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Enhancing Sustainability Through Drilling Machine Efficiency: A Comparative Analysis of TOPSIS and VIKOR Methods for Energy Optimization

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ABSTRACT

The focal objective of optimizing drilling processes is to mitigate challenges tied to the operation. However, the triumph of mineral drilling relies on the availability of pertinent data to ensure effectiveness. For efficient and successful drilling, an optimization approach necessitates access to pertinent data, especially concerning the physicochemical properties of the rock and operational parameters of the machine. In this study, our focus is on optimizing specific energy, a critical metric for assessing mining drilling efficiency. This measure evaluates the energy used during drilling per unit volume of rock extracted. Considering the complexity of factors involved, treating the selection of the operational mode governing specific energy as a form of multi-criteria decision-making is justifiable. This method involves an in-depth analysis of the problem's underlying structure. Experimental measures were used to validate the proposed optimization approach. The paper delves into evaluating the differences in rankings derived from the TOPSIS and VIKOR methods. A ranking similarity coefficient is employed to compare the rankings against experimental values. Ultimately, the available choices are prioritized, and the most suitable operating mode for the drilling machine is determined. The study's comparative analysis using TOPSIS and VIKOR methodologies leads to the discovery of the best operational modes for drilling machines, highlighting the subtle differences in how well the two methods work. By using a ranking similarity coefficient, this study not only shows what each method's rankings mean in real life compared to experimental values, but it also gives a plan for improving the efficiency of drilling machines by carefully adjusting their parameters. Such insights contribute significantly to the field of drilling optimization, showcasing a methodical approach to energy conservation and operational efficiency.

1. INTRODUCTION

Rock drilling equipment finds wide application across various fields such as surface drilling, tunnel construction, underground mining, and soil reinforcement, employing a combination of rotating, feed, and percussive forces for excavation [1]. The drill bit plays a pivotal role, directly influencing the rock surface. Achieving optimal design parameters for the drill bit, including head design, internal flushing channel design, button material, shape, dimensions, and arrangement, is essential to enhance drilling rates and efficiency. The configuration of drill-bit button layouts significantly influences rock drilling, demanding careful design considerations. The ongoing research focuses on understanding bit-rock contact and drilling mechanics. This involves measuring the force-penetration between the steel drill and the rock to determine the specific percussion energy required during drilling.

Exploration of the transmission of energy into the rock surface, drill bit interactions, and rock fracture process has been simulated by Chiang and Elías [2]. Bu et al. [3] performed numerical simulations of striking rates and penetration depth in various rock types using DTH (down the hole) hammer drilling. Seo et al. [4] formulated a mathematical model representing the hydraulic system of a THD (top hammer drill) drifter, analyzing beat count and percussive energy across different rock types.

Song et al. [5] employed the Taguchi technique to optimize percussion performance by simulating a pneumatic system and enhancing percussion capability. Similarly, Yoon et al. [6] optimized microdrills using the Taguchi methodology and surface response method. Daly et al. [7] conducted Hopkinson bar experiments to study drill-bit rock fragmentation mechanisms, varying pulse rates and drill-bit distances.

Drilling fluids have played a significant role since the 19th century in removing cuttings off rotary drills. The formulation and functions of drilling fluids evolved over the 20th century from simple mud-water combinations to complex mixtures of fluids and solids, garnering significant attention from engineers striving to maximize drilling potential while managing costs.

Specific energy stands as a critical indicator of drilling performance, especially in relation to bit cutting efficiency and rock hardness. It quantifies the intricate process of rock destruction, dependent on several factors such as rock type, cutter rake angle, cutter material, and the forces exerted on the rock surface. Specific energy computation varies for percussive and rotary drilling, considering the surface area of shattered rock and remaining rock after pounding, or the effort to cut a unit volume of rock in rotary drilling, respectively.

Teale [8] pioneered the concept of specific energy in rotary drilling, linking the labor required to break a rock volume to its physical characteristics, particularly compressive strength. Several researchers [9-16] have explored specific energy, offering definitions and correlations.

