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Optimum Selection of Drill Bits for Drilling Operations in Sarvak and Asmari Formations Using a Fuzzy Multiple Criteria Decision-Making Approach

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ABSTRACT

Proper decision making in drilling bit selection issue may contribute to drilling efficiency and considerable cost reduction. Since the bit selection is a Multiple Criteria Decision-Making (MCDM) problem, MCDM techniques are the most powerful approaches to be applied in such cases. In this study, among MCDM approaches and with respect to great accuracy and validity of results, fuzzy TOPSIS method is utilized for optimum bit selection for drilling operations in Sarvak and Asmari formations in an Iranian oil field. With this regard, three types of bits (i.e. 517, 527 and 537) candidate in Asmari & Sarvak formations are analysed using fuzzy TOPSIS method to rank and prioritize the alternatives, leading to choose the best option. Considering bits operating in Asmari formation, similarity factors for bit types of 517, 527 and 537 bits found to be 0.479, 0.438 and 0.382, respectively indicating bit type 517 can be considered a proper option compared to other ones. Similarly, achieved results from application of fuzzy TOPSIS approach in Sarvak formation shows 0.5405, 0.5019 and 0.5622 values for 517, 527 and 537 bit types respectively, demonstrating the bit type 537 is the most appropriate alternative in Sarvak formation.

1. Introduction

Utilization of oil and its derivatives are inevitable and very common in today's human life. Application of oil in downstream industries requires identification of the best techniques, methods and operations which contributes to minimizing costs and maximizing the efficiency and productivity of the projects in upstream industries. Identification and well understanding of methods and techniques that affect project's operational time, costs and

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performance are highly crucial issues for petroleum engineers in all upstream industries encompass petroleum exploration, drilling and production. Bit selection plays a major role in drilling cost management. An improper selection may adversely affect the drilling rate and increases bit replacement and substitution time and accordingly bring about operational costs & HAZOP issues. That's why optimum bit selection is so important in such field of activity. There are some factors such as formation type, bit hydraulic design, drilling fluid/mud and proper application of mechanical parameters (e.g. bit weight & rotation) as well as so many other aspects that need to be taken into consideration in proper bit selection during drilling operation of oil and gas wells. In addition, knowledge and competency level of supervisors in applying such factors and parameters is highly crucial. In petroleum drilling history, first oil well was drilled in 1859. Since then Hammer type technology were replaced by rotary tables in 1930 in order to enhance the operation rate and reach deeper points. Introduced in 1902, cone bits were in use until 1917 [12].

Bits can be classified into two drilling bits and coring bits in which various cutting tools and bearing, casing and teeth type, etc. are applied in each one [11]. Equipped with 2 or 3 cutters, first diamond bits were introduced in 1901 and applied mainly in shallow areas [28]. Having studied factors such as bit hydraulics, drilling fluid, weight on bit and its rotation efficiency, engineering design of bits were evolved during 1940-1990 to improve drilling and penetration rate. Empirical findings indicated that speeding up the mud running during drilling operation increases bit efficiency while smaller holes for fluid transfer through bit, rises the pressure and volume rate. Later on, durability concerns and application of tungsten-carbide bits contributed to longer lifetime of bits and accordingly its maximum utilization. After all, maximum surveying and drilling rate in fewer hours is the main ongoing objective of the bit manufacturing process [8].

Although bit cost is a minor item compared to whole well costs, its performance influence the whole well productivity, and that's why optimization of bit performance is one of the main drilling challenges. There are various techniques to optimize the bit performance. The most classic one could be defined as selecting a bit in accordance with a variety of existing data including CPF, SE, blunts, drill bit deviations logs and G&G data [22]. CPF (cost per foot) is one of the most applied criteria to analyse various bit performance which is a function of bit cost, formation structure, operation costs, environmental conditions and some other drilling parameters [29]. The equation for CPF is as below:

$$CPF = \frac{B + R(T + t)}{F} \tag{1}$$

Where B is the bit cost (US $), R is the rig costs (per hour), T is the bit transferring time into and out of the well (hour), t is the rotation duration (hour), and F is the length of drilled section.

Here, SE (Specific Energy) correlates the bit performance and the energy required by the bit which is defined as the energy required for unit rock volume calculated as follow:

$$SE = \frac{WOB \times \; RPM}{D \times \; \mathrm{ROP}} \tag{2}$$

Where WOB is the weight on bit (pound), RPM is the round per minute of drilling string (minute), D is the bit diagonal thickness (foot), and ROP is the penetration rate (foot per hour).

