

Article

Entropy-Weighted TOPSIS and Grey Relational Analysis Method for Optimizing Lost Circulation Formulations in Stress-Sensitive Fractured Formations

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Abstract

During drilling in stress-sensitive fractured formations, fracture aperture dynamically evolves with wellbore pressure fluctuations. The sealing layer often undergoes repeated cycles of sealing, destabilization, and re-sealing. Formulation selection based on a single metric or empirical selection cannot simultaneously satisfy multiple objectives, including pressure-bearing capacity, loss control, and dynamic adaptability. This study proposes an entropy-weighted TOPSIS and grey relational analysis method to optimize lost circulation formulations for stress-sensitive fractured formations. A hierarchical evaluation system is established with four criteria layers and eight indicator metrics. A baseline formulation framework is determined through static fracture sealing tests. Experimental data for different elastic-material systems are obtained using a self-developed DTDL dynamic fracture plugging apparatus. Indicator weights are objectively determined using the entropy weight method. A Grey-TOPSIS model is applied to compute grey relational closeness to the positive and negative ideal solutions, enabling formulation ranking and optimal scheme identification. A case study shows that the ternary elastic formulation with Rubber:Graphite:Net = 3:2:1 achieves the highest grey relational closeness and delivers the best overall sealing performance. The ranking remains unchanged when the distinguishing coefficient ρ varies from 0.1 to 0.9, confirming the robustness and feasibility of the proposed method. Compared with entropy-weighted TOPSIS and classical TOPSIS, the proposed method provides a more integrated treatment of the multi-metric data and better aligns the evaluation with the underlying sealing behavior in stress-sensitive fractures. Therefore, it leads to more reliable and comprehensive evaluation results for formulation selection. The results demonstrate that the proposed model provides reliable support and a methodological basis for formulation optimization in dynamic fracture loss control.



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Keywords: stress sensitive fracture; sealing; sealing formulation; entropy weight method; Grey-TOPSIS method

1. Introduction

Lost circulation control remains a persistent challenge in drilling operations [1]. It can lead to substantial drilling-fluid losses and increased nonproductive time. The challenge is more severe in stress-sensitive fractured formations, where wellbore pressure fluctuations can strongly affect fracture aperture [2,3]. Pressure fluctuations during drilling, tripping,

and pump start-up or shut-down require the sealing layer to maintain effectiveness under an evolving fracture geometry, which increases the likelihood of repeated cycles of sealing, destabilization, and re-sealing [4,5]. Conventional formulations dominated by rigid particles are typically designed for a fixed aperture. When the aperture gradually enlarges or changes abruptly, the sealing layer is prone to reopening, structural slippage, and partial failure, which increases the risk of repetitive losses. Introducing elastic materials with compressibility and rebound ability to enhance sealing layer adaptability to dynamic aperture variations has become an important research interest [6]. However, the elastic-material type and concentration strongly affect pressure-bearing capacity, leakage behavior, sealing stabilization time, and re-sealing performance. These metrics are coupled and often conflict with each other, making formulation optimization difficult using a single indicator or empirical selection.

Most existing formulation selection studies rely on comparative experiments followed by heuristic judgment, which can only reveal limited performance differences for lost circulation materials (LCMs) [7–9]. Because multiple metrics with distinct dimensions and scales must be considered simultaneously, formulations can show conflicting trends, including higher pressure-bearing capacity with greater leakage, lower loss volume with longer stabilization time, or wider aperture variation tolerance with weaker re-sealing capability. Selection results usually depend heavily on subjective preference and lack a theoretical basis for comprehensive evaluation. Metric interdependence is also pronounced under dynamic fracture conditions [10]. For example, sealing-layer compactness, filtration loss, and failure mechanism under aperture evolution can influence one another. Simple weighted summation or single-metric ranking cannot reliably represent the ideal formulation, which limits the accuracy of optimization conclusions. A quantitative, hierarchical evaluation framework based on multi-criteria decision-making is needed to improve the scientific rigor of formulation selection.

Multi-criteria decision-making (MCDM) methods have been increasingly applied to the selection and optimization of lost-circulation materials in drilling operations [11–13]. The entropy weight method provides objective weighting based on the dispersion of indicator data, reducing subjectivity in weight assignment [14]. The technique for order preference by similarity to an ideal solution (TOPSIS) ranks alternatives by seeking closeness to the positive ideal solution and distance from the negative ideal solution in a multi-metric space [15]. Grey relational analysis is suited for incomplete information and limited sample size because it evaluates similarity through relational grades between sequences [16]. Integrating entropy weighting with TOPSIS and grey relational analysis allows both indicator importance and sequence similarity to be considered within an ideal solution framework, improving the robustness and feasibility of the evaluation results. A combination of three methods can be applied to sealing formulation optimization to convert the multidimensional indicators obtained from experiments into a unified and comparable comprehensive score. It can also incorporate both dynamic fracture sealing indicators and conventional static fracture sealing indicators into the same evaluation framework, thereby providing a reproducible quantitative basis for selecting sealing formulations for stress-sensitive fractures.

Therefore, this study proposes an improved TOPSIS–Grey relational comprehensive evaluation method based on the entropy weight method to address the problem of lost circulation control in stress-sensitive fractures. An evaluation system is established, which includes pressure-bearing performance, loss-control performance, dynamic adaptability, and re-sealing capability and eight corresponding indicator metrics. To ensure the engineering feasibility of the candidate formulations and reduce interference from variable coupling, Permeability Plugging Apparatus (PPA) tests are conducted to determine a basic

bridging formulation framework. In addition, a self-developed DTDL device is used to obtain full-process sealing data for different elastic-system formulations under dynamically changing fracture widths, thereby providing reliable input data for the comprehensive evaluation. On this basis, the entropy weight method is applied to assign objective weights to the indicators, and the Grey-TOPSIS model is used to rank the candidate formulations and identify the optimal one. Furthermore, the proposed method is compared with the classical TOPSIS method and the entropy-weighted TOPSIS method. Sensitivity analyses on the distinguishing coefficient are carried out to verify its practicality and scientific validity.

2. Development of the Evaluation Framework and Indicator System

2.1. Evaluation Framework Design

For sealing formulation optimization under stress-sensitive fracture conditions, the evaluation focuses on characterizing the stability and re-sealing capacity of the sealing layer under fluctuations in fracture aperture. Because of the inherent coupling and trade-off relationship between the two evaluation methods, as well as differences in the dimensional units and preference directions of the specific indicators, formulation selection based on a single indicator or empirical rules often lacks consistency and reproducibility. Therefore, a hierarchical and quantifiable index system is required to support reliable formulation selection and quantitative comparison among candidates [17].

Referring to the construction framework of the objective layer, criterion layer, and indicator layer in multi-criteria comprehensive evaluation methods, this study defines the evaluation objects as candidate sealing formulations obtained under the same experimental conditions and establishes a comprehensive evaluation index system for sealing formulations based on the following three main principles. First, the selected indicators should characterize the key stages or major instability modes of the dynamic fracture-sealing process, so as to ensure consistency in the underlying analysis mechanism. Second, the indicators should be obtainable in experiments and have clear data-obtaining rules and judgment criteria so as to ensure the reliability and reproducibility of the data. Third, indicators that are strongly correlated or provide limited discrimination should be excluded to prevent redundancy. This helps maintain the discriminatory power of the comprehensive ranking.

