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Optimum selection of sand control method using a combination of MCDM and DOE techniques

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A B S T R A C T

The design of an optimal sand control method and production management is a complex problem due to the simultaneous influence of various factors. Typical effective variables for choosing an optimum sand control method include geological, technical, economical, and expert's experience on similar projects. Some technical factors, which affect the optimum method, are the type of exclusion, gravel size of gravel pack and pre-packed screen, slot width and liner slot length, and productivity index reduction. The situation could be more complicated due to the uncertainty associated with various contributing factors. Therefore, it is crucial to develop a novel approach in order to select the best sand control method with a maximum level of confidence.

In this study, to select an optimal sand control method, Multi Criteria Decision Matrix (MCDM) techniques including Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and, ELimination and Choice Expressing REality (ELECTRE) are used. To simulate fluid flow, an integrated model of reservoir, well, and surface facility is used based on actual oil field data collected from the south of Iran. Then, Design of Experiment (DOE) and Response Surface Methodology (RSM) are applied to optimize the controllable variables of the best selected sand control method by MCDM. Finally, Monte Carlo Simulation (MCS) is applied to perform sensitivity and uncertainty analysis in order to determine the crucial factors that control net present value (NPV).

The results show that the best sand control method based on AHP, TOPSIS, and ELECTRE is the slotted liner. After that, three different methods of pre-packed, gravel pack, and wire wrapped are respectively the most efficient sand control methods based on an average score of all the MCDM techniques. The results also indicate that although the pre-packed screen has the highest NPV, it is not the best sand control method due to the influence of other efficient criteria. The result of sensitivity analysis using MCS in terms of contribution to total variance shows that slot width, slot density, and slot height controls 60.5%, 38.8%, and 0.7% of the NPV variation within the range of factors, respectively.

1. Introduction

Methods of sand control were first utilized in water wells and then were later applied in oil and gas wells. There are several methods of sand control, which used to control the sand production, include mechanical and chemical methods. Mechanical methods involve the use of screens to retain the formation sand (with or without gravel) or use of gravel to hold formation sand (with or without a screen to retain the gravel) including gravel pack, pre-packed screen, slotted liner, and wire wrapped. Chemical methods employ a liquid resin which is injected from a wellbore into the unconsolidated rock surrounding the well. Chemical methods involve in-situ sand consolidation techniques and resin-coated gravel pack.

The design of an optimum sand control is a complicated process because choosing an optimum sand control method depends on different effective factors. These factors include the type of exclusion, gravel size of gravel pack and pre-packed screen, slot width and length of the slotted liner, PI reduction and operating costs. Optimum selection is further intricate due to the uncertainty associated with variables influencing sand control methods. Therefore, it is crucial to select the most appropriate method in terms of minimum skin (pressure drop), cost, and maximum net present value (NPV).

Many authors have studied various well completion methods under different downhole conditions. Some of them have discussed sand production consequences, while, few specialists have worked on sand control method selection.

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Tausch and Corley (1958) found the economics and selection of the sand control method, based on bridging and consolidation of sand grains, is a function of the expected producing rate, time periods of workovers, location, and condition of wells. Tiffin et al. (1998) proposed new criteria for screen and gravel selection for sand control. These criteria are mainly based on reservoir sand size distribution. Hodge et al. (2002) developed a valuation method for a stand-alone screen design, and gravel packed completion with consideration of plugging resistance and sand retention. Denney (2002) worked on field and laboratory tests to evaluate the relative effectiveness of two types of sand control methods used in the field with respect to optimizing operating expense. Farrow et al. (2004) used a new method based on the combination of a sand control matrix and flowchart.

Accordingly, the selection criterion was compared conforming to a probability of consequence ranking. Selection criteria were reservoir management, Particle Size Distribution (PSD), well condition and shales, installation risk and reliability, and cost. Mathisen et al. (2007) studied the importance of the selection of the screen process and fluid qualification. The authors presented a sand control selection method, which takes into account the effects of screen type, fluid qualification process, sand retention, and plugging properties. Slayter et al. (2008) presented a methodical framework with consideration of tasks (sand screen selection), activities (petrology analysis), and objectives (productivity) for designing a sand control. Chanpura et al. (2011) proposed a new method for selecting optimum stand-alone screen (SAS) based on sand-retention performance, and screen/sand pack permeability analysis to maximize productivity. Latiff (2011) presented a modified flowchart, which takes into account the effects of several parameters including the length of production zone, well inclination, and particle size distribution on sand control method selection. Chan et al. (2013) investigated the effect of various factors including well life, type of well completion, and particle size distribution on maximizing recovery of oil and gas per well for the long-term production life cycle. Khamehchi et al. (2015) studied the optimum sand control selection by considering screen types, mechanical skin, and economic assessment. They concluded that in the case of low oil production rate, factors of the reservoir productivity index, oil price, and time of capital return are more important than sand control skin. In general, it is better to preliminary analyze the predictive models, regardless the sand production is happening or not.

Many researchers have studied the sand-production prediction models using different methods including numerical, analytical models (Morita et al., 1989a, 1989b; Khamehchi and Reisi, 2015), and experimental tests (Van den Hoek et al., 1996; Fattahpour et al., 2012).

A review of previous studies shows that all sand control selection methods consider only a limited number of criteria in determining the best method. Nonetheless, there are many factors influencing the selection simultaneously. Due to the complexity and uncertainties found in the field of petroleum engineering, considering these factors is valuable (Latiff, 2011).

This study proposes a novel approach based on a combination of Multiple-Criteria Decision-Making (MCDM) and Design of Experiment (DOE) techniques. MCDM is a part of operations research, which explicitly appraises multiple inconsistent criteria in the decision making process. There are several MCDM methods including Analytic Hierarchy Process (AHP), ELimination and Choice Expressing REality (ELECTRE) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Zavadskas et al., 2014). After selection of best sand control method by applying MCDM, DOE and Response Surface Methodology (RSM) are used to optimize the parameters of the best-selected sand control method. DOE is a powerful technique to gain maximum information from a data set with the minimum number of experiments. In this regard, Full Factorial design (FFD) is used to perform required reservoir simulations. FFD is one type of DOE in which one can measure responses at all combinations of the factor levels. Also, Response Surface Methodology (RSM) is a collection of statistical methods to develop a significance mathematical relationship between various independent factors and one or more dependent variables. Finally, Monte Carlo simulation (MCS) is applied to perform sensitivity and uncertainty analysis of the derived proxy equation of NPV for the best-selected sand control method.

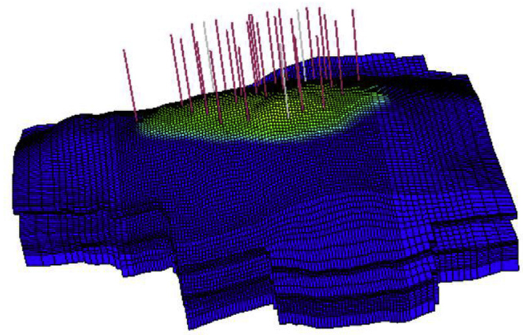

Fig. 1. 3D reservoir model.