WOB, *RPM* and *Bit* Torque are the three parameters Rabia utilized in order to calculate the SE [23]. A drilling model includes equations concerning penetration rate and bit corrosion together with in-between parameters (*WOB* and *RPM*) for bit selection appraisal and forecast [27]. Perrin has introduced the bit index using 4 dimensionless parameters as bit behaviour, bit performance, bit conduction & controllability and bit responsiveness to deviations. He has also pointed out to bit selection criteria in deviated drilling practice in which formation factors are not included [21]. ANN (Artificial Neural Network) is one of the most novel approaches utilized in bit selection process. Bilgesu applied ANN in 1997 for the bit selection appraisal and made use of drilling parameters in its model without including the formation features [7]. However Wilmot developed the Perrin model further including formation parameters [18]. Yilmaz also developed this model using formation average compressive strength though he was focused on the bit only and neglected optimum drilling parameters which are highly significant in bit selection appraisal [1, 29].

Since several factors affecting bit selection process, it can be considered a MCDM (Multi Criteria Decision Making) problem. One or some decision making approaches are usually nominated in each decision making process to foresee decision consequences in advance and prior to any selection. MCDM (Multi Criteria Decision Making) is one of such approaches that provide the user with appraisal of influencing parameters and potential options. Such techniques have been widely spread among researchers and experts in analyzing and prioritizing/ordering possible options in various industries specially those deal with qualitative parameters and rely on the expert judgment. In the same way there are a variety of MCDM techniques in terms of existing issues in decision making process [4, 5]. The MCDM is a combined set of techniques and methods that weights and prioritize/order a variety of criteria and assist the user in utilizing multi contradictory objectives such as cost minimization and performance maximization at the same time. Such multi objective problems are highly important in oil & gas industry. There are some norms and regulations applied for judgment and clarification of the decision effectiveness in the decision-making process. Decision criteria may be represented as attributes (MADM) or objectives (MODM). Considering MADM, user attempts to find an option among potential ones while level of each activity respect to various objectives is considered in MODM [30]. There are lots of studies conducted recently concerning application of MCDM in the oil industry such as; identification of various parameters and methods for selection of field development areas [3], a mathematical estimation for selection of artificial lift systems [2], selecting a well for hydraulic fracturing [17], subsea hazop/hazard study of BOP system [20], selection of the best completion method for gas wells [15], oil and gas supplier evaluation and selection [26], energy policy [14], renewable energy alternatives [9], identification and ranking risks of horizontal directional drilling or oil and gas wells [24]. Among MCDM techniques, TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) has been used in this research due to its higher accuracy and reliability of the results. Through the analysis, the fuzzy set theory has been applied to an ill-defined multiple criteria decision-making problem in order to efficiently resolve the ambiguity frequently arising in available data and provide more justice to the essential fuzziness in human preference and judgment [10, 16]. Instead of binary features, fuzzy logic encompasses a spectrum of values between 0 and 1. Uncertainty could be realized properly using such spectrum [6]. With this respect, Fuzzy TOPSIS (FTOPSIS) approach utilized for drilling bit selection problem. Considering FTOPSIS, the option closer to the ideal option and far from the anti-ideal one has the higher priority/order preference [19].

The aim of this paper is to apply FTOPSIS technique for optimum selection of drill bits in Sarvak and Asmari formations of an Iranian oilfield. Bit selection, as mentioned, plays a crucial role in petroleum drilling industry since it directly affects time and cost of the projects. No investigation has been carried out for drilling operations in this region (Marun oilfield) using MCDM approaches and that is why such studies need to be conducted for this oilfield. This paper first presents decision making process, FTOPSIS approach, and then application of this method to optimum drill bit selection in drilling operations for Sarvak and Asmari formations in Marun oilfield.