The evaluation indicators were developed using a systematic literature review method [18]. International drilling fluid testing guidelines and recommended standards were consulted, including API RP 13B-1/13B-2, ISO 10414-1, and ISO 13500 [19–21]. Findings from macroscopic and microscopic studies on lost circulation formulations were also incorporated [6,22,23].

2.2. Definition of the Criteria and Indicators

The criterion layer of the evaluation system is structured around four core capacities involved in dynamic fracture sealing, namely sealing pressure-bearing capacity, lost circulation control capacity, dynamic adaptability, and re-sealing capacity. The indicator layer comprises eight quantitative indicators that characterize key behavioral differences among candidate formulations across the full sealing sequence, including initial sealing, stable pressure bearing, disturbance-induced destabilization, and re-sealing (Figure 1). Each indicator has been explicitly defined and categorized as either a benefit-type or a cost-type indicator.

Sealing pressure-bearing capacity is defined as the ability of a formed sealing layer to sustain a differential pressure while maintaining structural integrity. It provides a baseline for assessing both the effective load-carrying performance and the ultimate capacity of the sealing system. Maximum pressure-bearing capacity is defined as the maximum differential pressure sustained by the sealing layer after formation. Because the experiments adopt stepwise loading with constant-pressure injection, seal formation shows a staged

evolution from initial bridging and packing to a stable and compact sealing layer. Pressure stabilization time is therefore used to measure how quickly the sealing layer enters a stable pressure-bearing condition once the target pressure is reached, serving as an efficiency metric for compact seal formation.

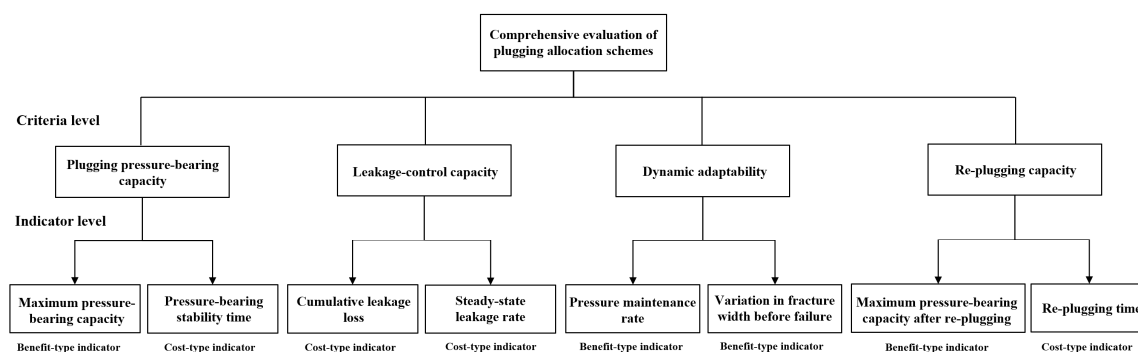


Figure 1. Evaluation index system for sealing formulations for stress-sensitive fractures.

Leakage-control performance characterizes how effectively the sealing layer mitigates lost circulation. Cumulative leakage loss and steady-state leakage rate are used to quantify overall loss and micro-leakage, respectively. This distinction helps identify non-ideal schemes that exhibit high pressure-bearing capacity but significant leakage. The steady-state leakage rate reflects microchannel connectivity and permeability-driven leakage after seal formation.

Dynamic adaptability is a key evaluation dimension introduced in this study for stress-sensitive fracture conditions, and it is used to describe the ability of the sealing layer to resist through-going failure and maintain effective sealing as the fracture aperture increases. Because the sealing layer often exhibits instantaneous failure during the dynamic widening of the fracture, making it difficult to stably obtain post-failure fluid-loss data as an evaluation indicator, this study adopts the pressure retention ratio to characterize the through-failure instability of the sealing layer at the moment of failure. In this study, the pressure retention ratio is defined as the ratio of the minimum pressure after failure, P_{min} , to the target pressure during the stable pressure-bearing stage, P_{target} , which is $R_p = P_{min}/P_{target}$. At the same time, the maximum fracture width variation at failure is used to characterize the upper aperture limit within which the sealing system can still maintain effective sealing during dynamic fracture widening, thereby reflecting its boundary to fracture-aperture evolution. It is defined as the difference between the fracture width at failure, W_f , and the initial width at the beginning of the dynamic widening stage, W_0 , which is $\Delta W_f = W_f - W_0$.

Re-sealing capability evaluates the reconstruction and recovery potential after destabilization. The maximum pressure-bearing capacity after re-sealing and the re-sealing time are used to quantify the recovered pressure-bearing level and recovery efficiency, respectively. These metrics reflect the applicability of a formulation under dynamic conditions in terms of failure response, structural reconstruction and recovery of pressure-bearing capacity.

3. Candidate Scheme Development and Experimental Data Acquisition

3.1. Candidate Formulation Design and Variable-Control Strategy

The sealing layer stability is governed by the pressure-bearing and anti-slippage capacity of the bridging skeleton, the compactness of the sealing layer, and the development of micro-leakage pathways. If particle size, morphology, aspect ratio, and frictional properties of all LCMs are treated as simultaneous variables, the candidate design expands exponentially, and the experimental cost becomes impractical. This also reduces the

ability of the subsequent evaluation to quantify and explain the mechanisms of sealing layer destabilization.

LCMs, commonly for naturally fractured formations, can be classified by function into bridging materials, filling materials, and reinforcing materials. Rigid bridging particles determine the bridging position and pressure-bearing capacity of the sealing skeleton. They are critical for resisting differential pressure fluctuations and suppressing overall slippage destabilization of the sealing layer. Filling materials are used to fill the voids between bridging particles and block filtration pathways, thereby reducing pore connectivity. They are mainly classified as flaky materials and fibrous materials based on their morphology. Reinforcing materials enhance the integrity of the sealing layer and improve resistance to erosion and shear. Therefore, candidate formulations should follow a three-step synergy: bridging for a pressure-bearing skeleton, pore filling for fluid-loss control, and elastic-material reinforcement of the seal structure.

An engineering-oriented pre-screening was first performed for the rigid bridging and filling components, including bridging particles, flaky materials, and fibrous materials. This step was used to define a stable baseline formulation that can form a reliable bridging skeleton and achieve effective densification under the target fracture conditions. The baseline framework was then held constant, and the elastic-material system was treated as the primary variable. This design isolates the contribution of elastic additives, whose compressibility and rebound recovery are expected to promote structural compliance and contact reconfiguration of the sealing layer under fracture-aperture disturbances. The effects of elastic-system selection and composition ratio on lost-circulation control in stress-sensitive fractures were subsequently compared. Five candidate materials were initially considered for the conventional bridging framework. Walnut shell was selected as the bridging particle, mica and roseite were selected as flaky materials, and sawdust and cottonseed hull were selected as fibrous materials, as shown in Figure 2. Five candidates were also examined for the elastic system, including rubber particles, elastic graphite, elastic mesh material, swelling rubber, and resin rubber, as shown in Figure 3.

