x_{ik} E\left[\tilde{d}_i\right]$$

$$\min C = \begin{cases} \sum_{i} \sum_{k=1}^{k} x_{ik} E\left[\tilde{C}_i\right] + T \times 1{,}515{,}151 + 1{,}212{,}121(T-60), & T \geq 60 \\ \sum_{i} \sum_{k=1}^{k} x_{ik} E\left[\tilde{C}_i\right] + T \times 1{,}515{,}151 + 757{,}575(T-60), & T < 60 \end{cases} \quad (17)$$

$$\max Q = aT + bC + cT^2 + dC^2 + eT \times C + f$$

$$s.t. \begin{cases} \sum_{k=1}^{k} x_{ik} \\ C \leq 278{,}787{,}878 \end{cases}$$

Results and discussion

Example verification

For application analysis, the improved TOPSIS selects non-inferior schemes for construction period, cost, and quality of the project. See Table 2.

Original decision matrix established; MATLAB computes correlation coefficient matrix R from it.

$$R = \begin{bmatrix} 1 & -0.9898 & -0.9878 \\ -0.9898 & 1 & 0.9907 \\ -0.9878 & 0.9907 & 1 \end{bmatrix}$$

R identifies a significant negative correlation between T and C, T and Q, alongside a strong positive correlation between C and Q, invalidating traditional TOPSIS method applicability for scheme sorting and selection.

Table 2: Project period-cost-quality non-inferior scheme set

Schemes	$\tilde{d}_i/month$	$\tilde{c}_i/us\$$	$\tilde{q}$
1	42	54500	0.8115
2	41	55200	0.8247
3	41	55400	0.8303

4	40	55700	0.8385
5	39	55900	0.8502
6	38	56300	0.8559
7	37	57100	0.8616
8	36	57800	0.8724
9	35	58000	0.8787
10	34	58200	0.8825
11	34	58300	0.889
12	33	58600	0.8921
13	32	59000	0.8973
14	31	59100	0.9006

Because Q is a benefit attribute of A, and T and C are cost attributes, A^{+}= (31, 54500, 0.9006) and A^{-}= (31, 54500, 0.9006) (42, 59100, 0.8115). The subjective weight of decision-makers obtained by the Delphi method is α= (0.36, 0.24, 0.40), and the objective weight of entropy value is β= (0.8145, 0.0318, 0.1537). When λ is 0.5, the combined weight ω= (0.6176, 0.0996, 0.2828), then Ω=diag (0.7859, 0.3156, 0.5318). Generalized Mahalanobis and weighted generalized Mahalanobis distances assess alternatives' proximity to the ideal solution, with schemes sorted, as shown in Table 3. The TOPSIS method using weighted generalized Mahalanobis distance identifies scheme 14 as optimal due to its shortest duration, while scheme 1 ranks worst; schemes are evaluated based on construction period benefits and drawbacks. Since Ω = diag (0.7859, 0.3156, 0.5318), the weight of the construction period target is relatively large, and the result of the scheme optimization reflects this emphasis, which conforms to the actual situation and validates the rationality of the traditional TOPSIS method based on weighted generalized Mahalanobis distance.

Table 3: Optimized results of the schemes

Scheduling schemes	Generalized Mahalanobis distance		Weighted generalized Mahalanobis distance	
	Closeness	Ranking	Closeness	Ranking
1	0.4913	6	0.3116	14
2	0.4787	10	0.3401	13

3	0.4749	11	0.3432	12
4	0.4892	7	0.3834	11
5	0.5248	1	0.4401	10
6	0.5211	2	0.4688	9
7	0.4748	12	0.4719	8
8	0.4550	14	0.4942	7
9	0.4740	13	0.5392	6
10	0.4854	9	0.5784	5
11	0.4949	4	0.5870	4
12	0.4935	5	0.6180	3
13	0.4881	8	0.6465	2
14	0.5087	3	0.6884	1

Using the TOPSIS method with generalized Mahalanobis distance, scheme 5 is deemed best while scheme 8 is the worst, though the optimization is seen as unreasonable. Comparison shows scheme 8 excels in construction period and quality, with the construction period prioritized, suggesting scheme 8 is indeed better. The findings are unreliable since generalized Mahalanobis distance overlooks the significance disparity among attributes. However, using weighted generalized Mahalanobis distance confirms scheme 8's superiority over scheme 5, aligning with actual circumstances.