2. Model description

In order to perform the required reservoir simulations with the sand control option, an actual carbonate reservoir was selected in the south of Iran. The geometry of the field has been modeled using corner-point geometry. This model contains $83 \times 115 \times 28$ grid blocks, of which 156631 blocks are active. The field contains 24 production wells that are completed in the oil column and 19 wells have sand production problems. The wells operate under constant-rate production constraints. After falling below a limiting bottom hole pressure, they will switch to a BHP-constraint. Fig. 1 shows the simulated 3D reservoir model of this oil field. Tables 1–3 presents more detailed information about the properties of the simulated reservoir.

The Particle Size Distribution (PSD) method is used for designing the sand control method. Using PSD method, samples of the formation sand are evaluated to determine the median grain size diameter and the grain size distribution. For this purpose, a sieve analysis is performed on a formation sand sample to select the proper-sized gravel-pack sand. In this regard, the weight of formation sample, retained by each size screen, can be specified by weighing the screens before and after sieving. Then, the cumulative weight percent of each sample against screen mesh size is plotted on semi-log coordinates to obtain a sand size-distribution plot. According to formation grain size distribution plot, reading the graph at the 50% cumulative weight shows the median formation grain size diameter (d50). This procedure is the basis of the sand control method designing, for example, grains of gravel pack method is defined when the median grain size of the gravel-pack sand, D50, is no more than six times larger than the median grain size of the formation sand, d50 (Zhang et al., 2014).

As can be seen from Fig. 2, formation sand size is between 0.00032 and 0.00125 m in diameter. The following shows that the formation grains are coarse. The sand control properties (Table 4) are designed Based on Fig. 2.

Table 1
Properties of the simulated reservoir.

Properties	Value
Producing tubing ID	2.996 in.
Top of producing sand face	13466 ft.
Wellhead temperature	77 F
Production fluid	Oil
Thickness of producing layer	100–300 ft.
Wellbore radius	0.36 ft.

Table 2
Fluid properties and reservoir data.

Properties	Value
Reservoir pressure	8800 Psi
Solution GOR	1.721 MSCF/STB
Oil gravity	33.71API
Gas gravity	0.83 sp. gravity
Oil viscosity	0.296 cP
Oil FVF	1.898 RB/STB
Reservoir temperature	294.3 F
Bubble point pressure	4887 Psi

Table 3
Well test data.

Properties	Value
Skin factor	0–25
Average reservoir permeability	110 md

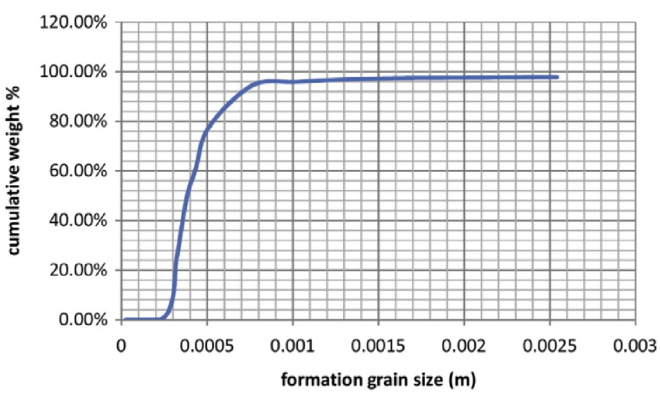

Fig. 2. Formation gran size distribution (adapted from Iranian oil company).

Table 4
Properties of the sand control methods.

Gravel pack	Value
Mesh size	30/50
Permeability	90 D
Length of penetration	0.5 ft.
Slotted liner	
Liner inner radius	2.706 in
Liner outer radius	2.907 in
Slot height	8 in
Slot width	0.04 in
Shot density	6 1/ft.
Wire wrapped	
Screen inner radius	2.63784 in
Outside permeability	1000 md
Pre-packed	
Screen inner radius	2.126 in
Screen outer radius	2.2368 in
Screen permeability	5000 md

3. Methodology

The major objective of this study is to find the best sand control method by considering inconsistent criteria. In this regard, MCDM methods are used. In MCDM topics, criteria such as economic and technical are called inconsistent criteria, which are qualitative or quantitative. Qualitative criteria include revenue, cost of installation, and skin. Quantitative criteria include limitation of installation, availability, and reliability. Solving an optimization problem by considering inconsistent criteria is more reliable and accurate relative to make a decision by considering only similar factors. Different MCDM methods with different complexity and presumptions exist. This occurs because the chosen score scales, weights and the resulting distributions of the scores within the criteria do not have the same impact on all the methods. For this reason, there is a knowledge gap about the validity of their outcomes. Complexity in MCDM methods is related to the mathematical process and the statistical features. Assumptions are related to weighting, intensity and, explanation for comparing i rows with j column in a matrix of pairwise comparisons (Tscheikner-Gratl et al., 2017).

Three methods of AHP, ELECTRE, and TOPSIS were selected based on expert experience and previews study because of their applicability in petroleum engineering. Therefore, in the current study, three methods of MCDM including AHP, ELECTRE, and TOPSIS are used to select the best sand control method. In the AHP method, a weight w is assigned to each criterion, which represents the importance of the criterion. The TOPSIS measures how good alternatives reach determined goals or aspirations. ELECTRE compares the alternatives pairwise for each criterion, finding the strength of preferring one over the other. The combining of these methods has better results due to the considering various aspects of MCDM approach.

Finally, the average rating method is used to combine the previous mentioned methods. The following sections review the MCDM methods in detail.

3.1. *MCDM (multiple-criteria-decision-making)*

MCDM is a subset of operations research which explicitly appraises multiple inconsistent criteria in decision making. Examples include daily life and in environments such as government, medicine, and business (Hashemi et al., 2016). The inconsistent criteria have a different nature, some of them are quantitative and others are qualitative which results in complexity of decision making. This complexity can be solved by MCDM methods. In selecting sand control methods, various inconsistent criteria take part in decision making (Weistroffer et al., 2005) and MCDM methods can significantly help the production engineer to select the best choice.

3.2. *Selection of multi-criteria decision-making (MCDM) methods (literature review)*

3.2.1. *Review of methods*

MCDM methods have a wide range of approaches (Zavadskas et al., 2014). These methods can be classified into three groups (Belton and Stewart, 2002):

- Value evaluation methods: For each alternative, a numerical score is created. In addition, a weight (w) is specified to each criterion that demonstrates the influence of the criterion (e.g., AHP).
- Reference level and goal models: These methods evaluate how proper alternatives impact reaching determined goals or aspirations (e.g., TOPSIS).
- Dominating models: These methods for each criterion contrast the alternatives pairwise and discover the strength of preferring one over the others (e.g., PROMETHEE, ELECTRE).

In this paper, all three groups of MCDM including AHP, ELECTRE, and TOPSIS are used to select the best sand control method, with considering all aspects of MCDM methods. The remaining sections focus on the AHP, ELECTRE, and TOPSIS, and describe how they work. Then, the best sand control technique is selected with consideration of six criteria including revenue, cost of operation and installation, sand screen skin, availability, limitation, and reliability.