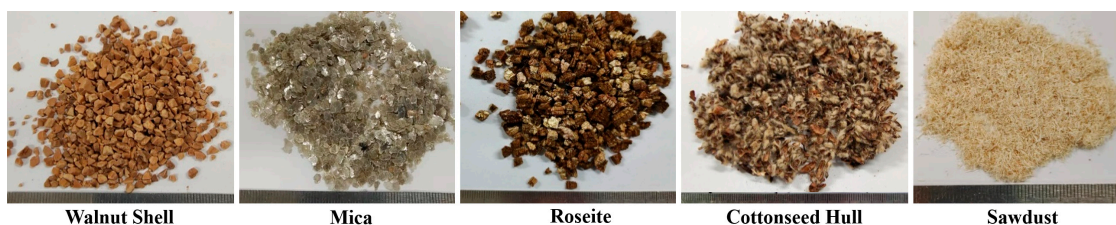


Figure 2. Photographs of selected evaluated bridging LCMs.

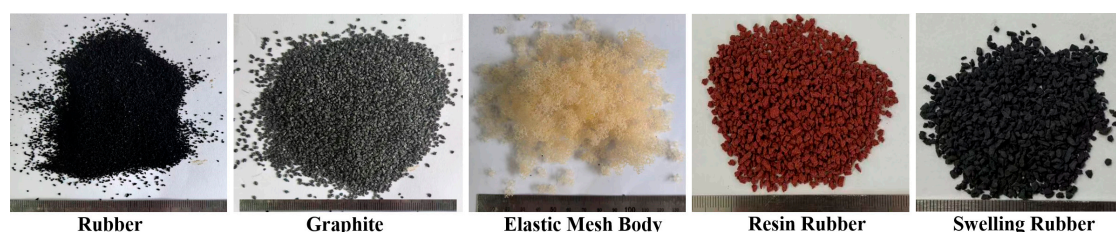


Figure 3. Photographs of selected evaluated elastic LCMs.

3.2. Key Material Parameter Characterization

Key parameters including particle-size gradation, particle morphology, frictional behavior, and mechanical strength are tested. Particle image processing combined with dynamic image analysis was used to characterize material morphology. Aspect ratio and sphericity were extracted to indicate bridging potential and slippage tendency (Figure 4a).

Walnut shell is predominantly granular and acts as a rigid bridging component of the formulation. In contrast, roseite and mica show large variability in aspect ratio and average sphericity, while walnut shell is relatively uniform. This geometric diversity allows mica and roseite to occupy the interstitial spaces within the bridging skeleton and improve sealing-layer strength. Particle-size distributions were obtained using a combined sieving and laser diffraction method. A sieve analyzer and a laser particle-size analyzer were used together to provide continuous coverage from millimeter-scale bridging particles to finer fractions, overcoming the scale limitation of a single method (Figure 4b,c). A prerequisite for LCM selection is a well-designed particle-size distribution. The particle-size distribution of the selected materials should be compatible with the target fracture aperture. Frictional properties were measured using a sliding wear test apparatus. Under a constant normal load, the normal force and traction force were recorded in real time to calculate the coefficient of friction, which reflects anti-slippage behavior under contact with fracture surfaces (Figure 4d,e). The coefficient of friction is calculated as $\mu = \frac{M}{r \cdot F}$. Where M is the friction torque, r is the ring radius, and F is the applied load. The test results indicate that the coefficient of friction decreases as particle size decreases. Mechanical strength was evaluated using a TAW-1000 deepwater pore pressure servo testing system to quantify load-bearing performance and resistance to particle crushing under applied loading (Figure 4f). The purpose is to determine whether the material is prone to crushing at the target pressure, which could induce sealing-layer instability. Experimental results are summarized in Tables 1–3 and Figure 5.

Table 1. Particle-size evaluation results of LCMs.

LCMs	Size Mesh	D10	D50	D90
Walnut shell	6–10 mesh	1400–1700	1700–2360	2360–3350
	10–20 mesh	830–880	1180–1400	1400–1700
	20–32 mesh	600–646	646–700	646–700
Mica	3–20 mesh	1000–1180	1400–1700	1700–2360
Roseite	3–20 mesh	1400–1700	2360–3350	3350–4750
Sawdust	—	<250	<250	380–425
Cottonseed hull	—	<250	250–450	425–680

D10, D50, and D90 denote the particle diameters at which the cumulative mass fraction reaches 10%, 50%, and 90%, respectively.

Table 2. Evaluation results of aspect ratio and sphericity of LCMs.

LCMs	Size Fraction	Evaluated Aspect Ratio	Average Sphericity
Walnut shell	3–20 mesh	1.404	0.883
	16–30 mesh	1.461	0.867
Roseite	3–20 mesh	2.513	0.727
Mica	3–20 mesh	2.641	0.605

Table 3. Evaluation results of the maximum compressive strength of LCMs.

LCMs	Size Mesh	Average Value
Walnut shell	8–10 mesh	16.81 MPa
	12–14 mesh	18.28 MPa
	16–18 mesh	19.90 MPa
Mica	8–10 mesh	19.02 MPa
	12–14 mesh	21.03 MPa
	16–18 mesh	22.41 MPa

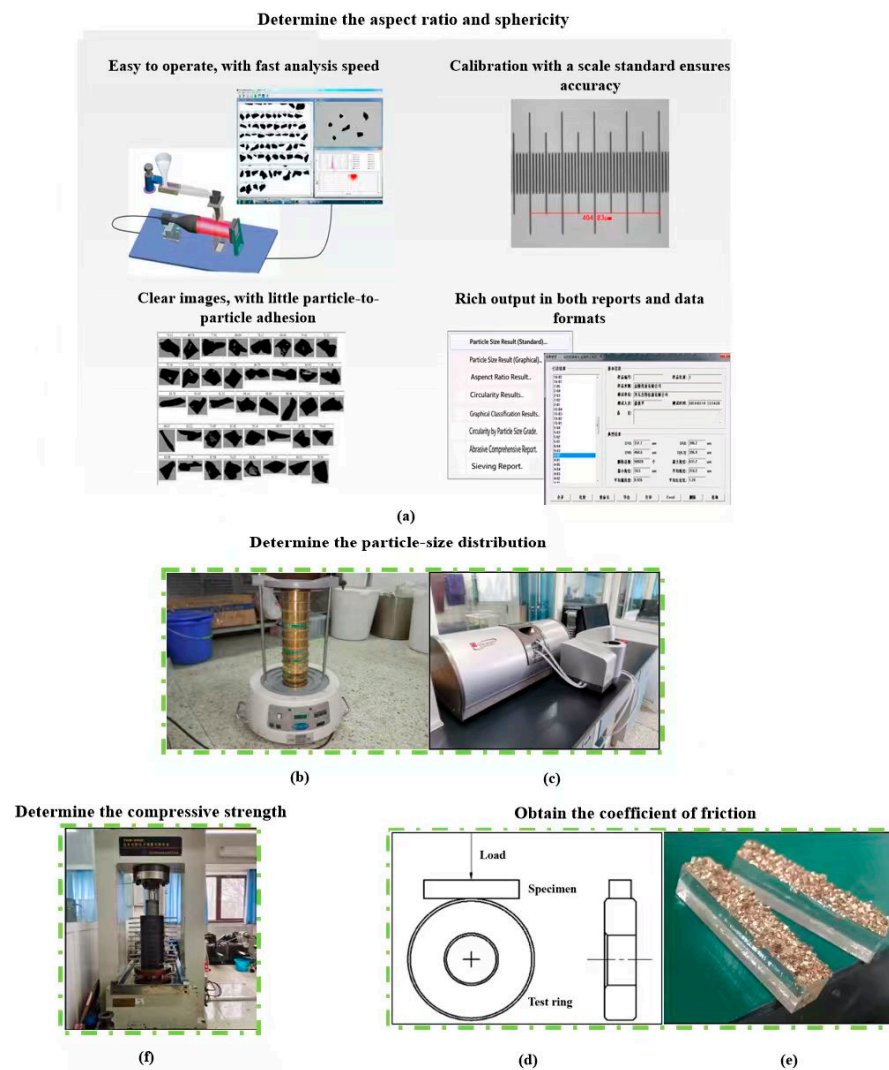


Figure 4. Performance testing of lost-circulation materials: (a) particle image processing combined with dynamic image analysis; (b) sieve analyzer; (c) laser particle-size analyzer; (d) schematic diagram of the sliding wear test; (e) friction specimen; (f) compressive strength test.