The drilling process requires managing various parameters like speed, feed rate, depth, and tool selection. Multi-Criteria Decision Making (MCDM) stands as a valuable tool to identify the most efficient combination of parameters for desired outcomes.

While some studies have weighed risk factors and accounted for uncertainty, the majority have utilized single ranking methods for risk prioritization. MCDM methods, recently applied in various fields, enhance the comprehensiveness and robustness of assessment systems [17-20]. Few studies on drilling machines have integrated MCDM methods [21-24].

In this study, granitic rock samples underwent testing in a piston drop-type percussion apparatus to propose a more reliable approach, integrating multiple MCDM methods to optimize operational parameters. Both TOPSIS and Vikor methods were utilized.

Building upon the existing body of knowledge, this study introduces a novel comparative analysis framework employing both TOPSIS and VIKOR methodologies to assess drilling machine efficiency. Distinct from previous efforts that predominantly focused on singular decision-making approaches, our research integrates these two well-established methodologies to offer a more robust evaluation of operational modes in percussive rotary drilling. In addition, using a ranking similarity coefficient to compare our results to experimental standards is a new way to show that the theoretical predictions are true in real life. This dual-methodology analysis, coupled with empirical validation, marks a significant advancement in the optimization of drilling processes, contributing a new perspective to the ongoing discourse on energy-efficient drilling operations [25].

2. METHODOLOGIES

Figure 1 provides a visual representation of the architectural layout for optimizing drilling machines.

The implementation of the recommended model involves four key stages:

a) Data collection: In this initial stage, data is gathered by measuring values for each parameter from the testing platform. This data serves as the foundation for the subsequent optimization process. To gain a comprehensive understanding and to ensure the reproducibility of our findings, it is necessary to detail the experimental conditions under which the data were collected. Measurements of parameters such as drilling speed, torque were obtained using torque sensors, speedometers. The data were collected over several sessions, with each session consisting of a full week of trials to ensure accuracy and mitigate any variations. Environmental conditions, including temperature and humidity, were strictly monitored and recorded, due to their potential impact on drilling performance.

b) Weight calculation using entropy method: The second stage involves the calculation of risk factor weights using the entropy method. This step helps assign appropriate importance to each parameter, considering their relative significance in the decision-making process.

c) Integrated MCDM approach with VIKOR and TOPSIS: The third stage proposes an integrated Multi-Criteria Decision Making (MCDM) approach, combining VIKOR and TOPSIS methods. This integration allows for a more comprehensive evaluation of alternatives based on multiple criteria.

d) Comparison of methods: The final stage involves comparing the outcomes of the two methods. This comparison is achieved by assessing the coefficient of ranking similarity, using specific experimental results as a reference point. It helps determine the extent to which VIKOR and TOPSIS align with each other and with the experimental data.