Table 5
Decision matrix.

	C_1	C_2	…	C_n
A_1	X_{11}	X_{12}	…	X_{11}
A_2	X_{21}	X_{22}	…	X_{2n}
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
A_m	X_{m1}	X_{m2}	…	X_{mn}
W	W_1	W_1	…	W_1

By reviewing previous research utilizing of MCDM methods in the petroleum industry, TOPSIS has been successfully applied for the prediction of the best artificial lift method (Alemi et al., 2010). Application of this method in the optimum selection of drainage gas recovery technology (Gong et al., 2007) was noted. As well as in the novel EOR strategy-decision system based on Delphi-AHP-TOPSIS methodology (Liang et al., 2015). Valbuena et al. (2016) used ELECTRE for defining the artificial lift system selection guidelines for horizontal wells. Also, Fatahi et al. (2011) selected the best artificial lift method for one of the Iranian oil fields by employing the ELECTRE approach. Wang et al. (2017) studied reservoir heterogeneity by AHP and Fuzzy Logic. Gerbacia and Al-Shammari (2001) used AHP in Strategic Reservoir Planning. Also, Wan et al. (2011) applied AHP in oil and gas pipeline route selection.

For applying the MCDM methods to select the best sand control approach, first, the following decision matrix that consists of various criteria and alternatives should be constructed. Table 5 shows the decision matrix.

In Table 5, A_1, A_2 … …. A_n are the possible alternatives which are chosen by decision makers. C_1, C_2, …C_n are the criteria for which alternatives are chosen, and X_{ij} is the ratio of A_i to C_j. W_j is the weight of C_j. The value of weight can be computed either via a direct way or from a pairwise comparison.

3.2.1.1. AHP. Analytical Hierarchy Process (AHP) is a structured approach to cope with complicated decision-making processes developed by Thomas L. Saaty in 1970. AHP is able to help decision makers acquire the best selection based on their needs and their understanding of the subject. AHP method combines mathematics and psychology in order to be able to select the best alternative. AHP presents an all-inclusive and rational method for solving a decision problem. AHP transforms evaluations to numerical values, which can be processed and contrasted over the entire problem. For each element of the hierarchy, a numerical weight is derived, allowing diverse criteria to be compared to one another in a consistent and rational way. This ability is the exclusivity that distinguishes AHP from other MCDM techniques (Samad et al., 2012). AHP is based on a paired comparison, which is used to define the relative priority of each criterion. This method, uses the standardized network to grade the priority of different choices of a complex decision making process. This is achieved by using different criteria and distinct indices with prioritized multi-surface structures. The ability to analyze a decision making issue with graded structure is the basic foundation in AHP (Saaty, 1977; Javaheri et al., 2006; Gbanie et al., 2013). Further details of the AHP approach are given in (Saaty, 1977).

Saaty (1980) designed the following procedure for the AHP process:

1) Define alternatives and criteria as a decision matrix such as Table 5.
2) Determine qualitative and quantitative criteria.
   - Quantitative criteria such as price, revenue, distance
   - Qualitative criteria such as hardness, security, beauty
3) Convert qualitative criteria to quantitative values using the bipolar reference space shown in Fig. 3.
4) Build the matrix of pairwise comparisons among criteria.
   By using Table 6, in a matrix of pairwise comparisons, i rows are compared with the j column such that the main diagonal is equal to one. Also, each element under the main diagonal is the reverse of the element above the main diagonal.
   The results of the pairwise comparison on criteria are summarized in an (n×n) matrix in which elements $a_{ij}(i, j = 1,2, \dots n)$ are shown by equation (1).

$$A=\begin{bmatrix} a_{11}a_{12} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1}a_{n2} & \cdots & a_{nn} \end{bmatrix},\ a_{ii} = 1,\ a_{ji} = {}^{1}\!/_{a_{ij}},\ a_{ij} \neq 0 \tag{1}$$

5) Make pairwise comparisons for each criteria in terms of the alternatives (similar to step 4).
6) Normalize matrix of pairwise comparisons by dividing the value of each matrix with the sum of the corresponding column.
7) After normalization, calculate the relative weight of each criteria by computing the average of each row.
8) Do the same steps for each alternative in terms of the criteria.
9) Multiply relative weights of criteria with the average of relative weight alternatives matrix.
10) Rank the alternatives according to the results of step 9.

After these steps, measure the inconsistency to determine whether or not there is a compatibility between the pairwise comparisons as follows:

1) Calculate the weighted sum vector with a multiplication of the pairwise comparisons matrix of criteria in the vector of relative magnitudes.
2) Divide the magnitudes of the weighted sum vector of criteria by the vector of relative magnitudes to obtain the consistency vector.
3) Calculate the average elements of this vector.

The mathematical procedure starts to normalize and calculate the relative weights for each matrix. The relative weights are determined by the right eigenvector (λ) corresponding to the largest eigenvalue (λ_{max}) as:

$$A\omega = \lambda_{max}\omega \tag{2}$$

When pairwise comparisons are quite consistent, the matrix A has rank 1 and $\lambda_{max} = n$. In this condition, weights can be calculated by normalizing any of the columns or rows of matrix A (Wang and Yang, 2007).

4) Calculate inconsistency ratio.

The accuracy of the output of the AHP is rigorously related to the consistency of the pairwise comparison adjudication (Dağdeviren, 2008). When (λ_{max}) diverges from n, the inconsistency of pairwise comparison matrices is limited. The divergence ($\lambda_{max} - n$) is used as a value of inconsistency. This value is divided by n-1. This results in an average of the other eigenvectors (Forman, 1998). Thus, “consistency index” (Cl), is calculated by equation (3).

$$Cl = (\lambda_{max} - n)/(n - 1) \tag{3}$$

To find out whether the evaluations are completely consistent, the final consistency ratio (CR) can be calculated as the ratio of Cl and random index (RI) by equation (4).

$$CR = Cl/RI \tag{4}$$

The random consistency indices (RI) are in accordance with the degree of consistency. With values on the 1–9 scale, as shown in Table 7 and n is the number of criteria. The degree of consistency automatically increases when completing random reciprocal matrices. The accepted

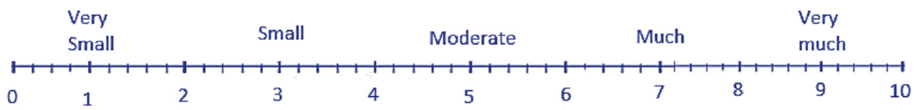

Fig. 3. Bipolar reference space.

Table 6
Intensity and explanation for comparing i rows with j column in a matrix of pairwise comparisons.

Intensity	Definition	Explanation
1	Equal importance	Two activities contribute
3	Moderate importance	Slightly favors one over another
5	Essential or strong	Strongly favors one over another
7	Demonstrated importance	Dominance of the demonstrated in practice
9	Extreme importance	Evidence favoring one over another of highest possible order of affirmation
2, 4, 6, 8	Intermediate values	When compromise is needed

upper limit for CR is 0.1. If CR > 0.1, in this case the calculation has to be repeated to result in better consistency. Calculating the consistency is used to evaluate the consistency of decision makers (Wang and Yang, 2007) (see Table 8).