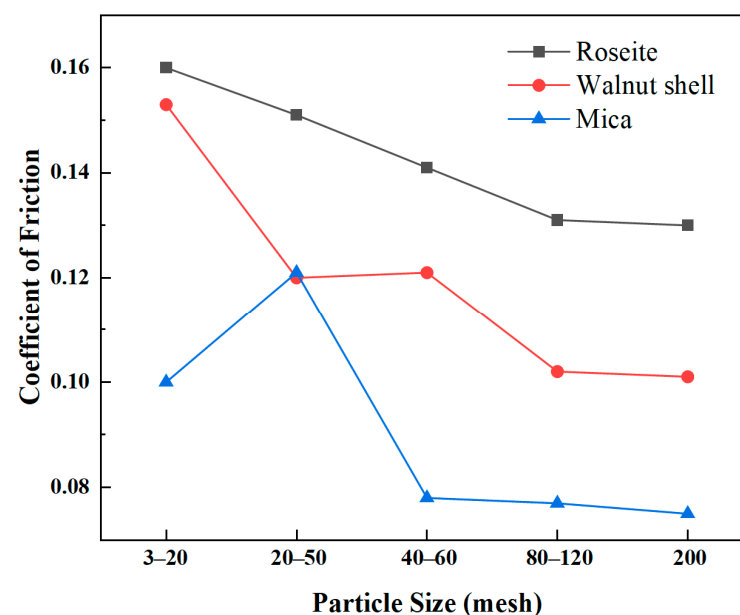


Figure 5. Coefficient of friction test results of lost circulation materials.

3.3. Basic Formulation Scheme Determination

Dynamic sealing tests are time consuming. They also demand greater material consumption and tighter operating condition control. In order to ensure that candidate formulations have basic sealing and pressure-bearing feasibility, PPA sealing tests were first conducted for different combinations of bridging particles, flaky materials, and fibrous materials (Figure 6a). The tests focused on sealing layer behavior, maximum pressure-bearing capacity, and loss-control performance.

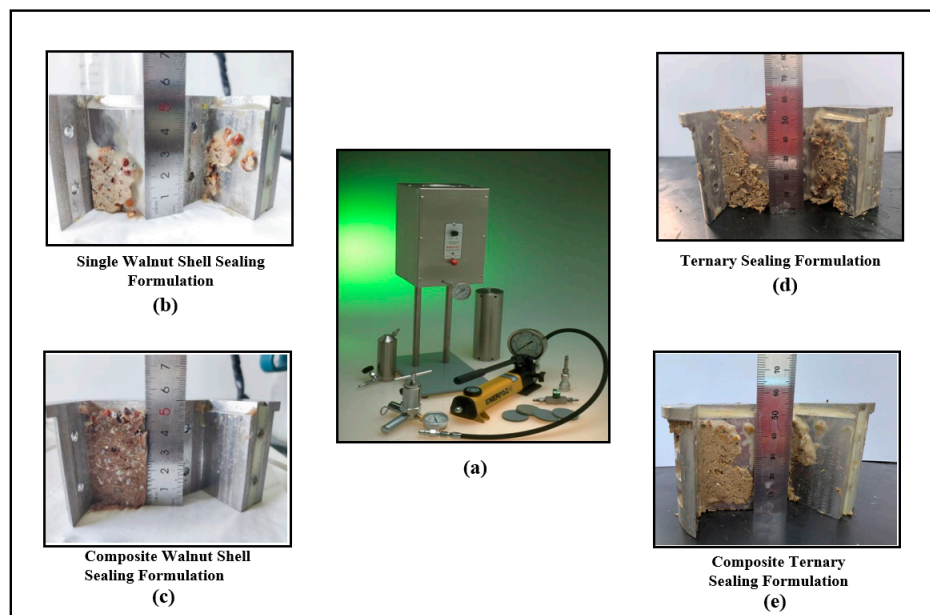


Figure 6. Photographs of the PPA test results: (a) PPA; (b) sealing performance with single walnut shell particle size; (c) sealing performance with composite walnut shell particle sizes; (d) sealing performance with ternary materials; (e) sealing performance with composite ternary materials.

PPA screening tests were intended to remove possible formulation schemes that fail to form an effective sealing layer. The subsequent evaluation focused on the role of elastic-material systems on dynamic adaptability.

The results indicate that a bridging skeleton constructed with 12–20 mesh and 20–28 mesh walnut shell particles forms a more stable structure under target conditions and has better loss-control performance (Figure 6b,c). After 3–20 mesh mica and sawdust are added to the composite formulation, the sealing layer becomes more compact, and both the loss volume and leakage are further suppressed (Figure 6d,e). The chosen composite formulation better satisfies the requirements for stable pressure bearing and disturbance resistance.

3.4. Elastic-Material System Determination

After the basic sealing formulation was established, the elastic-material system was treated as the primary variable for stress-sensitive fracture sealing evaluation. The objective was to clarify the mechanism of elastic materials in controlling sealing layer stability under aperture disturbances. Experiments were conducted using a self-developed DTDL dynamic fracture plugging apparatus. The apparatus enables stepwise aperture enlargement with real-time response to injection differential pressure. It records pressure evolution and loss behavior, providing comprehensive information from sealing layer compact, pressure-bearing phase, failure and re-sealing. These measurements serve as a consistent data source for the subsequent multi-metric evaluation.

Five elastic materials were initially examined, including recycled rubber particles, elastic graphite, elastic mesh body, swelling rubber, and resin rubber. Some representative results are shown in Figure 7. Sealing-layer location, compactness, and failure features can be used to diagnose the destabilization mechanism under aperture disturbance. Rubber particles exhibit high compressibility and strong rebound recovery. They can provide better filling and contact reconfiguration, which improves sealing layer tolerance to dynamic aperture variation. Elastic graphite combines moderate elasticity with flaky extensibility. It can improve contact between particles and help fill newly formed filtration pathways, which supports pressure retention after failure and may shorten re-sealing time. Elastic mesh material can provide a more stable spatial connection for the bridging skeleton. It tends to increase the pressure-bearing limit and reduce the time required to establish a seal layer. However, proper concentration control is required to prevent rapid fracture entrance sealing, which is prone to breakdown during circulation. Swelling rubber can markedly enhance adaptability after full expansion, but its effectiveness depends on fluid uptake and swelling within the fracture. This leads to a substantially longer stabilization time, reduces consistency in indicator extraction, and conflicts with the time-sensitive requirements of loss control and circulation recovery. Resin rubber can provide stronger interfacial adhesion because of the resin component, which can improve sealing layer integrity. However, partial resin release into the slurry will increase viscosity and alter rheology at formation temperature. This introduces additional variables and complicates comparison of intrinsic elastic-system schemes. Therefore, swelling rubber and resin rubber were chosen as elastic-material candidates but were excluded from the subsequent comprehensive model. This study focuses on three elastic systems, rubber particles (R), elastic graphite (G), and elastic mesh body (N), for formulation optimization. Each candidate formulation is tested three times under the same operating conditions, and the average value is used as the input for the comprehensive evaluation model. Experimental data showing excessively large deviations are excluded, and the corresponding experiments are repeated.