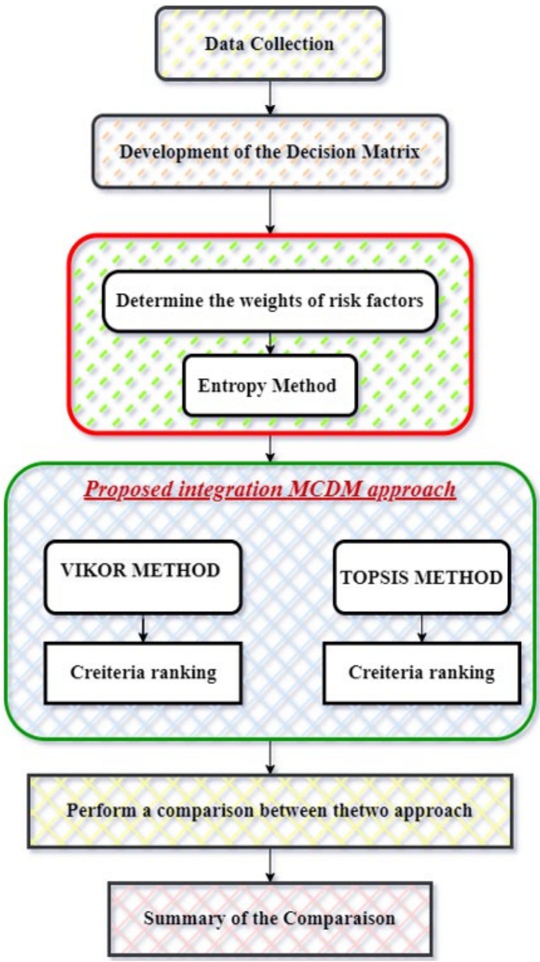

Figure 1. Illustration of the proposed drilling machine

This architectural layout provides a structured framework for optimizing drilling machines, offering a systematic approach that encompasses data collection, weight determination, multi-criteria decision-making, and method comparison to ensure a well-informed and reliable decision-making process.

2.1 Data collection

To facilitate the reproducibility of the experimental setup, it is crucial to clarify the specific configurations used during testing. Drilling experiments were conducted with rock samples of granitic composition. Drilling parameters were set to speed, feed rate, with selection based on preliminary tests to determine optimal conditions. Included setup also has a fluid circulation system, designed to simulate the operating environment as closely as possible.

A detailed drawing in Figure 2 illustrates a sophisticated drilling rig centered on two robust low-speed electrical systems. These systems include the hoist drive responsible for lifting and lowering the drill string and drill bit, and the top-drive that powers the drilling motor for rotary motion. The drill-string setup consists of the following parts:

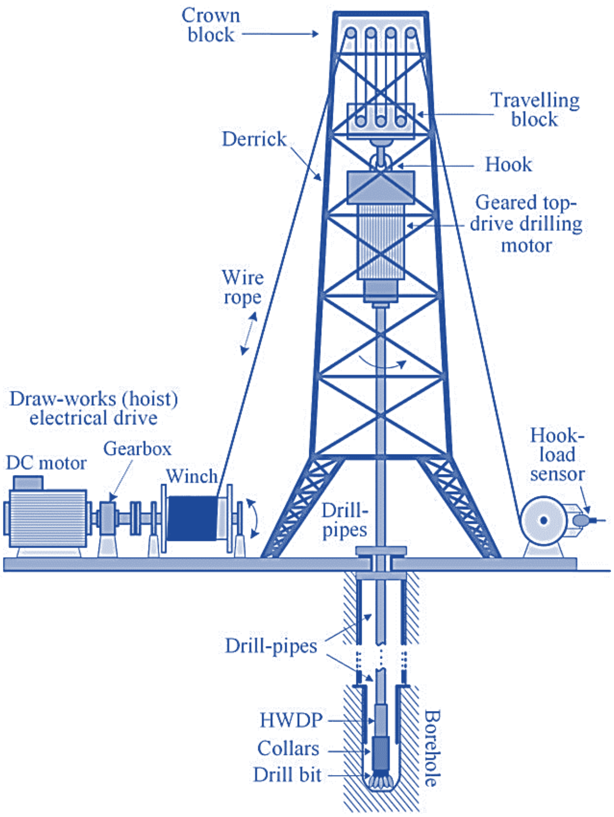

Figure 2. Illustration of the proposed drilling machine optimization technique

(i) The drill-bit and sturdy, thick-walled pipes known as drill collars collectively form what's referred to as the bottom-hole assembly (BHA).

(ii) Heavy-weight drill pipes (HWDP) serve the purpose of providing a seamless connection between the rigid drill collars and the more flexible drill pipes. This transition helps prevent fatigue-related concerns that could occur with standard drill pipes close to the bottom-hole assembly.

(iii) The main body of the drill-string primarily consists of standard drill pipes with relatively thinner walls compared to the heavy, thick-walled pipes.