5) Read inconsistency random index from Table 7.

3.2.1.2. ELECTRE. ELECTRE method is one of the methods under the umbrella of multiple criteria decision making (Hwang and Yoon, 1981) presented by Bernard Roy. This method is generally applied to three main problems: choosing, ranking, and sorting (Roy, 1968). Its first idea about concordance, discordance, and outranking notions emanated from real-world applications (Roy and Vanderpooten, 1997). To evaluate the outranking relations among the alternatives, ELECTRE uses concordance and discordance indicators (Almeida, 2007). The ELECTRE process encompasses the following steps (Mary and Suganya, 2016):

- Computation of concordance matrix
- Computation of discordance matrix
- Computation of credibility matrix
- Ascending preorder and descending

The ELECTRE process presents the following steps in detail:

1) Define alternatives and criteria as a decision matrix similar to AHP.
2) Determine qualitative and quantitative criteria.
3) Convert qualitative criteria to quantitative ones using bipolar reference space.
4) Normalize the decision matrix using norm method as shown in equation (5).

$$N = [n_{ij}]\ ,\ \ n_{ij} = \frac{a_{ij}}{[\sum_{i=1}^{m} a_{ij}^2]^{\frac{1}{2}}} \tag{5}$$

5) Evaluate individual criterion weight using Shannon maximum entropy

For this purpose, these steps should be implemented:

Table 8
Decision matrix.

	C_1	C_2	…	C_n
A_1	X_{11}	X_{12}	…	X_{11}
A_2	X_{21}	X_{22}	…	X_{2n}
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
A_m	X_{m1}	X_{m2}	…	X_{mn}

1. Suppose that the decision matrix is as follows:
2. Calculate P_{ij} by using the following equation:

$$P^{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} = \forall_{i,j} \tag{6}$$

3. The entropy of the *j*th criteria is calculated as follows:

$$E_j = -k \sum_{i=1}^{m} [P_{ij} \ln P_{ij}] \quad ; \quad \forall_j \tag{7}$$

Then, calculate the degree of deviation d_j and unreliability of j criteria to show how much the criteria related to j offers important information to the decision maker.

$$d_j = 1 - E_j \quad ; \quad \forall_j \tag{8}$$

4. Calculate weight w_j using the following equation:

$$w_j = \frac{d_j}{\sum_{i=1}^{n} d_j} \quad ; \quad \forall_j \tag{9}$$

6) Calculate balanced normalized matrix (V). For this purpose, multiply the normalized matrix with the square matrix ($W_n \times_n$). The main diagonal elements of which are criterion weights and the other elements are zero.

$$V = N \times W_{n\times n} \tag{10}$$

7) Compute concordance matrix and discordance matrix.

In this step, all alternatives are evaluated relative to all criteria and then sets of concordance and discordance matrices are constructed.

3.2.1.2.1. Concordance set ($S_{k,l}$). The concordance set ($S_{k,l}$) is constructed by l and k alternatives. This set consists of criteria in which alternative A_k is more favorable than alternative A_l. To find this favorability, one must consider the type of decision-making criteria, namely the positive or negative aspects.

For criteria with a positive aspect:

$$A_{k,j} = \{j|v_{kj} \geq v_{ij}\} \quad , \quad j = 1, \ldots, m \tag{11}$$

For criteria with a negative aspect:

$$A_{k,j} = \{j|v_{kj} \leq v_{ij}\} \quad , \quad j = 1, \ldots, m \tag{12}$$

The discordance set ($D_{k,l}$) includes criteria for which alternative A_k

Table 7
Random consistency indices (RI) (Saaty, 1995).

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

is less favorable than alternative A_l.

For criteria with a positive aspect:

$$D_{k,j} = \{j|v_{kj} \le v_{ij}\} \quad , \quad j = 1, \ldots, m \tag{13}$$

For criteria with a negative aspect:

$$D_{k,j} = \{j|v_{kj} \le v_{ij}\} \quad , \quad j = 1, \ldots, m \tag{14}$$

With previous steps, the concordance matrix is constructed. This is an m × m matrix; the main diagonal of which has no element. The other elements of this matrix are created by summing up the weights of the criteria that belong to the concordance set.

Hence,

$$I_{kl} = \sum w_j \quad , \quad j \in A_{k,l} \tag{15}$$

I_{kl} expressing relative importance of A_k to A_l.

The value of this index is between 0 and 1. The higher this value is, the greater the favorability of A_k to A_l.

3.2.1.2.2. Discordance set (NI). Discordance set (NI) is an m × m matrix. The matrix main diagonal does not have any element. The other elements of this matrix are obtained from the balanced normalized matrix. This element is calculated according to the following equation:

$$NI_{kl} = \frac{Max|v_{kj} - v_{lj}| \quad , \quad j \in D_{k,l}}{Max|v_{kj} - v_{lj}| \quad , \quad j \in All\ criteria} \tag{16}$$

This index calculates the u-favorability ratio of discordance set k and j to total discordance of all criteria.

8) Compute the effective concordance matrix and effective discordance matrix.

3.2.1.2.3. Effective concordance matrix (H). For constructing this matrix, a threshold should be defined. If any matrix element is larger or equal to this threshold, that element in matrix (H) takes the value of one. Otherwise, it takes the value of zero. The following equation is used to determine an index for the threshold:

$$\bar{I} = \sum_{l=1}^{m} \sum_{k=1}^{m} I_{kl}/\ m(m-1) \tag{17}$$

So

$$if \quad I_{kl} \ge \bar{I} \quad \rightarrow \quad H_{kl} = 1 \tag{18}$$

$$if \quad I_{kl} \le \bar{I} \quad \rightarrow \quad H_{kl} = 0$$

This matrix indicates preference of an alternative over another.

3.2.1.2.4. Effective discordance matrix (G). The threshold of this matrix is calculated as follows:

$$\overline{NI} = \sum_{l=1}^{m} \sum_{k=1}^{m} NI_{kl}/\ m(m-1) \tag{19}$$

The elements of this matrix are obtained as follows:

$$if \quad NI_{kl} \ge \overline{NI} \quad \rightarrow \quad G_{kl} = 0 \tag{20}$$

$$if \quad NI_{kl} \ge \overline{NI} \quad \rightarrow \quad G_{kl} = 1$$

9) Multiply effective concordance matrix with effective discordance matrix.

For this purpose, multiply H and G and obtain the final matrix (F). In this matrix, the row is preferred to the column. According to this, alternatives are ranked.

3.2.1.3. TOPSIS. TOPSIS is an acronym for Technique for Order of Preference by Similarity to Ideal Solution. This method is one of the types of multi-criteria decision-making approach that is developed by Hwang and Yoon (1981). TOPSIS can be applied easily to solve a problem with various criteria relative to the other multi-criteria decision making methods.

TOPSIS presents a more pragmatic form of modelling compared to other methods, which include or exclude alternative solutions (Greene et al., 2011). TOPSIS has been successfully applied in the petroleum industry for EOR selection.