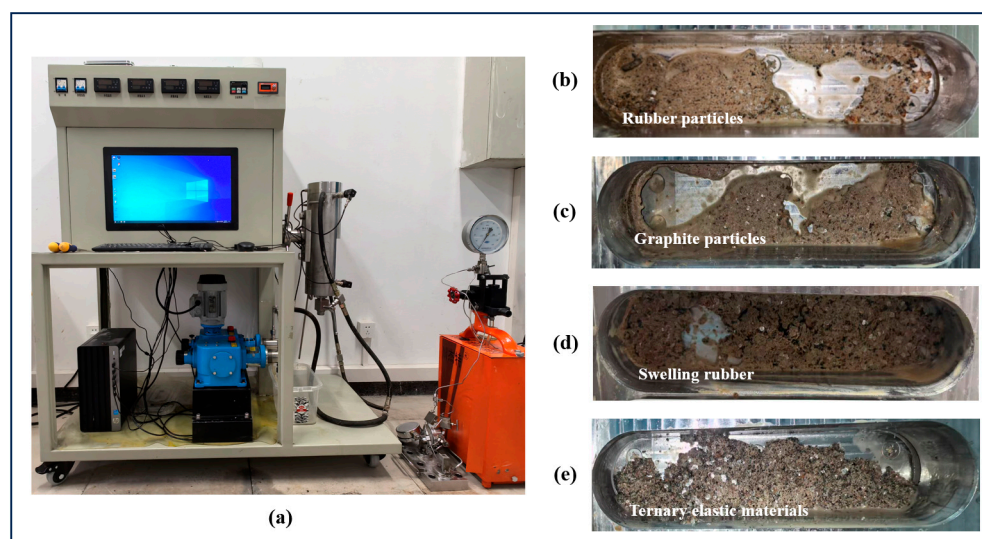


Figure 7. Dynamic fracture sealing experiments: (a) DTDL dynamic fracture sealing apparatus; (b) sealing layer with rubber particles; (c) sealing layer with graphite particles; (d) sealing layer with swelling rubber; (e) sealing layer with composite ternary elastic materials.

Ten candidate formulations were designed in a hierarchical structure. A single-material baseline was defined to establish the indicator profile of a single elastic component and to serve as a benchmark for quantifying the incremental benefit of composite formulation. A single-component case was not included for the elastic mesh body because this material

is associated with the risk of premature bridging. Binary formulations included three R:G ratios, 1:2, 1:1, and 2:1, representing graphite-dominant, balanced, and rubber-dominant states. These cases were used to assess whether ratio changes can induce performance transitions or ranking reversals. Two additional binaries, R:N = 3:1 and G:N = 3:1, were selected to capture particle–network constraint mechanisms. Ternary formulations were then used to evaluate synergy and composition sensitivity. The 1:1:1 ratio represents a balanced ternary condition. The 2:3:1 and 3:2:1 ratios provide graphite-leaning and rubber-leaning cases, enabling an assessment of whether ternary synergy persists under biased compositions and how it affects contributions across the criteria-level indicators.

4. Development of Entropy-Weighted Grey–TOPSIS Model

4.1. Entropy-Weighted Grey–TOPSIS Theory

The entropy weight method is an objective weighting approach that determines indicator importance from the dispersion of the data itself. A lower entropy value indicates that the indicator values are more dispersed across alternatives. This implies higher information content and stronger discrimination in formulation evaluation. Therefore, the indicator should receive a larger weight. TOPSIS is an effective multi-criteria evaluation method that makes full use of the original data. Its results can clearly quantify performance gaps among alternatives. Grey relational analysis is well suited to systems where multiple factors interact through complex nonlinear relationships. It evaluates grey relational grades between a reference sequence and each comparable sequence to quantify their closeness.

TOPSIS can simultaneously account for multiple indicators and supports a comprehensive comparison of candidate schemes. However, the inclusion of qualitative indicators may introduce subjectivity into the evaluation [24]. Grey relational analysis requires fewer assumptions on the raw data and remains straightforward to implement. It can handle complex and uncertain problems by ranking alternatives according to their relational closeness to the optimal scheme. Its limitation is that the interpretation of quantitative differences may be less intuitive [25]. Introducing grey relational analysis into the TOPSIS method enables closeness to the ideal solution to be characterized from both quantitative performance and relational similarity. This dual-reference formulation improves the accuracy of lost circulation formulation evaluation. Further integrating entropy weighting into the Grey–TOPSIS model leverages the strengths of both approaches. The comprehensive method provides a more rigorous treatment of multi-metric data, which is particularly appropriate for formulation optimization in lost circulation control (Figure 8).

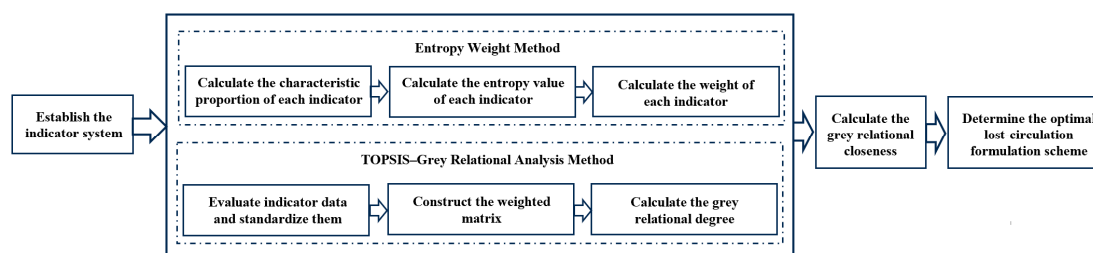


Figure 8. Comprehensive evaluation procedure based on Grey–TOPSIS relational analysis.

4.2. Model Implementation and Calculation Steps

Consider an evaluation matrix $X = (x_{ij})$ with i candidate schemes and j evaluation indicators in the selection of the optimal lost-circulation formulation. Each element X_{ij} denotes the value of the indicator j scheme i . The specific calculation procedure is as follows.

a. Construct the original matrix X , in which the raw values of the evaluation indicators for each candidate scheme are arranged as row vectors.