The drilling process relies on the coordinated rotation of the top-drive electrical motor and the draw-works hoist electrical drive. The top-drive imparts torque to the drill-bit through the drill-string, while the draw-works hoist facilitates the longitudinal movement of the drill-string and drill-bit, creating the necessary downward force on the bit (Weight-on-Bit), indirectly measured using a hook-load sensor. During this process, the drill-bit pulverizes the rock bed material, which is then removed by drilling fluid (mud) circulated by mud pumps (not depicted in Figure 2).

Both the draw-works hoist and rotary high-power electrical drives usually operate within a cascade control system. Here, the overarching speed controller governs the inner current/torque control loop. These variable speed drives (VSDs) include embedded control features that allow for the implementation of advanced drilling control functions like the active damping system for drill-string torsional vibrations. They also have the capability to receive commands from supervisory control systems.

To ensure operational safety, these drives incorporate high transmission ratio gearboxes, enabling high-torque/low-speed operation-typical for standard drilling procedures. Moreover, they exhibit notable compliance and friction effects within their working mechanisms.

For safety and operational integrity:

(i) The torque exerted during rotary drive drilling (i.e., drill-string torsional torque) must not surpass predefined limits to prevent structural issues with the drill-pipe.

(ii) If the drill-bit (BHA) or drill-string becomes lodged in the borehole, the rotary drive must safely stop, and the torsional tension on the drill-string should be gradually released in a controlled manner.

(iii) Limitations on the draw-works drive speed downwards are crucial to prevent hazardous unwinding of the steel-wire rope from the winch drum. Simultaneously, precise control over the bit's normal force is essential to prevent damage.

This methodical approach allowed for a comprehensive evaluation of the drill's performance under various conditions and provided a reliable set of data for further analysis and decision-making in the study.

2.2 Determine the weights of risk factors using entropy method

The entropy approach is employed to determine the weight or significance of various elements or criteria in a specific condition. It utilizes a decision matrix that is constructed based on a set of data associated with these elements. This decision matrix is created to represent the importance or contribution of each element to the decision-making process, and it typically involves assigning values or weights to each element based on their characteristics or attributes. According to the information theory's criteria for the amount of uncertainty that a discrete probability distribution conveys [26], there is general agreement that a broad distribution signals more uncertainty than one that is closely packed. For the jth criterion, the entropy of the set of normalized results is given by:

$$E_j = -\frac{\left[\sum_{i=1}^{m} P_{ij}\,ln(P_{ij})\right]}{ln(m)} \quad (1)$$

j=1, 2…, n and i=1, 2…, m

The normalized decision matrix provides the P_{ij}, which is:

$$P_{ij} = \frac{r_{ij}}{\sum_{i}^{m} r_{ij}} \quad (2)$$

where, r_{ij} is an element of the decision matrix, E_j as the information entropy value for j^{th} criteria. Hence, the criteria weights, W_j is obtained using the following expression:

$$W_j = \frac{1 - E_j}{\sum(1 - E_j)} \tag{3}$$
j=1, 2…, n and i=1, 2…, m

where, (1-E_j) is the level of information diversity involved in the jth criterion's results.

2.3 Determine the weights of risk factors using entropy method

2.3.1 VIKOR approach

VIKOR, which stands for "Multi-Criteria Optimization and Compromise Solution" in its abbreviated form, is a multi-criteria decision-making (MCDM) method used to evaluate and rank alternatives when multiple criteria are involved. The VIKOR approach provides a systematic framework for determining the most suitable alternative in a decision-making context.

The VIKOR method assumes that decision-making is a process of compromising rather than finding optimal solutions, especially in scenarios with conflicting criteria. It seeks a solution that is closest to the ideal and provides maximum group utility for the majority and a minimum of individual regret for the opponent. The choice of VIKOR for this study is motivated by its adaptability in dealing with uncertain and imprecise data, often encountered in the evaluation of drilling machine performance.