2. Decision Making Process

Operation complexity, high operating costs and huge organizational structure requires application of proper decision making methods to be adopted by senior managers. Decision maker could be assumed as a driver in a cross-road/intersection and should choose a way to go. Potential options form the feasible area. Herbert Simon is a researcher who believes that management and decision-making are equivalent terms. According to him, decision making is an essence to management and one of the most difficult (and sometime dangerous) tasks to managers. There are six main steps in decision making process as problem definition, criteria identification, developing options, selecting a decision making model, evaluating and prioritizing/ordering options as well as assessment of decision results. The problem is done/ solved in the last (6th) step if results are satisfying otherwise decision criteria should be reassessed again to achieve better decisions. Criteria may be contradictory in some cases. Improve in one criterion may adversely affect the other one. A decision maker may reach a reasonable decision by considering whole such issues. As mentioned earlier, among MCDM methods, FTOPSIS has been utilized in the present paper. The FTOPSIS accurately determines the criterion weights and prioritize/order the potential options. Human thought in many cases are involved with uncertainties that affects his/her decisions. FTOPSIS is one of the Fuzzy decision making methods preferred in such cases in which decision matrix and/or criterion weights are evaluated through generated fuzzy numbers. Hence issues of classic TOPSIS are somehow obviated. Based on this method, an option closer to the ideal option and far from the anti-ideal one has the higher priority/order that is, the option that minimizes the operation costs and maximizes performance/efficiency at the same time. Hwang and Chen have applied FTOPSIS stages in a problem of "*n*" criterion and "*m*" options. The problem could be explained as follow [13]:

***Step 1*:** Development of the decision matrix in terms of criteria and options.

$$X = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix} \tag{3}$$

In case of triangle fuzzy numbers; $\tilde{r}_{ij} = (a_{ij}, b_{ij}, c_{ij}), i \in \{1, 2, ..., m\}, j \in \{1, 2, ..., n\}$ and in case of trapezoidal fuzzy numbers; $\tilde{r}_{ij} = (a_{ij}, b_{ij}, c_{ij}, d_{ij}), i \in \{1, 2, ..., m\}, j \in \{1, 2, ..., n\}$.

***Step 2*:** Development of criterion weight factor matrix.

Weight factor (importance factor) of various criteria is defined as $W = [W_1, W_2, ..., W_n]$ in this step. Weight factors are usually determined by decision maker(s) individually or in a group of experts using some questionnaires.

***Step* 3:** Descaling instead of complex calculations.

Linear descaling has been applied to convert the scale of various criteria into comparable ones. In case of positive (benefit) criteria, descaled matrix could be concluded through the following equations

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{C_j^*}, \frac{b_{ij}}{C_j^*}, \frac{c_{ij}}{C_j^*} \right), C_j^* = \max_i \{a_{ij}\} \tag{4}$$

In case of negative (cost) criteria, descaled matrix could be concluded through the following equations:

$$\tilde{r}_{ij} = \left(\frac{C_j^-}{c_{ij}}, \frac{C_j^-}{b_{ij}}, \frac{C_j^-}{a_{ij}} \right), C_j^- = \min_i \{a_{ij}\} \tag{5}$$

Then, the weighted descaled (normalized) fuzzy decision matrix could be arranged as below:

$$\tilde{V} = (\tilde{v}_{ij}) , \quad \tilde{v}_{ij} = \tilde{r}_{ij}.w_j \tag{6}$$

***Step* 4:** Defining fuzzy ideals.

There are two sets defined to identify ideal (Fuzzy Positive Ideal Solution or FPIS) and anti-ideal (Fuzzy Negative Ideal Solution or FNIS) in which $\tilde{v}_i^+$ is the best value of criterion *i* among all options while $\tilde{v}_i^-$ is the worst one within the weighted fuzzy decision matrix:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+) \tag{7}$$

$$A^{-} = \left(\tilde{v}_1^{-}, \tilde{v}_2^{-}, \ldots, \tilde{v}_n^{-}\right) \tag{8}$$

In which $\tilde{v}_i^{-}$ and $\tilde{v}_i^{+}$ are the minimum and maximum $\tilde{v}_{ij}$, respectively.