Reservoir project balance optimization: period-cost-quality

For nonlinear regression analysis of basic data, the SPSS21.0 software is used, and the estimated values of the parameters are a=−0.327, b=0.001, c=0.008, d=e=0, f=77.786. MATLAB and the IBBPSO algorithm are used to solve the model. The IBBPSO algorithm's parameters are as follows: the population size is 20, the immune memory bank size is 20, the crossover probability is 0.9, the mutation probability decreases from 0.5 to 0.1, the precocious judgment threshold δ is 0.001, and the maximum number of iterations is 100. Figure 2 depicts a 3D scatter diagram of optimization results, while Figures 3~5 depict a 2D diagram of duration-cost, duration-quality, and cost-quality relationships.

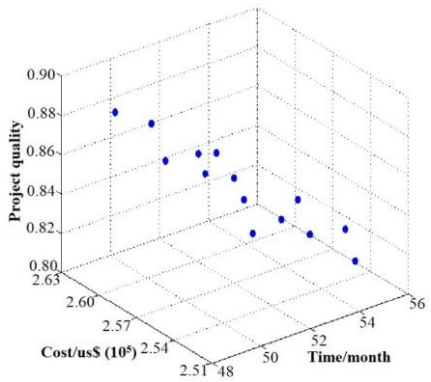


Figure 2: 3D reservoir project optimization results

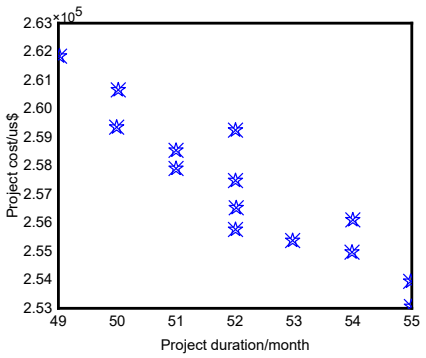


Figure 3: Reservoir project optimization duration- cost diagram

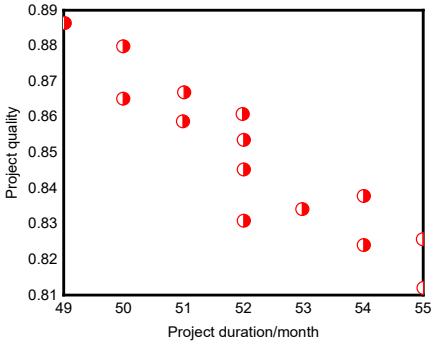


Figure 4: Reservoir project optimization duration-quality diagram

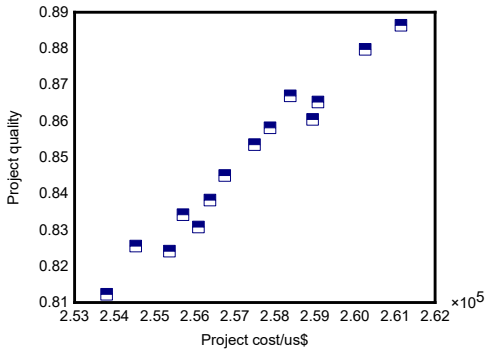


Figure 5: Reservoir project optimization cost-quality

As shown in Figure 3, the construction duration and cost are nearly inversely proportional, meaning a shorter construction period requires higher investment, supported by research from Mendomo Meye et al (2022). Figure 4 indicates that quality declines as construction duration increases. While water conservancy projects lack waste grades, they require rework, repairs and reinforcement. Improved quality decreases rework and speeds up construction, according to Mendomo Meye et al. (2022). Figure 5 reveals a generally proportional relationship between quality and cost; enhancing quality increases manpower, equipment, and resources, leading to higher costs, as noted by Mendomo Meye et al. (2022). The outcome shows that the three construction objectives—duration, cost, and quality—are interrelated, where improving one typically requires compromising another aspect.

The simplified reservoir project consists of 9 activities, each averaging 2.8 execution modes regarding the number of solutions. Consequently, the feasible solution space is 2.8^9, which signifies that there are 10,578 combined schemes with differing duration, cost, and quality. The IBBPSO algorithm identifies 14 non-dominated solutions within a vast search space, enabling decision-makers to narrow their choices. The IBBPSO algorithm is employed to optimize 14 Pareto solutions, with the optimization results presented in Table 4.

Table 4 indicates the reservoir project's optimized construction period is 49 to 55 months, shorter than the planned 60 months. The optimized cost ranges from \$253,818,181 to \$261,287,878, below the budgeted \$277,787,878. Optimal quality levels are 0.8123 to 0.8862, meeting operational quality standards in engineering practice Mendomo Meye et al. (2022).