The VIKOR Method's steps are:

Step 1: Normalize the decision matrix

To normalize, apply the following formula:

$$f_{ij}(\text{x}) = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{4}$$
j=1, 2…, n and i=1, 2…, m

Step 2: Determine the best and worst benefits of each criterion

The best and worst benefits can be determined by the following formula:

If the criterion is positive, then:

$$f_j^* = Max_i f_{ij}, f_j^- = Min_i f_{ij} \tag{5}$$
j=1, 2…, n

If the criterion is negative, then:

$$f_j^* = Min_i f_{ij}, f_j^- = Max_i f_{ij} \tag{6}$$
j=1, 2…, n

The positive ideal solution (f^*) and negative ideal solution (f^-) can be expressed as follows:

$$f^* = \{f_1^*, f_2^*, f_3^*, \dots, f_n^*\} \tag{7}$$

$$f^- = \{f_1^-, f_2^-, f_3^-, \dots, f_n^-\} \tag{8}$$

Step 3: Calculate the S_i and R_i values

The values S_i and R_i, representing the group utility and individual regret, respectively, can be calculated by the formulas below:

$$S_i = \sum_{j=1}^{n} w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)} \tag{9}$$

$$R_i = Max_j \left[w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)} \right] \tag{10}$$

where, w_j denotes the weight of the criteria.

Step 4: Comprehensive evaluation score (Q)

Compute the comprehensive evaluation score for each alternative by combining the utility values and considering the weights assigned to criteria. The value Q, representing the VIKOR index for each alternative can be calculated by the following formula:

$$Q_i = \gamma \frac{(S_i - S^*)}{(S^- - S^*)} + (1 - \gamma) \frac{(R_i - R^*)}{(R^- - R^*)} \tag{11}$$

where,

$$S^* = Min_i\{S_i\}; S^- = Max_i\{S_i\};$$
$$R^* = Min_i\{R_i\};\ R^- = Max_i\{R_i\}.$$

And γ is the maximum group utility represented by value 0.5.

Step 5: Rank the alternatives, sorting by the S, R and Q values

Alternatives are ranked by sorting the S, R, and Q, values in decreasing order such that the best rank is assigned to the alternative with the smallest VIKOR value. The results are three ranking lists.

VIKOR is particularly useful when decision-makers are looking for a compromise solution that takes into account both the best and worst-case scenarios for each criterion. It balances the need to maximize benefits and minimize drawbacks, making it a valuable tool in various decision-making scenarios, including project selection, supplier evaluation, and product design.

2.3.2 TOPSIS approach

The TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) approach is a Multi-Criteria Decision Making (MCDM) method used for ranking and selecting the best alternative from a set of options based on multiple criteria. It is a systematic and structured technique that helps decision-makers make informed choices. Here's TOPSIS Steps [27], To further clarify the TOPSIS methodology, it is based on the principle that the chosen alternative should have the shortest Euclidean distance from the Positive Ideal Solution (PIS) and the furthest Euclidean distance from the Negative Ideal Solution (NIS). This presupposes a perfectly compensatory decision-making model in which high scores on some criteria can offset low scores on others. TOPSIS was chosen because it is good at handling both qualitative and quantitative data, which makes it a good choice for making the complicated, multi-criteria decisions that are needed to improve drilling processes:

Step 1: Create a normalized matrix

$$f_{ij}(\text{x}) = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{12}$$

Step 2: Determine the weighted normalized matrix

$$V_{ij} = r_{ij} \times W_j \tag{13}$$

where, W_j is the weights of criteria and given by entropy method.