***Step* 5:** Defining the distances to the fuzzy ideals.

Distance between each option and ideal (FPIS) and anti-ideal (FNIS) solutions could be calculated through the following relations:

$$S_i^{+} = \sum_{i=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^{+}\right), \; i = 1, 2, \ldots, m \tag{9}$$

$$S_i^{-} = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^{-}\right), \; i = 1, 2, \ldots, n \tag{10}$$

It needs to note that the distance between two triangular fuzzy numbers $\tilde{M}_1 = \left(a_1, b_1, c_1\right)$ and $\tilde{M}_2 = \left(a_2, b_2, c_2\right)$ denoted by d , could be calculated as follow:

$$d(\tilde{M}_1, \tilde{M}_2) = \sqrt{\frac{1}{3}\left[\left(a_1 - a_2\right)^2 + \left(b_1 - b_2\right)^2 + \left(c_1 - c_2\right)^2\right]} \tag{11}$$

***Step* 6:** Defining similarity index.

The similarity index could be concluded in the final step as follows:

$$cc_i = \frac{s_i^{-}}{s_i^{+} + s_i^{-}} \tag{12}$$

In order to arrange/order the fuzzy decision matrix and fuzzy weight vectors, Tables 1 and 2 have been utilized respectively.

Table 1: Linguistic variables for option prioritization/order preference

Linguistic Variable	Corresponding Fuzzy Number
Very low	(0,0,1)
Low	(0,1,3)
A little bit	(1,3,5)
Nearly OK	(3,5,7)
Much	(5,7,9)
High	(7,9,10)
Too high	(10,10,9)

Table 2: Linguistic variables for evaluation of criteria weights

Linguistic Variable	Corresponding Fuzzy Number
Inconsiderable	(0,0,1)
Unimportant	(0,0,1)
Nearly Unimportant	(0,1,3)
Indifferent	(1,3,5)
Nearly Important	(3,5,7)
Important	(5,7,9)
Highly Important	(7,9,10)
Extremely Important	(10,10,9)

3. Optimization Process

Marun oil field is the 3rd largest oil field in Iran located in North West of Omidiyeh, 40 km away from South East of Ahwaz, Khuzestan province. In-situ field volume for oil and gas in place estimated to be 22 billion barrels and 462.1 trillion cubic feet (Figure 1). The field is comprised of two oil reservoirs known as Asmari & Bangestan, together with a gas reservoir known as khami. Aghajari formation is the exposed part of the field and Asmari formation is the main source rock which is divided into 6 reservoir layers, located 45 km away from south east of Ahwaz. Production capacity of the reservoir is 25000bpd in average. Bangestan is the 2nd oil reservoir of the field located at the same place with the production capacity of 18500 bpd. Sarvak formation is one of the Bangestan geological formations and is known for its major hydrocarbon reservoir throughout the Zagros area. The formation is located in parallel with Kazhdumi formation that has an upper interface with Ilam formation

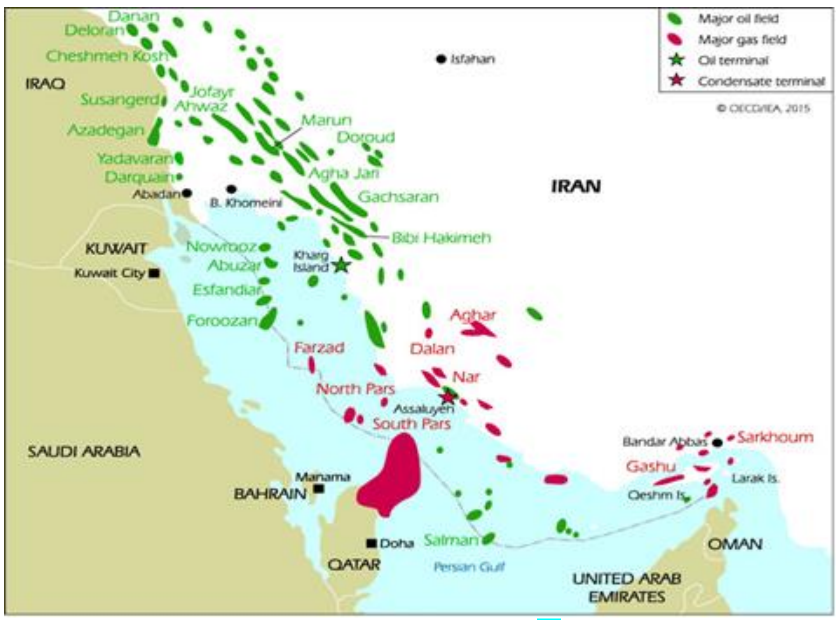

Figure 1: Oil fields in Iran [25]

3.1 Optimization of the bit selection process

There are three bits coded as 517, 527 and 537 suggested for drilling in Sarvak & Asmari formations of the Marun field. The decision maker tends to choose a bit among abovementioned bits using 4 criteria as Specific Energy (SE), Formation Drill-ability (FD), Cost per Foot (CF) and Rate of Penetration (ROP). Appraised in terms of the criteria and criteria weight factors, Options performance is evaluated using results of the questionnaires filled by drilling experienced experts. Evaluation outcomes were statistically analyzed and resulted in decision matrix & weight factors shown in Tables 1-8 as follow.