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} = (x_{ij})_{m \times n} \quad (1)$$

In Equation (1), $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$.

b. The original data matrix is normalized using the min–max method to eliminate dimensional differences. Let x_{ij}^* denote the standardized value of the raw data for each indicator.

$$X^* = \begin{pmatrix} x_{11}^* & \cdots & x_{1n}^* \\ \vdots & \ddots & \vdots \\ x_{m1}^* & \cdots & x_{mn}^* \end{pmatrix} = (x_{ij}^*)_{m \times n} \quad (2)$$

In Equation (2), $x_{ij}^* = \frac{(x_{ij} - \min x_{ij})}{(\max x_{ij} - \min x_{ij})}$ for benefit type indicators

$x_{ij}^* = \frac{(\max x_{ij} - x_{ij})}{(\max x_{ij} - \min x_{ij})}$ for cost type indicators.

c. Calculate the proportion matrix P_{ij} and the information entropy matrix E_j for each indicator of the lost-circulation formulations:

$$P_{ij} = x_{ij}^* / \sum_{i=1}^m x_{ij}^* \quad (3)$$

$$E_j = -k \cdot \sum_{i=1}^m P_{ij} \cdot \ln P_{ij} \quad (4)$$

In Equations (3) and (4), $k = 1/\ln m$. If $P_{ij} = 0$, then $E_j = 0$ is defined.

d. Calculate the weight coefficient of each indicator: The weights of the evaluation indicators are determined by information redundancy. Accordingly, the weight matrix is expressed as $W = (w_j)$.

$$w_j = (1 - E_j) / \sum_{i=1}^n (1 - E_j) \quad (5)$$

In Equation (5), w_j denotes the weight of the j th evaluation indicator.

e. Calculate the weighted normalized decision matrix. $Y = (y_{ij})_{m \times n}$

$$y_{ij} = w_j \cdot x_{ij}^* \quad (6)$$

f. Determine the reference samples of the weighted normalized matrix Y , namely, the ideal sample Y^+ and the worst sample Y^- .

$$Y^+ = (y_1^+, y_2^+, \dots, y_n^+) \quad (7)$$

$$Y^- = (y_1^-, y_2^-, \dots, y_n^-) \quad (8)$$

g. Calculate the grey relational coefficient matrices between each sample and the ideal sample Y^+ and the worst sample Y^- , denoted as $R^+ = (r_{ij}^+)_{m \times n}$ and $R^- = (r_{ij}^-)_{m \times n}$, respectively, where:

$$r_{ij}^+ = \frac{\min_{i=1}^m \min_{j=1}^n |Y_j^+ - Y_{ij}^-| + \rho \max_{i=1}^m \max_{j=1}^n |Y_j^+ - Y_{ij}^-|}{|Y_j^+ - Y_{ij}^-| + \rho \max_{i=1}^m \max_{j=1}^n |Y_j^+ - Y_{ij}^-|} \quad (9)$$

$$r_{ij}^- = \frac{\min_{i=1}^m \min_{j=1}^n |Y_j^- - Y_{ij}^-| + \rho \max_{i=1}^m \max_{j=1}^n |Y_j^- - Y_{ij}^-|}{|Y_j^- - Y_{ij}^-| + \rho \max_{i=1}^m \max_{j=1}^n |Y_j^- - Y_{ij}^-|} \quad (10)$$

In Equations (9) and (10), ρ is the distinguishing coefficient, which is usually taken as $\rho = 0.5$.

h. Calculate the grey relational degree matrices R^* and R^0 for each scheme

$$R^* = R^+ \cdot W^T \quad (11)$$

$$R^0 = R^- \cdot W^T \quad (12)$$

i. Calculate the grey relational relative closeness Q_i .

$$Q_i = r_i^* / (r_i^* + r_i^0), i = 1, 2, \dots, m \quad (13)$$

The grey relational closeness Q_i is evaluated for each candidate scheme. As Q_i increases toward 1, the evaluated scheme is considered closer to the optimal solution.

j. For the classical TOPSIS method, the entropy weights are replaced by equal weights $w_j = 1/m$.

k. Calculate the distances to the positive and negative ideal solutions for two comparative methods

$$D_i^+ = \sqrt{\sum_{j=1}^m \left(\max_i(y_{ij}) - y_{ij} \right)^2}, \quad D_i^- = \sqrt{\sum_{j=1}^m \left(\min_i(y_{ij}) - y_{ij} \right)^2} \quad (14)$$

l. Calculate relative closeness Q_i for two comparative methods

$$Q_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (15)$$

5. Results and Discussion

5.1. Indicator Weighting

The comprehensive evaluation method includes four criteria layers, and the raw data for the eight indicators of ten candidate formulations are provided in Table 4.

The original matrix X can be obtained from the data. Based on the original data matrix, dimensionless normalization is performed to yield the standardized matrix X^* as follows:

$$X^* = \begin{bmatrix} 0.7308 & 0.0000 & 0.9167 & 0.9565 & 0.0000 & 0.6850 & 0.1023 & 0.0000 \\ 0.0000 & 0.5644 & 0.0000 & 0.0000 & 0.8868 & 0.0000 & 0.0000 & 0.6764 \\ 0.1346 & 0.4134 & 0.4271 & 0.3913 & 0.4717 & 0.1952 & 0.0767 & 0.5655 \\ 0.0577 & 0.5238 & 0.2292 & 0.1739 & 0.7170 & 0.0638 & 0.0256 & 0.6227 \\ 0.8654 & 0.3130 & 0.6979 & 0.5652 & 0.0566 & 0.4643 & 0.0128 & 0.3773 \\ 0.5192 & 0.8595 & 0.5208 & 0.7391 & 0.7170 & 0.4357 & 1.0000 & 1.0000 \\ 0.8654 & 0.8845 & 0.8854 & 0.8696 & 0.7736 & 0.2781 & 0.8974 & 0.9675 \\ 1.0000 & 1.0000 & 1.0000 & 0.9565 & 1.0000 & 1.0000 & 0.8974 & 0.9593 \\ 1.0000 & 0.5912 & 0.9375 & 1.0000 & 0.3774 & 0.6408 & 0.1795 & 0.1187 \\ 0.2885 & 0.6799 & 0.9635 & 1.0000 & 0.5660 & 0.5770 & 0.1667 & 0.7215 \end{bmatrix}$$

According to the calculation procedure of the entropy weight method described in Section 4.2, the entropy value and weight of each indicator were obtained. The de-

tailed calculation results are presented in Table 5. Accordingly, the weight matrix W can be determined.

Table 4. Experimental parameter values of each evaluation scheme.

Scheme		Sealing Pressure-Bearing Capacity		Leakage-Control Capacity		Dynamic Adaptability		Re-Sealing Capacity	
		Maximum Pressure-Bearing Capacity (MPa)	Pressure-Bearing Stability Time (min)	Cumulative Leakage Loss (mL)	Steady-State Leakage Rate (mL/min)	Pressure Retention Ratio	Maximum Fracture Width Variation at Failure (mm)	Maximum Pressure-Bearing Capacity After Re-Sealing (MPa)	Re-Sealing Time (min)
1	R	8.3	10.8	133	3	17%	0.614	1.8	16.3
2	G	4.5	6.7	325	25	64%	0.206	1.2	6.7
3	R:G = 1:1	5.2	7.8	226	16	42%	0.322	1.6	8.2
4	R:G = 1:2	4.8	7	265	21	55%	0.244	1.4	7.4
5	R:G = 2:1	9	8.5	188	12	20%	0.482	1.3	11
6	R:G:N = 1:1:1	7.2	4.9	206	8	55%	0.465	6.8	2.2
7	R:G:N = 2:3:1	9	4.5	143	5	58%	0.405	6	1.4
8	R:G:N = 3:2:1	10	3.5	111	3	70%	0.786	6	1.5
9	R:N = 3:1	10	6.2	123	2	37%	0.604	2.6	14.6
10	G:N = 3:1	6	5.6	118	2	47%	0.578	2.5	5.1

Table 5. Weight coefficients of indicators for lost-circulation formulation optimization.