Step 3: Obtain the maximum z^+ and minimum scores z^- for each column

$$Z^+ = \underbrace{max}_{n}\{V_{ij}\} = \{Z_1^+, Z_2^+, Z_3^+\} \tag{14}$$

$$Z^- = \underbrace{min}_{n}\{V_{ij}\} = \{Z_1^-, Z_2^-, Z_3^-\} \tag{15}$$

$$\boldsymbol{\alpha_n^+} = \sqrt{(V_{i1} - Z_1^+)^2 + (V_{i2} - Z_2^+)^2 + (V_{i3} - Z_3^+)^2} \tag{16}$$

$$\boldsymbol{\alpha_n^-} = \sqrt{(V_{i1} - Z_1^-)^2 + (V_{i2} - Z_2^-)^2 + (V_{i3} - Z_3^-)^2} \tag{17}$$

i=1, 2…, n

Step 4: The final ranking index should be created

The FRIn [28] is a credible ranking index that defines the basis for the ultimate ranking. For MCDM techniques, we take into account the separation distance, which may be stated as follows, between the positive ideal solution and the negative ideal solution for the ranking index in the suggested model.

$$FRI_n = \left(\frac{\boldsymbol{\alpha_n^-}}{\sum_{n=1}^{m}\boldsymbol{\alpha_n^-}}\right) - \left(\frac{\boldsymbol{\alpha_n^+}}{\sum_{n=1}^{m}\boldsymbol{\alpha_n^+}}\right) \tag{18}$$
$$-1 \le FRI_n \le 1$$

3. RESULTS AND ANALYSIS

The current work focuses on optimization of percussive rotary drilling. The information is analyzed to make clear the Reference Ranking (Res), VIKOR and TOPSIS techniques of Multi-Criteria Decision Making (MCDM) analysis, as well as the methodology and results of the analysis.

Table 1. Experimental results for the rotating percussive drill

Counter - Weight (Kg)	Cadence Measured (HZ)	Power Measured Water (Watts)	Energy (J)
0	42.72	968	58080
10	42.16	936	56160
20	42.02	950	57000
0	35.48	680	40800
10	35.42	678	40680
20	35.4	666	39960

Table 2. Decision matrix for percussive rotary drilling evaluation

Alternatives	P1	P2	P3	P4	P5
A1	42.72	968	58080	25.15	2.25
A2	42.16	936	56160	25.83	2.35
A3	42.02	950	57000	26.38	2.6
A4	35.48	680	40800	14.9	2.15
A5	35.42	678	40680	15.54	2.2
A6	35.4	666	39960	15.59	2.37

From the experimental results presented in Table 1, a decision matrix was created and is shown in Table 2. This matrix allowed for the systematic evaluation of alternatives based on multiple criteria, including Cadence of Percussion, Power Consumption, Energy Consumption, Volume of Rock Drilled, and Drilling Speed.

To further validate the findings and ensure their robustness, comprehensive statistical analyses were conducted. Descriptive statistics provided an overview of the central tendencies and dispersion of the dataset, highlighting the consistency and variability of the measurements across different conditions. Additionally, inferential statistical methods, including ANOVA (Analysis of Variance), were employed to assess the significance of the differences observed between the rankings produced by the TOPSIS and VIKOR methods. The statistical analysis confirmed that the differences in rankings were statistically significant ($p < 0.05$), reinforcing the reliability of the methodologies used in this study.

We estimate the weights (Table 3) using the entropy method.

Table 3. Weights estimation using the entropy method

Parameters	P1	P2	P3	P4	P5
W_j	0.0577 1804	0.2152 095	0.2152 095	0.4826 805	0.02918 242

Table 4. Comparative rankings of percussive rotary drilling alternatives by VIKOR, TOPSIS, and reference

	(Res)*	VIKOR	TOPSIS
A1	3	6	3
A2	2	1	2
A3	1	2	1
A4	6	3	6
A5	5	4	4
A6	4	5	5
	WS	0.97135417	0.41666667

Table 4 provides a summary of the rankings obtained using both the VIKOR and TOPSIS methods, as well as the reference ranking (Res). It is a valuable resource for comparing the rankings generated by the two methods with the reference ranking. For the VIKOR method, A2 is ranked as the most preferred alternative, followed by A3, A4, A5, A6, and A1. For the TOPSIS method, A3 is ranked as the most preferred alternative, followed by A2, A1, A5, A6, and A4. The reference ranking of the real experiment indicates that A3 is the most preferred alternative, followed by A2, A1, A6, A5, and A4. Figure 3 show the ranking obtained using different methods.