In a nutshell, the reservoir project's optimized construction period, cost, and quality align reasonably, allowing decision-makers to choose a scheme that meets their preferences and effectively manages these three objectives.

Table 4: Reservoir optimization results

Solution number	Duration/month	Cost/us$	Quality

1	55	253,818,181	0.8123
2	55	254,580,303	0.8256
3	54	255,448,484	0.8241
4	54	256,439,393	0.8382
5	53	255,798,484	0.8345
6	52	256,136,363	0.8309
7	52	256,818,181	0.8452
8	52	257,606,060	0.8535
9	52	259,065,151	0.8608
10	51	257,954,545	0.8585
11	51	258,484,848	0.8670
12	50	259,189,393	0.8649
13	50	260,312,121	0.8795
14	49	261,287,878	0.8862

Reservoir optimized multi-attribute decision-making

Drawing from the optimized reservoir project outcomes and the preferences of decision-makers, the TOPSIS method, founded on the weighted generalized Mahalanobis distance, is applied to facilitate multi-attribute decisions. The original multi-attribute decision matrix features 14 alternatives, with construction period, cost, and quality attributes all being multi-attribute decisions. The objective weight β = (0.5990, 0.1539, 0.2471) is calculated using the improved entropy weight method described in this paper, and it is determined by the data in the original decision matrix and remains constant.

Subjective weights of decision-makers affect outcomes variably due to their uncertainty, influencing analysis of decision results significantly, analysis follows.

Impact of decision-makers' biases on outcomes analyzed

Since construction duration and cost are cost-type attributes, and quality is an efficiency attribute, the positive ideal solution is A^+ = (49; \$253,818,181; 0.8862), and the negative ideal solution is A^- = (55; \$261,287,878; 0.8123). If decision makers focus on project duration, the subjective weight, preference index, and objective weight are set to $\lambda = 0.5$, β = (0.5990, 0.1539, 0.2471), respectively. Then the weight ω_1 = (0.6020, 0.1246, 0.2734) is combined, so Ω_1 = diag (0.7759, 0.3530, 0.5229). If decision-makers

focus more on the engineering cost, let the subjective weight α_2 = (0.30, 0.60, 0.10), the preference index λ = 0.5, the objective weight β = (0.5990, 0.1539, 0.2471), then $\omega 2$ = (0.4790, 0.3434, 0.1776), $\Omega 2$ = diag (0.6921, 0.5860, 0.4214). If the decision makers lay more emphasis on engineering quality, the subjective weight α_3 = (0.30, 0.10, 0.60), the preference index λ = 0.5, the objective weight β = (0.5990, 0.1539, 0.2471), then ω_3 = (0.4543, 0.1330, 0.4127), Ω_3 = diag (0.6740, 0.3647, 0.6424).

The weighted generalized Mahalanobis distance ranks alternatives' closeness to the ideal solution, shown in Table 5.

Table 5: Closeness degree and scheme ranking

Schemes	Subjective weight α_1		Subjective weight α_2		Subjective weight α_3	
	Closeness	Ranking	Closeness	Ranking	Closeness	Ranking
1	0.3889	14	0.5592	1	0.3663	14
2	0.4321	12	0.5586	2	0.4259	12
3	0.4022	13	0.5091	9	0.3879	13
4	0.4384	11	0.4958	10	0.4423	10
5	0.4739	9	0.5478	3	0.4624	9
6	0.4613	10	0.5269	6	0.4371	11
7	0.5132	7	0.5376	4	0.5065	8
8	0.5234	6	0.5144	8	0.5283	6
9	0.4927	8	0.4366	14	0.5099	7
10	0.5623	5	0.5298	5	0.5638	5
11	0.5872	3	0.5268	7	0.5995	3
12	0.5632	4	0.4851	11	0.5658	4
13	0.5954	2	0.4640	12	0.6168	2
14	0.6111	1	0.4408	13	0.6337	1

The scheme optimized results under different subjective weights are shown in Table 6 based on the statistics of the above results.

As shown in Table 6, when α = (0.60, 0.10, 0.30), scheme 14 with the shortest construction period is chosen as the best scheme, and the scheme ranking results are arranged smoothly according to the benefits and drawbacks of the construction period.