Objective Layer	Criteria Layer	Indicator Layer	E_j	w_j
Optimization evaluation model for sealing formulations for stress-sensitive fractures	Sealing pressure-bearing capacity	Maximum pressure-bearing capacity (MPa)	0.8977	0.1197
		Pressure-bearing stability time (min)	0.8862	0.1332
	Leakage-control capacity	Cumulative leakage loss (mL)	0.8955	0.1223
		Steady-state leakage rate (mL/min)	0.8912	0.1273
	Dynamic adaptability	Pressure retention ratio	0.8920	0.1264
		Maximum fracture width variation at failure	0.8816	0.1386
	Re-sealing capacity	Maximum pressure-bearing capacity after re-sealing (MPa)	0.7838	0.2843
		Re-sealing time (min)	0.8855	0.1330

5.2. Normalized Decision Matrix

To improve the objectivity of the evaluation, an entropy-weighted evaluation matrix is constructed. Specifically, according to the weight coefficient of each indicator, the diagonal weight matrix W^* is established. By combining the standardized matrix with the weight coefficients, the weighted normalized decision matrix $Y = (y_{ij})_{m \times n}$ is obtained.

$$Y = \begin{bmatrix} 0.0875 & 0.0000 & 0.1121 & 0.1218 & 0.0000 & 0.0950 & 0.0291 & 0.0000 \\ 0.0000 & 0.0752 & 0.0000 & 0.0000 & 0.1121 & 0.0000 & 0.0000 & 0.0899 \\ 0.0161 & 0.0551 & 0.0522 & 0.0498 & 0.0596 & 0.0271 & 0.0218 & 0.0752 \\ 0.0069 & 0.0698 & 0.0280 & 0.0221 & 0.0906 & 0.0089 & 0.0073 & 0.0828 \\ 0.1033 & 0.0417 & 0.0853 & 0.0719 & 0.0072 & 0.0644 & 0.0036 & 0.0502 \\ 0.0622 & 0.1145 & 0.0637 & 0.0941 & 0.0906 & 0.0604 & 0.2843 & 0.1330 \\ 0.1033 & 0.1178 & 0.1083 & 0.1107 & 0.0979 & 0.0386 & 0.2552 & 0.1287 \\ 0.1197 & 0.1332 & 0.1223 & 0.1218 & 0.1264 & 0.1386 & 0.2552 & 0.1276 \\ 0.1197 & 0.0788 & 0.1147 & 0.1273 & 0.0477 & 0.0889 & 0.0511 & 0.0158 \\ 0.0345 & 0.0906 & 0.1178 & 0.1273 & 0.0716 & 0.0798 & 0.0474 & 0.0960 \end{bmatrix}$$

From matrix Y , the positive ideal solution Y^+ and the negative ideal solution Y^- of the evaluated schemes can be determined.

$$Y^+ = \left(\max_{1 \leq i \leq 8} y_{ij} \mid i = 1, 2, \dots, 8 \right) = (y_1^+, y_2^+, \dots, y_n^+) \\ = (0.1197, 0.1332, 0.1223, 0.1273, 0.1264, 0.1386, 0.2843, 0.1330)$$

$$Y^- = \left(\min_{1 \leq i \leq 8} y_{ij} \mid i = 1, 2, \dots, 8 \right) = (0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000)$$

5.3. Calculation of the Grey-TOPSIS Relational Closeness

The positive ideal grey relational coefficient r_{ij}^+ and the negative ideal grey relational coefficient r_{ij}^- of the evaluation indicators for each candidate scheme are calculated to obtain the grey relational coefficient matrices R^+ and R^- . By incorporating the weights of the evaluation indicators, the grey relational degree matrices R^* and R^0 of the five lost-circulation formulations are obtained as follows.

$$R^* = (0.6264, 0.5558, 0.5741, 0.5716, 0.6039, 0.7248, 0.7482, 0.8091, 0.6764, 0.6616)^T \quad (16)$$

$$R^0 = (0.6736, 0.7442, 0.7259, 0.7284, 0.6961, 0.5752, 0.5518, 0.4909, 0.6236, 0.6384)^T \quad (17)$$

According to Equations (16) and (17), the grey relational closeness values of the five lost-circulation formulations can be calculated. Accordingly, the comprehensive evaluation result matrix Q based on the entropy weight method combined with Grey-TOPSIS relational analysis is expressed as $Q = (0.4819, 0.4274, 0.4416, 0.4397, 0.4646, 0.5577, 0.5753, 0.6222, 0.5203, 0.5090)^T$.

5.4. Sensitivity Analysis

The Grey-TOPSIS ranking can be influenced by both indicator weights and the distinguishing coefficient used in grey relational analysis. A sensitivity analysis was performed to confirm that the ranking is robust to proposed schemes. The distinguishing coefficient ρ directly affects the calculated relational grades and the final closeness values. In this study, ρ is set to 0.5 as the baseline case. The value of ρ is then varied over the selected range, and the corresponding changes in Grey-TOPSIS closeness are evaluated. The results are summarized in Table 6.

Table 6. Sensitivity analysis of Grey-TOPSIS closeness values under different distinguishing coefficients.

Distinguishing Coefficient	Scheme 1	Scheme 2	Scheme 3	Scheme 4	Scheme 5	Scheme 6	Scheme 7	Scheme 8	Scheme 9	Scheme 10
$\rho = 0.1$	0.4235	0.3016	0.3838	0.3486	0.411	0.6709	0.7039	0.8117	0.6205	0.6278
$\rho = 0.3$	0.4651	0.3952	0.4252	0.4117	0.4551	0.5923	0.6172	0.6909	0.5487	0.5494
$\rho = 0.5$	0.4819	0.4274	0.4416	0.4397	0.4646	0.5577	0.5752	0.6222	0.5203	0.509
$\rho = 0.7$	0.4924	0.4433	0.4507	0.4536	0.4603	0.5319	0.5458	0.5806	0.5022	0.4923
$\rho = 0.9$	0.4999	0.4545	0.4565	0.4623	0.4543	0.514	0.5242	0.5529	0.4907	0.4819

The calculated grey relational closeness Q values were plotted to visualize the effect of ρ selection on the Grey-TOPSIS evaluation. The sensitivity comparison is shown in Figure 9.

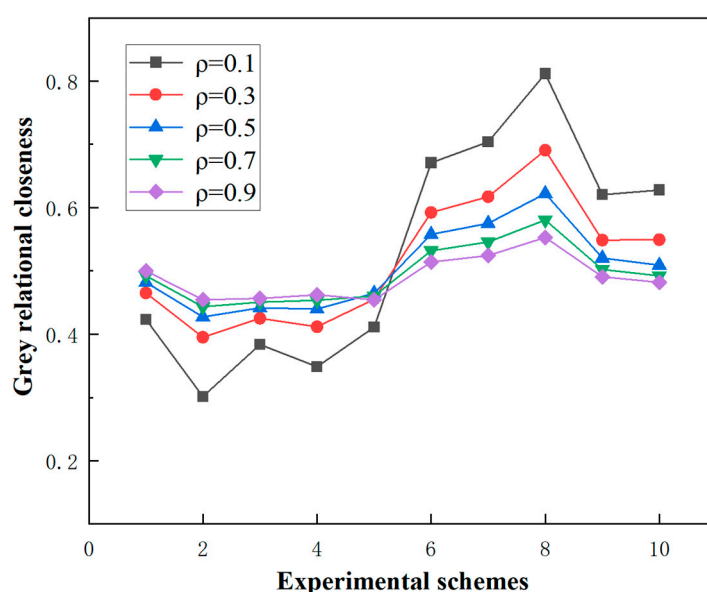


Figure 9. Sensitivity analysis of Grey-TOPSIS closeness under different distinguishing coefficients.