The concept of TOPSIS is that the elected alternative should have the longest geometric distance from the negative ideal solution (NIS) and the shortest geometric distance from the positive ideal solution (PIS) (Assari et al., 2012). TOPSIS assumes that the criteria are uniformly increasing or decreasing. When parameters or criteria in multi-criteria problems are in incompatible dimensions, normalization is usually required (Yoon and Hwang, 1995; Zavadskas et al., 2006).

TOPSIS method is composed of the following steps:

1) Define alternatives and criteria as a decision matrix.
2) Determine qualitative and quantitative criteria.
3) Convert qualitative criteria to quantitative ones using bipolar reference space.
4) Normalize the decision matrix using a norm method such as the ELECTRE method.
5) Evaluate individual criterion weight using Shannon maximum entropy as explained in the ELECTRE method.
6) Calculate the balanced normalized matrix, for this purpose multiply the normalized matrix with square matrix (Wn*n), for which their main diagonal elements are criterion weights and the other elements are zero (such as ELECTRE method).
7) Define negative ideal solution (NIS) and positive ideal solution (PIS) and then calculate the geometric distances from the positive ideal, and geometric distance from the negative ideal.

For this purpose, define the following indices:

Positive ideal solution (V_j^+) = [vector of the best value of each criteria]

Negative ideal solution (V_j^-) = [vector of the worst value of each criteria]

And then calculate;

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \quad i = 1,2,\ldots,m \tag{21}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, \ i = 1,2,\ldots,m \tag{22}$$

d_i^+ and d_i^- are geometric distance from the positive ideal and the negative ideal, respectively.

8) Calculate relative proximity (CL) with the following equation:

$$CL_i^* = \frac{d_i^-}{d_i^- + d_i^+} \tag{23}$$

According to the amount of CL, the best method is chosen.

3.3. Procedure of applying MCDM methods and specifying the criteria and alternative

The procedure of applying MCDM tools to select the best sand control is shown briefly in Fig. 4.

3.3.1. Selecting the criteria and alternative

Five criteria including revenue, skin, cost of installation, availability, limitation, and reliability are selected to determine the best sand control method. Also, four considered sand control methods are gravel pack, slotted liner, wire wrapped, and prepacked. Fig. 5 shows the criteria and alternatives.

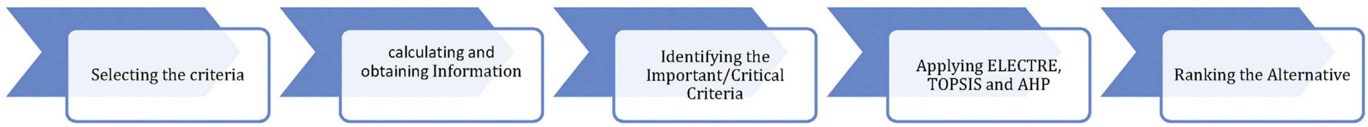

Fig. 4. Procedure of applying MCDM tools to select the best sand control.

For constructing the decision matrix and defining the alternatives, available information and experts' questionnaires are used. In the following, the selected criteria are described briefly.

- **Revenue** including incomes from oil and gas minus water disposal cost. In this paper, one of the fields in southern Iran with formation particle production was simulated for 42 years from 2001 to 2043. The prediction period spans from 2011 to 2043. The production system is an integrated model of reservoir, wells with sand control completion, and surface equipment.
- **Skin** in this matrix refers to skin caused by pressure drop in sand control.
- **Cost of installation** consists of cost of tools, necessary equipment, rig time, and man power. Table 9 shows the approximate costs of sand control equipment and operations, and the cost of work-overs.
- **Availability** means the ability to access tools with consideration of different conditions like political sanction of spare parts, offshore.
- **Limitation** criteria are the indication of restriction in installing tools in wells such as diameter of well and tool, type of metal, erosion, corrosion and designing with regard to prevention sands.
- **Reliability** shows the future aspect of tools like break down due to mechanical failure, plugging, and the term reliability embraces not only equipment, such as tools, and fixtures, but also the operational, technical, and activities, extending from tool specifications to daily maintenance and operation, required to maintain the efficiency of equipment over its useful life (Edge et al., 1991).

When selecting a sand control method, one has to consider the design limitations, complexity of installation, availability, mechanical risk, reliability, plugging erosion, well specifications, productivity, total cost and costs of work-over. The comparison between four sand control methods has been shown in Table 10. Table 10 was constructed by information that was gathered from experts' questionnaires and literature.

The decision matrix can be constructed by using the above considerations. Table 11 shows the prepared decision matrix to select the best sand control method based on MCDM techniques.

Table 9
Equipment and operations Cost (Khamehchi et al., 2015).

Equipment and operations	(1000$)
Gravel pack method	
Necessary tools	500
Perforation or under reaming	600
Fluids and gravels	900
Pump	800
Rig time (15 days)	15 × 30
Gravel pack placement operation	2700
Man power	400
Total	6350
+ Work-over operation (Gravel pack replacement)	10400
Slotted liner method	
Slotted pipe (3 branches)	3 × 400
Rig time (10 days)	10 × 30
Man power	100
Total	1600
+ Work-over operation	500
Wire wrapped screen method	
Screen (3 branches)	3 × 1000
Rig time (10 days)	10 × 30
Total	3300
+ Work-over operation	500
Pre-packed screen method	
Screen (4 branches)	4 × 1200
Rig time (10 days)	10 × 20
Total	5000
+ Work-over operation	400

4. Results and discussion

4.1. AHP for sand control method selection

In the previous section, alternatives and criteria were selected based on the literature review and experts' questionnaire. The result of applying the AHP method for selecting sand control is given in Table 12. Also, the inconsistency in determining whether or not there is a compatibility between the pairwise comparisons was calculated. The number 0.1 is the accepted upper limit for CR. CR for the matrix of pairwise comparisons among criteria was calculated as 0.09. This shows compatibility between the pairwise comparisons. The results show that slotted liner, pre-packed, wire wrapped and, gravel pack are the best alternatives for the sand control method, respectively.

4.2. ELECTRE for sand control method selection

The result of applying ELECTRE for selecting sand control is given in Table 13. The results show that slotted liner, pre-packed, wire wrapped, and gravel pack are the best alternatives for the sand control method,

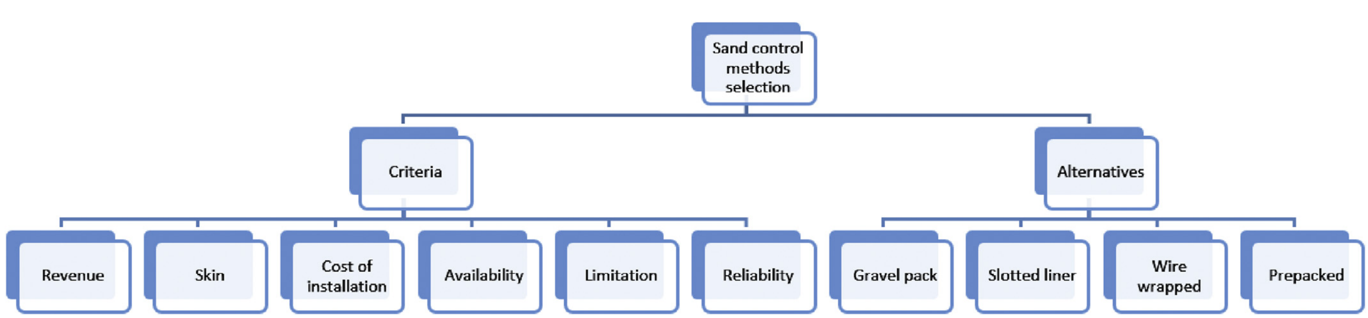

Fig. 5. The criteria and alternatives.