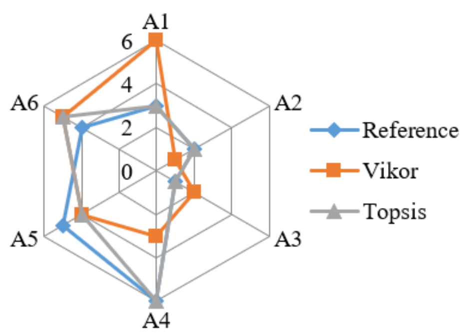

Figure 3. Alternative ranking obtained using different methods

The WS of similarity coefficient for the TOPSIS method is 0.971, indicating a high degree of similarity between the rankings obtained using TOPSIS and the reference ranking (Res). This suggests that the TOPSIS rankings closely match the reference ranking for specific energy.

The WS coefficient of similarity for VIKOR is 0.416, indicating a medium level of similarity between the VIKOR rankings and the reference ranking. While there is some resemblance, the VIKOR rankings do not align as closely with the reference ranking as those produced by the TOPSIS method.

These results and coefficients provide valuable insights into the performance of the VIKOR and TOPSIS methods in ranking the alternatives based on specific energy. The WS coefficients help assess the degree of similarity between the method-generated rankings and the reference ranking, aiding in the evaluation of their effectiveness in the decision-making process.

In comparing our study's findings with existing literature, it's evident that our results corroborate the effectiveness of MCDM methods in optimizing drilling processes It is in line with the studies conducted in the studies [24] and [26]. Specifically, our use of TOPSIS and VIKOR methods for evaluating drilling efficiency mirrors the approach by the study [27], who also applied MCDM techniques in a mining context. However, the stronger correlation and agreement observed between TOPSIS rankings and the reference rankings in our study contrast with the moderate alignment reported in the research [28] on failure mode analysis. This discrepancy could be attributed to the different operational contexts and the specific criteria and weights applied in our MCDM analysis. Such variations underscore the adaptability of MCDM methods across different operational challenges, though they also highlight the importance of carefully selecting and weighting criteria based on the specific decision-making scenario.

The optimal values you've provided represent the recommended settings or parameters for your drilling process. These values are likely determined through the application of the Multi-Criteria Decision Making (MCDM) methods, such as VIKOR and TOPSIS, as well as the analysis of experimental data. Here's a summary of the optimal values:

•Cadence of Percussion: 42.02 Hz: This optimal cadence of percussion represents the recommended frequency for the drilling process.

•Power Consumption: 950 Watts The recommended power consumption level for efficient drilling.

•Energy Consumption: 57000 Joules: The optimal energy consumption during the drilling process.

•Volume of Rock Drilled: 26.38 cm^3: The recommended volume of rock drilled for achieving the desired outcomes.

•Drilling Speed: 2.6 mm/s: The optimal drilling speed to ensure efficiency and productivity.

•Counter-Weight (Kg): 20 kg: The recommended counter-weight to be used during drilling, which can help balance and stabilize the equipment.

These optimal values represent the best combination of parameters based on the criteria and the analysis conducted in the present study. They serve as a valuable guide for ensuring efficient and effective drilling operations, and they are the result of the MCDM approach used to make informed decisions.

Despite the comprehensive analysis and significant contributions of this study, it's important to recognize its limitations. The study's experimental setup, while robust, is limited by the specific physicochemical properties of the rock samples and operational parameters tested, which may not encompass the full variability encountered in different drilling environments. Also, using only the TOPSIS and VIKOR methods, even though they are strict, makes it harder to model how complicated real-world drilling operations are. This means that other or additional MCDM methods should be looked into in future studies. Addressing these limitations could further refine our understanding of drilling optimization and extend the applicability of the findings.