As shown in Figure 9, changing q causes fluctuations in the relative closeness values. However, the ternary elastic formulation with a 3:2:1 ratio consistently yields the highest Grey–TOPSIS closeness among all candidates. Using the maximum-closeness criterion, the optimal scheme remains unchanged across the tested q values. These results indicate that the entropy-weighted Grey–TOPSIS approach provides robust and reliable ranking for multi-metric optimization of lost-circulation formulations in stress-sensitive fractures.

5.5. Comparison Analysis with Classical TOPSIS Method and Entropy-Weighted TOPSIS Method

Matrix Q based on the entropy-weighted TOPSIS method is expressed as $Q = (0.1932, 0.2460, 0.3485, 0.3140, 0.3823, 0.6057, 0.6409, 0.6971, 0.2719, 0.2900)$.

Matrix Q based on the classical TOPSIS method is expressed as $Q = (0.2259, 0.2800, 0.3678, 0.3540, 0.4128, 0.6183, 0.6899, 0.7768, 0.3279, 0.3249)$.

Three methods yielded the rankings of the ten candidate formulations, as summarized in Table 7.

Table 7. Ranking of formulation schemes.

Scheme	Formulations	EGT	ET	T
1	R	6	10	10
2	G	10	9	9
3	R:G = 1:1	8	5	5
4	R:G = 1:2	9	6	6
5	R:G = 2:1	7	4	4
6	R:G:N = 1:1:1	3	3	3
7	R:G:N = 2:3:1	2	2	2
8	R:G:N = 3:2:1	1	1	1
9	R:N = 3:1	4	8	7
10	G:N = 3:1	5	7	8

EGT represents the entropy-weighted Grey–TOPSIS method, ET represents the entropy-weighted TOPSIS method, and T represents the classical TOPSIS method.

The three methods produce the same top three ranking, with R:G:N = 3:2:1, outperforming 2:3:1 and 1:1:1. This consistency indicates that the ternary formulations deliver a more balanced performance and remain closer to the positive ideal solution under different evaluation frameworks. The superior performance of the ternary formulation is attributed to functional complementarity among the three elastic components. The elastic mesh body acts as a three-dimensional constraint that strengthens the bridging skeleton and increases packing compactness, making micro-crack development within the sealing layer more difficult during aperture fluctuations. Rubber improves tolerance to aperture enlargement by providing deformable filling and rebound-assisted contact reconstruction. Elastic graphite accelerates recovery after destabilization, which is reflected by a shorter re-sealing time. These contributions are not interchangeable, and removing any component weakens at least one key capability required for stress-sensitive fracture sealing.

The entropy-weighted Grey–TOPSIS method moves R:N = 3:1 and G:N = 3:1 upward and places the single-component R formulation at sixth. These shifts are mainly driven by the higher weights assigned to the maximum fracture-width variation at failure and the pressure-bearing capacity after re-sealing. Such weighting is aligned with operational needs in stress-sensitive fractures, where larger tolerance to aperture disturbances helps prevent repeated fluid loss events, and strong re-sealing pressure capacity supports rapid recovery after a failure. The entropy-weighted TOPSIS and classical TOPSIS results should be interpreted with caution. Entropy-weighted TOPSIS does not explicitly represent inter-indicator dependence, while classical TOPSIS derives relative closeness purely from Euclidean distances to the ideal solutions. Consequently, both methods may provide a less comprehensive representation of the multi-indicator characteristics, and the decision support can be less informative for stress-sensitive fracture sealing problems.

6. Conclusions

1. This study focuses on lost circulation control in stress-sensitive fractured formations. A comprehensive evaluation system is established with four criteria layers and eight indicator metrics covering pressure-bearing performance, loss-control performance, dynamic adaptability, and re-sealing capability. An entropy-weighted Grey–TOPSIS method is proposed for formulation selection. Experimental data are transformed to a consistent preference direction and normalized to remove unit effects. Indicator weights are determined objectively using the entropy weight method. Grey relational coefficients are incorporated within an ideal solution framework to capture similarity among indicator sequences. This method enables quantitative ranking and selection of lost circulation formulations under small sample and limited information conditions.

2. A tiered evaluation route is adopted for basic sealing formulation schemes. Static fracture sealing tests are used as a feasibility basis, and dynamic fracture sealing tests are used for validation. The basic formulation framework is defined as walnut shell, mica, and sawdust. The comprehensive experimental dataset provides consistent and comparable inputs for scheme ranking evaluation. This design avoids mechanism ambiguity caused by simultaneous variation of multiple formulation variables.

3. Among the candidate formulations, the scheme with R:G:N = 3:2:1 achieves the highest grey relational closeness and is identified as the optimal option. Its overall performance is closer to the positive ideal state across pressure-bearing capacity, loss control, dynamic adaptability, and re-sealing capability. The formulation better meets the stability requirements associated with aperture evolution in stress-sensitive fractures.

4. Sensitivity analysis was performed with the distinguishing coefficient ρ varied from 0.1 to 0.9, yielding an unchanged ranking. This result indicates that the entropy-weighted Grey–TOPSIS model is robust with respect to ρ selection. The proposed approach is suitable for multi-metric, comprehensive evaluation of lost circulation formulations under stress-sensitive fracture conditions.

5. All three methods yield the same ranking for the ternary formulations. This consistency indicates that the identified optimum is robust and repeatable across evaluation frameworks. In contrast, the proposed combined method provides finer discrimination among binary formulations by placing greater emphasis on metrics related to dynamic adaptability and re-sealing performance. This feature offers more targeted decision support for lost-circulation control during drilling.

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Abbreviations

The following abbreviations are used in this manuscript:

LCMs	Lost circulation materials
MCDM	Multiple-criteria decision-making
TOPSIS	Technique for order preference by similarity to an ideal solution
List of Variables with Definitions and Units	
M	Friction torque
r	Ring radius

F	Applied load to the ring
m	Number of candidate formulation schemes
n	Number of evaluation indicators
i	Index of candidate scheme, $i = 1, 2, \dots, m$
j	Index of indicator, $j = 1, 2, \dots, n$
X	Original decision matrix constructed from raw indicator data
x_{ij}	Raw value of indicator j for scheme i
x_{ij}^*	Normalized value of indicator j for scheme i
P_{ij}	Proportion matrix of scheme i under indicator j
E_j	Information entropy matrix of indicator j
w_j	Entropy weight of indicator j
Y	Weighted normalized decision matrix
Y^+	Ideal sample
Y^-	Worst sample
ρ	Distinguishing coefficient in grey relational analysis, $0 < \rho < 1$
γ_{ij}^+	Grey relational coefficient between scheme i and the positive ideal under indicator j
γ_{ij}^-	Grey relational coefficient between scheme i and the negative ideal under indicator j
R^+	Grey relational degree to the positive ideal for scheme i
R^-	Grey relational degree to the negative ideal for scheme i
Q_i	Grey relational closeness of scheme i to the ideal solution, $0 \leq Q_i \leq 1$
D^+ / D^-	Positive/negative ideal solution
D_{10}	10th percentile particle size (μm)
D_{50}	50th percentile particle size (μm)
D_{90}	90th percentile particle size (μm)
R	Rubber particle
G	Elastic graphite particle
N	Elastic mesh body
R:G:N	Mass ratio of rubber, graphite, and mesh in a ternary elastic formulation

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