Table 10
Information gathered from experts' questionnaires and the literature (Saucier, 1974; Kaiser et al., 2002; King et al., 2003; Terwogt et al., 2006; Wilson, 2013).

	Design Failure	Production Failure	Reliability	Cost
Gravel pack	Error in screen diameter, length, or slot/weave size opening. Error in gravel volume calculation or measurement. Screen running damage, same as SOC, plus less than 100% screen/casing annular gravel volume displaced; any gravel bridge in equipment. Sand size: Small/medium	Positive skin factors due the change in system permeability. Zonal isolation is very good due to the selectivity and large zonal isolation. Wellbore restrictions. High complexity. Known/trusted method. Low inflow area subject to erosion moderately and easily plugged. Enhanced completion longevity.	Better control than open hole due to the known volume. Low to Moderate reliability.	High cost of installation and operation complexity. High cost according to the casing run, cementing and perforating.
Slotted liner	Poor quality in heterogeneous formations. Limited flow area. In high rate wells there is the possibility of erosional failure. Cannot control fine sands.	The highest production failure. Zonal isolation may be a problem. Plugging and screen collapse, erosion or damage during installation. Sand size: medium/large. Low complexity. Ease of installation Low rotational strength. Low inflow area subject to erosion. Easily plugged	Poor quality in heterogeneous formations can be improved by inflow control devices and good testing. Low reliability.	Low, but some expenses rise due to the amount of sand production, disposal costs. Inexpensive manufacture.
Wire wrapped	Greatly reduced flow friction. Can provide reasonable sand control under proper conditions. Moderate complexity. Inaccurate wire spacing can allow production of formation sand or plugging.	Reduces risk of screen plugging/clogging. Higher flow area compared to slotted liners. Low skin due to pressure drop. Can be damaged when installed through doglegs, high angle and horizontal sections because of vertical orientation between wrapped wires and support rods	High manufacturing efficiency. Profile materials can be stainless Steel.	Moderate to high cost. Fast installation results in saving costs and rig time.
Pre-packed	Stable sand control (no incomplete packing). Fast installation without external gravel pack, saving costs and rig time. Precise and uniform sand control due to custom packing of the screens. Excellent sand control.	Moderate Low skin due to pressure drop.	Less damage occurs during installation. Corrosion resistance of stainless steel mesh. Highly susceptible to plugging over time. Suitable only for well sorted, large grained, high permeability formations with little or no clay materials or other fines.	Expensive tools. Fast installation results in saving costs and rig time.

Table 11
Decision matrix to select the best sand control method.

	Revenue (US$)	Skin	Cost of installation (US$)	Availability	Limitation	Reliability
Gravel pack	63450318257.76	9.595	6350000	High	Very High	Moderate
Slotted liner	63736507202.97	3.647	1600000	Very High	Very Low	Low
Wire wrapped	63737079173.70	7.233	3300000	Very Low	Moderate	High
Pre-packed	63985386733.05	5.091	5000000	Moderate	Low	Very High

Table 12
Sand control methods ranking for AHP method.

Method	Value	Rank
Gravel pack	0.081297	4
Slotted liner	0.539812	1
Wire wrapped	0.130885	3
Pre-packed	0.273121	2

Table 13
Sand control method ranking with ELECTRE method.

Method	Rank
Gravel pack	3
Slotted liner	1
Wire wrapped	3
Pre-packed	2

respectively.

4.3. TOPSIS for sand control method selection

The result of TOPSIS based on relative proximity (CL) is given in Table 14. The results show that slotted liner, gravel pack, pre-packed, and wire wrapped are the best alternatives for the sand control method, respectively.

In order to find the best sand control method, a collection of economic and technical criteria was used. These criteria had a different concept that lead to difficult choices. These criteria and scoring were done by using experts' questionnaires in order to construct the decision matrix. As shown in Fig. 6, which is obtained from the TOPSIS method, revenue has the lowest weight and limitation has the highest weight. The revenue includes oil and gas income with water disposal cost subtracted. The well with more skin (due to sand control pressure drop) has less oil and gas production. Therefore, the reservoir depletion was slower and water and gas coning were postponed, which resulted in less water production. Eventually, the income deficit from oil and gas was compensated by lesser water production.

The three MCDM methods have slightly different results and are not equal. The discrepancy occurs because of different weights, score scales, and distributions of scores. The decision maker must be aware of the strengths and weaknesses of all methods. Therefore, in some conditions, it would be logical to use one of the simplest methods. Nonetheless, to test the consistency, a better comparison and to increase the reliability of the results, the application of various methods are indeed trialworthy. Finally, to select the best sand control method, the average

Table 14
Relative proximity (CL) and sand control method ranking with TOPSIS method.

Method	CL	Rank
Gravel pack	1.209414218	2
Slotted liner	1.228327857	1
Wire wrapped	1.035756481	4
Pre-packed	1.12760924	3

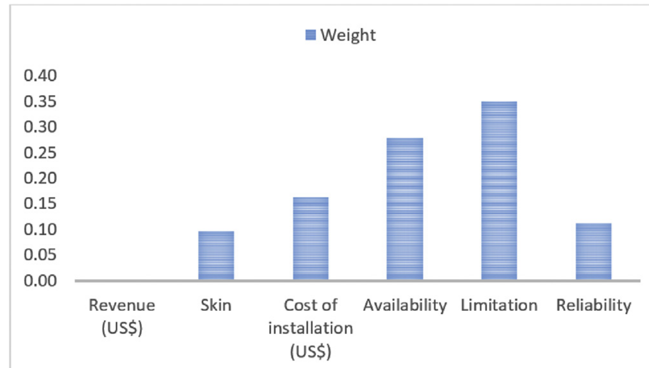

Fig. 6. Weights obtained from TOPSIS method for different criteria, revenue has the lowest weight and limitation has the highest weight.

Table 15
Results of three methods and average score of different sand control methods.

	TOPSIS	ELECTRE	AHP	Average score
Gravel Pack	2	3	4	3
Slotted liner	1	1	1	1
Wire wrapped	4	3	3	3.333333
Pre-packed	3	2	2	2.333333

rating method was used. This method determines the best option based on the average rankings obtained from different MADM priority methods. Table 15 shows the results of the three methods and the average score of the different sand control methods.