When α = (0.30, 0.60, 0.10), scheme 1 with the lowest cost is regarded as the best scheme, and the scheme ranking results are roughly arranged according to the cost's upsides and downsides. When α= (0.30, 0.10, 0.60), the best scheme is chosen as scheme 14 with the highest quality. The scheme ranking results are roughly arranged by quality, reflecting the decision makers' emphasis on the main goals. The objective weight of the entropy value of the comprehensive decision matrix is studied, and it is revealed that the combined weight has the greatest influence on the decision result. When the objective weights of the construction period, cost, and quality are not significantly different, subjective weights overwhelm decision-making achievements.

The TOPSIS method optimized by weighted generalized Mahalanobis distance aids reservoir project managers in decision-making, project scheduling, and systematic project control.

Table 6 : Optimizing scheme results variably

α	ω	Scheme sorting
(0.60, 0.10, 0.30)	(0.6020, 0.1246, 0.2734)	14>13>11>12>10>8>7>9>5>6>4>2>3>1
(0.30, 0.60, 0.10)	(0.4790, 0.3434, 0.1776)	1>2>5>7>10>6>11>8>3>4>12>13>14>9
(0.30, 0.10, 0.60)	(0.4543, 0.1330, 0.4127)	14>13>11>12>10>8>9>7>5>4>6>2>3>1

Sensitivity analysis of preference index λ

Since different preference indices will have different influences on combination weights, affecting scheme ordering and optimization, the following is a sensitivity analysis to evaluate the degree of influence of preference indices λ on decision results.

To discuss the influence of on the decision results, the subjective weight α = (0.30, 0.60, 0.10), 0.60, 0.10) and the objective weight β = (0.5990, 0.1539, 0.2471) are used. Table 7 and Table 8 show the degree of closeness and the ranking of schemes with different λ values.

Table 7: Degree of closeness and scheme ranking with λ =0.1~0.5

hemes	**λ = 0.1**		**λ = 0.2**		**λ = 0.3**		**λ = 0.4**		**λ = 0.5**	
	Closeness	**Ranking**	**Closeness**	**Ranking**	**Closeness**	**Ranking**	**Closeness**	**Ranking**	**Closeness**	**Ranking**
1	0.6627	1	0.6379	1	0.6122	1	0.5860	1	0.5592	1
2	0.6378	2	0.6186	2	0.5990	2	0.5790	2	0.5586	2
3	0.5743	4	0.5586	4	0.5425	6	0.5260	6	0.5091	9
4	0.5323	7	0.5235	7	0.5145	8	0.5052	10	0.4958	10

5	0.5927	3	0.5819	3	0.5708	3	0.5594	3	0.5478	3
6	0.5659	5	0.5565	5	0.5468	4	0.5370	5	0.5269	6
7	0.5522	6	0.5487	6	0.5451	5	0.5414	4	0.5376	4
8	0.5092	9	0.5105	9	0.5117	9	0.5130	9	0.5144	8
9	0.4032	12	0.4112	12	0.4194	13	0.4279	13	0.4366	14
10	0.5097	8	0.5145	8	0.5195	7	0.5246	7	0.5298	5
11	0.4903	10	0.4991	10	0.5081	10	0.5173	8	0.5268	7
12	0.4365	11	0.4482	11	0.4602	11	0.4726	11	0.4851	11
13	0.3844	13	0.4035	13	0.4232	12	0.4434	12	0.4640	12
14	0.3373	14	0.3621	14	0.3878	14	0.4140	14	0.4408	13

Table 8: Degree of closeness and scheme ranking with λ =0.6~1.0

hemes	**λ = 0.1**		**λ = 0.2**		**λ = 0.3**		**λ = 0.4**		**λ = 0.5**	
	Closeness	**Ranking**	**Closeness**	**Ranking**	**Closeness**	**Ranking**	**Closeness**	**Ranking**	**Closeness**	**Ranking**
1	0.5324	6	0.5046	10	0.4772	11	0.4500	13	0.4229	14
2	0.5382	1	0.5173	5	0.4967	9	0.4763	10	0.4561	11
3	0.4922	10	0.4748	13	0.4576	14	0.4404	14	0.4235	13
4	0.4864	11	0.4768	12	0.4673	12	0.4579	12	0.4486	12
5	0.5362	2	0.5241	4	0.5122	8	0.5004	8	0.4888	8
6	0.5169	7	0.5063	8	0.4961	10	0.4858	9	0.4758	10
7	0.5339	5	0.5299	3	0.5261	4	0.5222	6	0.5184	7
8	0.5157	8	0.5171	6	0.5185	7	0.5198	7	0.5212	6
9	0.4452	14	0.4542	14	0.4630	13	0.4718	11	0.4806	9
10	0.5350	4	0.5404	2	0.5457	2	0.5510	2	0.5562	4

11	0.5362	2	0.5460	1	0.5556	1	0.5652	1	0.5747	2
12	0.4977	9	0.5106	7	0.5234	5	0.5360	5	0.5485	5
13	0.4846	12	0.5060	9	0.5270	3	0.5480	4	0.5688	3
14	0.4676	13	0.4954	11	0.5228	6	0.5500	3	0.5771	1

The sorting results of schemes with different λ values are obtained based on the statistics of the above results, as shown in Table 9.