In lightening the implications of our research on the field of drilling optimization, it becomes evident that the application of MCDM methods, particularly TOPSIS, offers a robust framework for enhancing drilling efficiency. The significant alignment between TOPSIS rankings and reference rankings underscores the method's reliability in reflecting actual operational performance. This revelation is pivotal for drilling operations, suggesting that incorporating MCDM approaches can lead to more informed and effective decision-making processes.

Moreover, the comparative analysis between TOPSIS and VIKOR provides valuable insights into the selection and prioritization of drilling parameters, which can be instrumental in designing optimization strategies tailored to specific drilling objectives. The practical application of these findings extends beyond the theoretical realm, offering a methodical approach for industry practitioners to optimize drilling operations, reduce energy consumption, and mitigate environmental impacts.

This study's findings contribute to the evolving narrative on sustainable drilling practices, emphasizing the critical role of advanced analytical methods in achieving operational excellence and sustainability. Future research could delve into the integration of other MCDM methods, exploring their potential to further refine drilling optimization techniques and expand their applicability across different drilling environments.

4. CONCLUSIONS AND FUTURE RESEARCH

The study delves into optimizing percussive rotary drilling using a range of decision-making techniques, such as VIKOR, TOPSIS, and Reference Ranking within a framework of Multi-Criteria Decision Making (MCDM). By analyzing factors like percussion cadence, power and energy consumption, rock drill volume, and drilling speed, a decision matrix was constructed from experimental data, allowing a systematic evaluation of various alternatives.

Table 4 presents the rankings obtained from VIKOR and TOPSIS alongside the reference ranking (Res), serving as a valuable tool for comparing and understanding the alignment among these methodologies. VIKOR identified A2 as the most favored, followed by A3, A4, A5, A6, and A1, while TOPSIS ranked A3 as the preferred alternative, consistent with its performance in the real experiment.

In this sustainable context, the TOPSIS method demonstrates a notable similarity to the reference ranking (Res), especially regarding specific energy, indicating a strong correlation. Conversely, the VIKOR coefficient displays a moderate level of similarity, suggesting a resemblance to the reference ranking but not as strong as observed in TOPSIS.

This study, emphasizing the application of MCDM techniques, presents optimal settings for the drilling process derived from the analysis. These settings - including percussion cadence, power and energy consumption, drilled rock volume, and drilling speed - ensure both efficiency and effectiveness in drilling operations.

The recommended settings-42.02 Hz percussion cadence, 950 Watts power consumption, 57000 Joules energy consumption, 26.38 cm^3 rock drilled, and a drilling speed of 2.6 mm/s-are vital parameters for achieving superior drilling outcomes. Additionally, the suggested counter-weight of 20 kg aids in equipment balance and stability.

Moreover, this application isn't limited to this study alone but extends to our region's phosphate and iron ore domains, showcasing the benefits of MCDM in informed decision-making. The adaptability of these techniques proves valuable not just in drilling but also in areas like mineral processing and resource management, aligning with sustainable development principles.

Looking forward, future research could explore other MCDM methods like Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and ELECTRE, tailoring them to specific ore processing decisions. Moreover, integrating fuzzy logic with MCDM could enhance decision-making, particularly in handling uncertainties in data, offering a promising approach when information is imprecise or incomplete.

As we conclude our study, we look forward with anticipation to the future of scholarly endeavors. Our conclusion resonates with modernity, seamlessly weaving futuristic research trajectories into our findings. By aligning with contemporary trends and emerging frontiers in the field, we ignite excitement for pioneering investigations that lie ahead, setting the stage for groundbreaking discoveries and innovative methodologies. Moving forward, we envision research agendas that push the boundaries of sustainability and technological innovation in drilling operations, embracing cutting-edge methodologies and exploring novel avenues for energy optimization. In essence, our conclusion encapsulates the essence of our study while also paving the way for a future where sustainability and efficiency are central tenets of drilling machine operations, answering the call for both present and future scholarly endeavors.

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