According to the average rating method, in this Iranian carbonate reservoir, a slotted liner is the best tool to control sand particles. Pre-packed is in second and gravel pack comes in third rank. The wire wrapped alternative is the last option for controlling sand particles.

4.4. Optimization of the best sand control method

After selecting the best sand control method, namely slotted liner, a combination of DOE, RSM, and MCS is applied to perform optimization and uncertainty analysis. DOE provides a tool to investigate the effects of parameters in results concurrently. DOE has a feasibility to provide a predictive knowledge of a complicated, multi-variable process (Lazić, 2005). DOE has have been successfully applied to a wide range of problems in the petroleum and natural gas industry including: a risk optimization approach to water drive gas reservoir production optimization, well placement and individual well controls optimization, and cutting transport efficiency prediction (Naderi and Khamehchi, 2016, 2017, 2018). To develop proxy models, sets of simulations should be carried out to obtain the importance and priority of parameters and their interactions. By the methodical design of simulations, DOE allows exploring a full range of parameters swiftly and efficiently. For generating a response surface model, the three level full factorial design was selected. Full Factorial design (FFD) is used to perform required reservoir simulations. FFD is one type of DOE in which one can measure responses at all combinations of the factor levels. In this design, the number of required simulations for n factors with three levels is equal

Table 16
Ranges of data used in this study.

Parameter	Symbol in study	Minimum	Moderate	Maximum
Height (in)	H	4	8	12
Width (in)	W	0.01	0.04	0.07
Shot density (1/ft.)	D	2	6	10

Table 17
Three level full factorial design (3^3) in DOE.

RunOrder	StdOrder	H	W	D	NPV (US$)
1	21	3	1	3	6.33052E+10
2	18	2	3	3	6.37897E+10
3	1	1	1	1	4.50346E+10
4	13	2	2	1	6.21307E+10
5	20	3	1	2	6.25501E+10
6	5	1	2	2	6.29665E+10
7	17	2	3	2	6.38226E+10
8	7	1	3	1	6.13482E+10
9	10	2	1	1	5.56138E+10
10	14	2	2	2	6.39365E+10
11	2	1	1	2	5.95152E+10
12	4	1	2	1	5.99384E+10
13	27	3	3	3	6.38134E+10
14	3	1	1	3	6.12830E+10
15	11	2	1	2	6.17698E+10
16	23	3	2	2	6.36884E+10
17	22	3	2	1	6.29019E+10
18	12	2	1	3	6.24249E+10
19	16	2	3	1	6.31549E+10
20	15	2	2	3	6.36772E+10
21	6	1	2	3	6.34467E+10
22	26	3	3	2	6.36461E+10
23	9	1	3	3	6.36663E+10
24	8	1	3	2	6.35712E+10
25	24	3	2	3	6.37681E+10
26	19	3	1	1	5.85852E+10
27	25	3	3	1	6.35203E+10

to 3^n. Due to the fixed ratios of well bore in this study, only slot height, slot width and density are considered and liner inner radius and liner outer radius remain constant. Table 16 shows the input parameters for each simulation run. According to the three level full factorial method, 27 simulations should be performed which are shown in Table 17. Data are expressed in relative values between 1 (for minimum valve), 2 (for moderate value) and 3 (for maximum value).

The significance of derived response functions was investigated by analysis of variance (ANOVA) as shown in Table 18. From Table 18, it is very obvious that the interactions among variables have a considerable effect on the NPV. In this analysis, α is equal to 0.1. Alpha is a parameter whose value is applied by the user. (Alpha to enter: Enter the alpha value that is used to determine whether a term can be entered into the model. Alpha to remove: Enter the alpha value that is used to determine whether a term is removed from the model). If P-Value ≤ α, then the dependency is statistically significant. In each step, the variable with the least impact will be omitted from the model. When all variables in the ANOVA table have been taken a P-Value less than or equal to the alpha to remove, the process stops. Simply, a P-Value shows us the information about the reality of a result. Technically, this parameter is a decreasing index of the reliability of an outcome, and the larger it is, the confidence in the reality of the results reduces (Plackett and Burman, 1946).

Table 18
ANOVA table.

Source	Degrees of freedom	Adj Sum of squares	Adj Mean squares	F-Value	P-Value
Model	18	3.69E+20	2.05E+19	8.33	0.002
Linear	6	2.39E+20	3.98E+19	16.17	0
H	2	3.82E+19	1.91E+19	7.76	0.013
W	2	1.09E+20	5.46E+19	22.15	0.001
D	2	9.16E+19	4.58E+19	18.59	0.001
2-Way Interactions	12	1.30E+20	1.09E+19	4.41	0.022
H*W	4	2.85E+19	7.12E+18	2.89	0.094
H*D	4	3.00E+19	7.49E+18	3.04	0.085
W*D	4	7.19E+19	1.80E+19	7.3	0.009
Error	8	1.97E+19	2.46E+18		
Total	26	3.89E+20			

To evaluate the relative strength of the effects among factors, main effects plot for NPV based on FFD is shown in Fig. 7. In these figures, the means for each level of a factor are plotted and linked with a line. Factorial points and Center points are shown by different symbols. A reference line is also shown at the grand mean of the response data by dots. As shown in the main effect plot for NPV, respectively the width, the shot density, and the height, have the most effect on NPV variations. As can be seen, NPV always increases by increasing these three parameters.

The changing any factor and holding the value of the second factor constant has also importance in this analysis. Fig. 8 shows the interaction plots of NPV. An interaction plot is a plot of means for each level of a factor by holding the level of a second factor constant. The relative strength of the effects across factors can be compared using interaction plots. However, the interpretation, as also for the main effects, is meaningful only if the interaction effects are statistically significant. By considering the interaction effects in the statistical model the complex nature of the optimization process becomes more understandable (Fegade et al., 2013). The most significant interaction effects on NPV are W × D and H × D.

Table 19 shows the coefficient of determination (R^2) and the adjusted coefficient of determination (R^2adj) for the proxy equation of NPV 94.94% and 83.54%, respectively. These parameters used to show the quality of fit for the regressions. To show how well the data fit a statistical model, R^2 is considered between zero and one. This parameter shows the percentage of variability in the process defined by the fitted model. Therefore, the closer the R^2 to 100 is, the higher the regression quality. 100% indicates that the regression line perfectly fits the data, while a value of zero percent indicates that the regression does not fit the data at all. The R^2adj is defined in terms of the coefficient of determination which has the effect of the number of independent variables on regression goodness of fit. A little difference between R^2adj and R^2 means that the unnecessary terms have not been included in the model (Myers and Montgomery, 1995).

Analyzing Table 17 using RSM and performing optimization reveals that run order 7 (Height = 8 in and width = 0.07 in, Shot density = 6 1/ft.) and NPV = 63.8226 billion dollars is the optimum design for slotted liner. The optimum design for slotted liner results in a greater income of 86092797.03 dollars (0.135%).