Table 9 shows that when λ≤0.5, scheme 1 is the optimal scheme, while schemes 2 and 5 are both sub-optimal. The smaller λ, the more subjective weight is preferred, and the order of the three objective weights in the subjective weight is **cost → duration → quality**. Scheme 1 is optimal due to lowest cost; other schemes follow in cost order, highlighting the main cost objective.

Table 9: Scheme sorting with different λ values

λ	Scheme sorting
λ= 0.1	1>2>5>3>6>7>4>10>8>11>12>9>13>14
λ= 0.2	1>2>5>3>6>7>4>10>8>11>12>9>13>14
λ= 0.3	1>2>5>6>7>3>10>4>8>11>12>13>9>14
λ= 0.4	1>2>5>7>6>3>10>11>8>4>12>13>9>14
λ= 0.5	1>2>5>7>10>6>11>8>3>4>12>13>14>9
λ= 0.6	2>11=5>10>7>1>6>8>12>3>4>13>14>9
λ= 0.7	11>10>7>5>2>8>12>6>13>1>14>4>3>9
λ= 0.8	11>10>13>7>12>14>8>5>2>6>1>4>9>3
λ= 0.9	11>10>14>13>12>7>8>5>6>2>9>4>1>3
λ= 1.0	14>11>13>10>12>8>7>5>9>6>2>4>3>1

When λ > 0.5, scheme 11 is the optimal or sub-optimal scheme. The larger λ is, the more objective weight is preferred. The order of the three objective weights in the objective weighting is construction **duration → quality → cost**. As a result, scheme 11 is the optimal or sub-optimal scheme, with a shorter construction period and higher quality. The larger λ, the more likely it is that the plans will be sorted based on the pros and cons of the construction period and quality, reflecting the emphasis on construction

period objectives and quality objectives.

In synopsis, when decision-makers' preference index λ varies, the optimized TOPSIS method using weighted generalized Mahalanobis distance aligns with primary objectives, aiding in resource allocation and project scheduling while systematically managing the project's three major goals.

Conclusions

This analysis focuses on multi-attribute decision-making in the context of managing construction projects for water conservation and proposes the most effective scheme using an upgraded TOPSIS method. The insights gained from this study are significantly beneficial for enhancing the principles of objective management theory and technology in water conservation initiatives. The subsequent section presents the main findings of the research:

(1) the most effective scheme is identified from the trade-off optimization findings through the application of a weighted generalized Mahalanobis distance, following a classic TOPSIS method. The formula for calculating the weighted generalized Mahalanobis distance is first introduced and applied to the conventional TOPSIS method. This upgraded TOPSIS approach can efficiently tackle the relationships between attribute indices, the balance of subjective and objective weights, and the non-invertibility of the covariance matrix. A case study is provided to validate the logic and effectiveness of the enhanced TOPSIS method. The results from this example demonstrate that the weighted generalized Mahalanobis distance, based on a traditional TOPSIS method, is a more effective intelligent decision-making tool for evaluating schemes in water projects.

(2) As a case study, the application research of the time-cost-quality trade-off optimization and decision-making is carried out in an actual reservoir project. The decision-making results lay a theoretical basis for project planning and construction schedules. The application research of a practical reservoir is a meaningful test for theoretical results, demonstrating the rationality and operability of the time-cost-quality trade-off optimization model and multiple attribute decision-making method in the construction of a water conservancy project.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

This article does not contain any studies involving human participants or animals performed by any of the authors. Not applicable.

Consent for publication

All authors have provided consent for publication of this manuscript.

Competing interest:
The authors declares no conflicts of interest to report regarding the present study.

Contributions

Serges Mendomo Meye: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualisation. ***Paul Fabrice Nguema***: Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Analysis, Conceptualisation, Supervision.

Commented [HE1]: An Author Contribution declaration in the manuscript is provided according to the Editor requirement.

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