A schematic of the problem options and criteria in the decision making process is shown in Figure 2.

3.1 Optimum selection of drilling bit using FTOPSIS

For the Asmari formation, considering Step 1 in FTOPSIS, decision matrix is arranged first using experts viewpoint and Table 1 as well as converting qualitative factors into quantitative ones (Table 3).

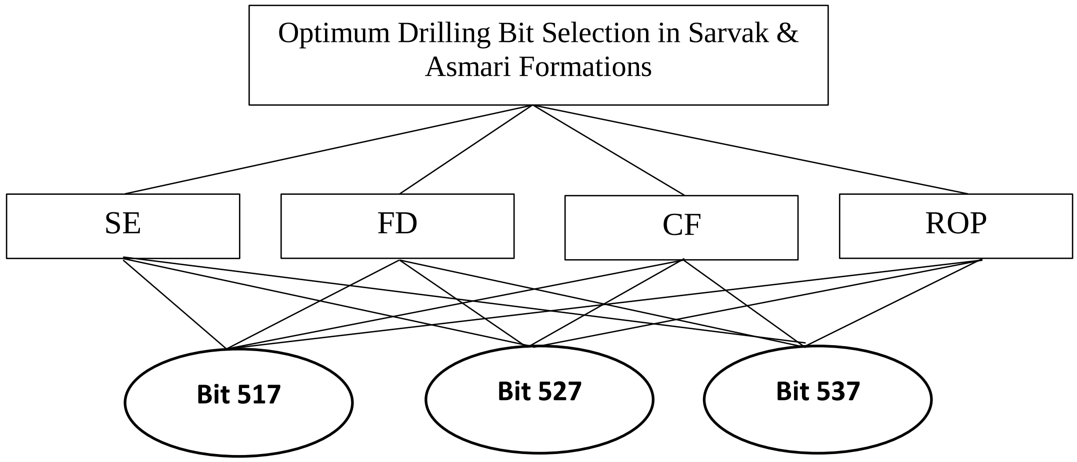

Figure 2: Hierarchy structure of bit selection problem

Table 3: Decision matrix

	SE	FD	ROP	CF
517	(9,10,10)	(3,5,7)	(7,9,10)	(5,7,9)
527	(3,5,7)	(0,1,3)	(9,10,10)	(1,3,5)
537	(1,3,5)	(7,9,10)	(5,7,9)	(3,5,7)

Considering Step 2, criteria weight factor table could be arranged using expert viewpoints as Table 4.

Table 4: Criteria weight factor

Criterion	**SE**	**FD**	**ROP**	**CF**
Weight	(0.7,0.9,1)	(0.5,0.7,0.9)	(0.9,1,1)	(0.9,1,1)

Considering Step 3, linear descaling method has been applied in order to arrange the descaled matrix. Three positive criteria as SE, FD and ROP are descaled through Equation (4) while the negative CF criterion is descaled through Equation (5). The results are given in Table 5.

Table 5: Descaled decision matrix

	SE	FD	ROP	CF
517	(0.9,1,1)	(0.3,0.5,0.7)	(0.7,0.9,1)	(0.111,0.143,0.2)
527	(0.3,0.5,0.7)	(0,0.1,0.3)	(0.9,1,1)	(0.2,0.333,1)
537	(0.1,0.3,0.5)	(0.7,0.9,1)	(0.5,0.7,0.9)	(0.143,0.2,0.333)

Considering Equation (6), weighted fuzzy decision matrix is calculated through multiplication of weight factor of each criterion to the fuzzy descaled matrix. The results are given in Table 6.