4.5. Sensitivity and uncertainty analysis of NPV

Sensitivity studies of the NPV response function were conducted using analysis of variance and performing MCS. Prior to Monte Carlo simulation, it is necessary to assign the appropriate probability distribution function for factors. A probability distribution function is a function that applied to specify a particular probability distribution. To evaluate the possibility of the occurrence of a specific event, probability distribution functions is first developed. Then, MCS begins with a model, often built in a spreadsheet, which includes input distributions and output functions of the inputs (Sánchez et al., 2007). In this regard, based on the available information, we assigned three distributions of normal, triangular, and uniform for all factors of slot height, slot width, and slot density (Gilman et al., 1998).

The result of Monte Carlo simulation by considering Latin Hypercube Sampling (LHS) and generating 1000 random numbers from

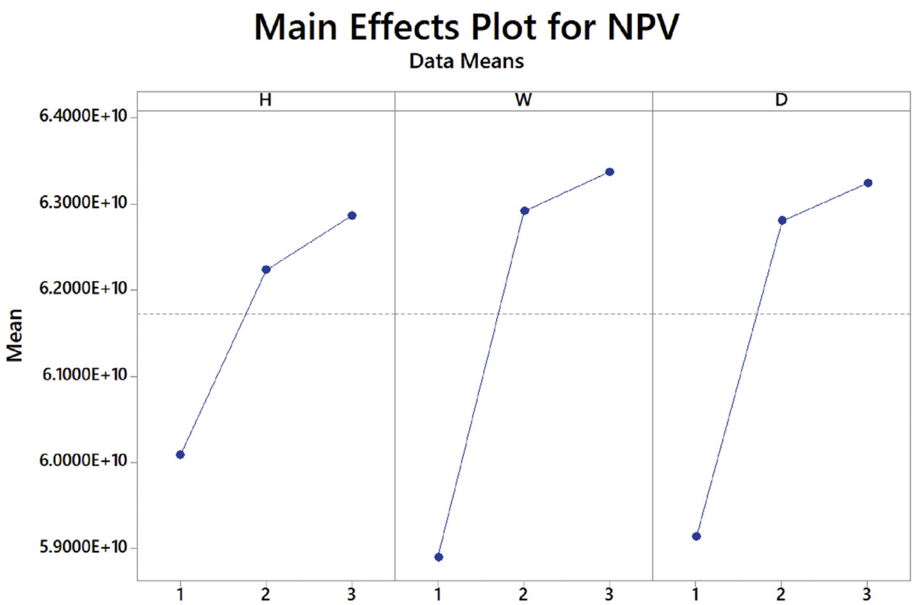

Fig. 7. Main effect plots for NPV. The main effect plots illustrate the relative strength of the effects across different levels of factors.

the entire range of factors is given in Fig. 9.

It can be seen from Fig. 9 that the values of P10, P50, and P90 for NPV are 60.91%, 63.38%, and 64.27%, respectively. Also, the minimum and maximum NPV is equal to 55.93%, and 64.86%, respectively. The result of sensitivity analysis in terms of contribution to total variance shows that slot width, slot density, and slot height controls 60.5%, 38.8%, and 0.7% of the NPV variation in the range of factors, respectively.

In sum, the results of sensitivity and uncertainty analyses show that the greatest uncertainty in estimating the best variables of slotted liner is associated with two factors of slot width and slot density. Therefore, these factors should carefully be characterized prior to the design of the best slotted liner for sand control, in order to, maximize NPV.

Table 19
Response functions statistics.

R-sq	R-sq (adj)
94.94%	83.54%

5. Conclusion

The purpose of the current study was to determine the best sand control method based on considering economic and technical criteria. Therefore, three types of MCDM tools were used for this purpose. MCDM methods had nearly similar ranking results. By using the average rating approach, the slotted liner was selected as the best sand control technique. The second aim of this study was to investigate the effects of optimum slotted liner parameters (height, width, and shot

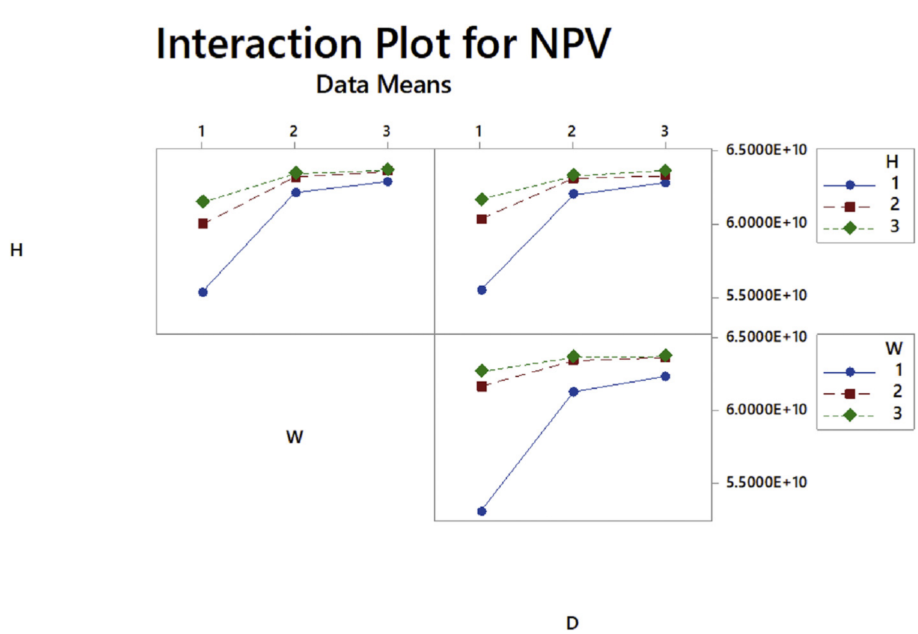

Fig. 8. Interaction plot for NPV. An interaction arises when the effect of one factor depends on the level of the other factors. Parallel lines in an interaction plot show no interaction. The greater difference in slope between the lines indicates a higher degree of interaction.

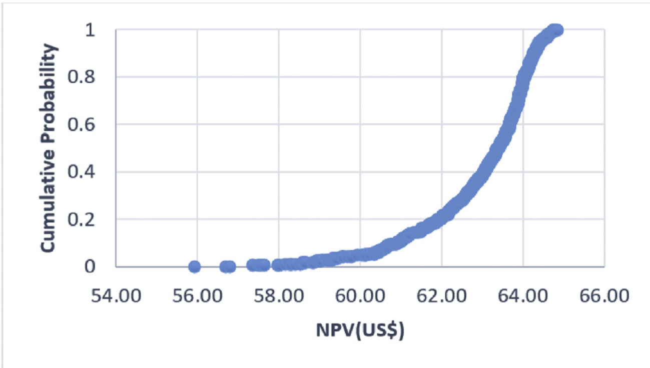

Fig. 9. The result of Monte Carlo simulation.

density) on income; which resulted in a greater income of 86092797.03 dollars (0.135%). The investigation of the sensitivity and uncertainty analysis also has shown that the greatest uncertainty in estimating the best variables of the slotted liner is associated with two factors of slot width and slot density. Therefore, these factors should carefully be characterized prior to designing the best slotted liner for the sand control in order to maximize NPV.

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