Table 6: Weighted descaled decision matrix

	SE	FD	ROP	CF
517	(0.63,0.9,1)	(0.15,0.35,0.63)	(0.63,0.9,1)	(0.0991,0.143,0.2)
527	(0.21,0.45,0.7)	(0,0.07,0.27)	(0.81,1,1)	(0.18,0.333,1)
537	(0.07,0.27,0.5)	(0.35,0.63,0.9)	(0.45,0.7,0.9)	(0.2,0.333,0.129)

Equations (9) and (10) are applied for ideal and anti-ideal solutions respectively that resulted in following measures;

$$V^{+} = \left[(1,1,1),(0.9,0.9,0.9),(1,1,1),(1,1,1)\right]$$

$$V^{-} = \left[(1,1,1),(0.9,0.9,0.9),(1,1,1),(1,1,1)\right]$$

Distance of each option compared to ideal and anti-ideal solutions together with similarity index could be calculated through Equation (9) and (10), respectively. The results are given In Tables 7, 8 and 99.

Table 7: Distance of each option from ideal solution

Distance	**SE**	**FD**	**ROP**	**CF**	
1.857	0.221	0.559	0.221	0.856	$d(A_1,A^+)$
2.095	0.582	0.794	0.109	0.610	$d(A_2,A^+)$
2.243	0.741	0.353	0.366	0.783	$d(A_3,A^+)$

Table 8: Distance of any option respect to anti-ideal one

Distance	**SE**	**FD**	**ROP**	**CF**	
1.706	0.788	0.425	0.423	0.700	$d(A_1,A^-)$
1.634	0.432	0.610	0.495	0.547	$d(A_2,A^-)$
1.391	0.274	0.665	0.297	0.155	$d(A_3,A^-)$

Table 9: Similarity Index

Distance	**Bit 517**	**Bit 527**	**Bit 537**
From ideal solution	1.857	2.095	2.243
From anti-ideal solution	1.706	1.634	1.391
Similarity Index	0.479	0.438	0.382

This means that options ordering concerning Asmari formation is as 517 > 527 > 537.

In the same way, similarity index is calculated as follow concerning Sarvak formation, as listed in Table 10.

Table 10: Similarity Indexes of bits for Sarvak formation.

Distance	**Bit 517**	**Bit 527**	**Bit 537**
From ideal solution	1.3879	1.6349	1.629
From anti-ideal solution	1.633	1.648	2.092
Similarity Index	0.5405	0.5019	0.5622

In the same way, the order preference concerning Sarvak formation is as 517>537 > 527.

4. Conclusions

Multiple Criteria Decision-Making (MCDM) methods result in proper and more realistic outcomes compared to other decision-making approaches. Using fuzzy set theory, it is possible to overcome uncertainty and vagueness from subjective perceptions and experiences through the decision making process. With this respect, using Fuzzy TOPSIS (FTOPSIS) approach, the uncertainty and vagueness from subjective perceptions can be effectively incorporated in the analyses leading to a more efficient decision. In petroleum drilling engineering, bit selection plays a major role in drilling operations; therefore it requires to be managed appropriately. Since optimum bit selection in petroleum drilling operation is a MCDM problem, FTOPSIS approach utilized to choose the most suitable bit for drilling operation in Asmari and Sarvak formations in one of Iranian oilfields (Marun). With this regard, some questionnaires prepared in advance and distributed among experts of the field to be applied in FTOPSIS technique. Primarily, three types of drill bits, 517, 527 and 537, considered as applicable candidate for drilling of cited formations. Then they prioritized and ranked in accordance with effective criteria such as Specific Energy (SE), Formation Drill-ability (FD), Cost per Foot (CF) and Rate of Penetration (ROP). Due to lack of information regarding compressive strength of rock formations, this criterion was not taken into account through the analysis. Results demonstrated that in Asmari formation, similarity index of three 517, 527 and 537 bits (alternatives) calculated as 0.479, 0.438 and 0.382 respectively using FTOPSIS method. The bits are ranked and prioritized as 517 (1st), 527 (2nd) and 537 (3rd), indicating bit type 517 can be consider a proper option compared to other ones. In Sarvak formation, similarity index of three 517, 527 and 537 bits were found were found to be 0.5404, 0.5019 and 0.5622, respectively using FTOPSIS method. The bits are ranked and prioritized as 537 (1st), 517 (2nd) and 527 (3rd), demonstrating the bit type 537 is the most appropriate alternative in Sarvak formation. It is suggested that other multi-criteria methods such as fuzzy PROMETHEE and ELECTRE can be used to handle bit selection problems in the future investigations.

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