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Groundwater Assessment Using Feature Extraction Algorithm Combined with Complex Proportional Assessment Method and Standard Deviation

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Abstract: Groundwater (GW) quality evaluation includes a variety of biological, chemical and physical parameters. The fundamental problem with water quality assessment is the difficulty with which a large number of parameters are evaluated. If all criteria have been used to evaluate the quality of GW, then computational difficulty will certainly increase. In this paper, a new hybrid three-stage assessment approach based on Feature Extraction Algorithm (FEA), standard deviation (SD) and Complex Proportional Assessment Method (COPRAS) was proposed. In the first stage the redundant criteria for GW quality assessment is removed using FEA. Secondly, the weights of the reduct parameters are evaluated based on SD. Finally, GW sites are ranked using (COPRAS). Sixteen GW samples were gathered from several GW wells. The collected samples were investigated for 12 various physicochemical water quality criteria to evaluate GW quality. The results reveal that sulfates (SO4), nitrate (NO3), Fluorides (F), sodium (Na), and Escherichia coli (E. coli) are the main parameters for GW quality assessment. Furthermore, the optimal concentrations of physicochemical parameters: (SO4), (NO3), (F), (Na), and (E. coli) are 18.9(mg/L), 8.18(mg/L), 0.222(mg/L), 21(mg/L), 1.9(MPN/100mL), respectively, with 40 WQI.The suggested approach is compared to three MCDM methods to validate the performance of the proposed methodology. The assessment results gained by the FEA combined with COPRAS and SD significantly minimize computational difficulty, reasonable and accurate. The approach presented in this study improves the system for evaluating GW quality.

Keywords: Multi criteria decision making (MCDM), Groundwater (GW), Standard deviation (SD), Complex proportional assessment method (COPRAS).

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1. Introduction

Water is a vital resource for the property of life on earth. Groundwater (GW) is one of the world's essential water resources, used for basic needs, such as drinking, cooking, industry and agriculture. As a result of the exponential population growth, and the overuse of GW sources, the quality of GW is continuously deteriorating. In specific, as in amount, GW quality should be considered seriously. A major concern for human life is the quality of water which relates to the physical, biological and chemical characteristics of water, as it is directly related to human health. As the evaluation of water quality is one of the most important issues in GW studies, a number of methods for evaluating quality of the water have been constructed. One of the old approaches is the Schuler map; this approach includes an evaluation of drinking water in relation to chemical parameters separately and at an aquifer level [1]. Geographical information system (GIS) was used in the study area to analyze the spatial distribution of the groundwater quality index [2]. The World Health Organization (WHO) guidelines for a range of drinking water indices have been established [3]. Multi-Criteria Decision-Making (MCDM) methods are considered to be effective techniques in diverse areas, such as; contractors assessment, projects management, products selection, construction of roads, etc.

TOPSIS (Technique for Order Preference by Similarity Ideal Solution) was used as supplier selection method [4].For mobile services evaluation, the VIKOR methodology (Vlsekriterijumska Optimizaciya I Kompromisno Resenje) was applied [5]. Multi-Objective Optimization by Ratio Analysis (MOORA) approach was used to determine and maximize the influence of the identified process factors [6]. EDAS has been used successfully to determine the optimal set of operating parameters of a diesel engine [7]. In [8] the Fuzzy-AHP weighted is carried out with Fuzzy ordered Average (FOWA) for groundwater quality index development. Another method based on Fuzzy comprehensive evaluation has been proposed in [9] for GW assessment. A methodology was developed for the ranking of water quality using the Order of Preference Technique Similar to Ideal Solution (TOPSIS) and the Entropy Weight Method [10]. In [11], to establish numerous water quality indices (WQI) and a method for grading groundwater wells, Fuzzy VIKOR dependent water quality evaluation methodology was suggested. COPRAS is an MCDM tool utilized by multiple researchers to solve several different problems. The benefits of COPRAS methodology are; COPRAS approach is very simple to implement, as it needs much less computation than other techniques and the principal advantage of COPRAS relative to other MCDM methods is to be able to compute degree of utility [12]. Weight determination is a critical feature of water quality management, since the weights of the criteria will certainly affect the evaluation results. Thus, enhanced information has been provided about how to select an effective form of determination. A wide range of techniques of weight parameters evaluation are used to compute the quality of the water [13-14]. Standard deviation weight methodology is used in this study to evaluate the weights of the water assessment factors despite its simplicity and accessibility. In addition to weight determination, parameter selection seems to be another critical problem when determining quality of the water. During water quality investigation, a wide number of factors are gathered, but not all criteria are significant with the same degree, and some factors are also insignificant to the results of the evaluation. When all factors that collected are added to determine water quality, it would certainly be difficult to evaluate. It is common to select criteria dependent on individual expertise to decrease the parameters of information system, but this is impractical and to some degree inefficient. Different methods to reduce dimensions of input spaces are available, such as Principal Component Analysis (PCA) [15] and Factor Analysis (FA) [16]. In this paper, FEA combined with COPRAS and SD is proposed to select the most appropriate GW well among the feasible alternatives. FEA is used to execute variable reduction before water quality evaluation, SD is applied to calculate the weights of variables, and COPRAS is applied to evaluate water quality. The advantage of the suggested approach is not only in improving support to the decision-making process in selecting the best alternative but also in dealing with datasets with a large number of input variables, FEA can obviously minimize the parameters of input space and calculation difficulty. A considerable amount of time is saved at the same time. The rest of this paper is structured as follows. FEA method with its calculation steps, COPRAS with its computation steps and SD are presented in Section 2. The methodology of the suggested approach is given in section 3. The implementation of the proposed approach is validated with the best GW well selection problem in section 4. Lastly, in section 5 the conclusions are discussed.

2. Methods

2.1 Feature extraction algorithm

Some information is necessary in an information system for analysis of the system characteristics, but some information is unnecessary. Feature extraction algorithm (FEA) can be used to eliminate the redundant data while preserving the quality of sorting of the current circumstances. The features extracted are the reduct. For an information system $S = (U, A, V, f)$, where U is a finite nonempty set of objects and A is a finite nonempty set of attributes, $V$is a nonempty set of values, and f is an information function that maps an object in U to exactly one value in V , the feature reduction steps is given as follows[17]:

Step1: Evaluate the value S_a^d which used as a measure to rank attributes and subsequently select the best attribute for superset of reduct by:

$$\begin{aligned} S^d &= n^2 - \sum_{i=1}^{m} \left(n^i\right)^2 \\ SP_a^d &= \sum_{P=1}^{k} \left(\left(n_p\right)^2 - \sum_{i=1}^{m} \left(n_p^i\right)^2 \right) \qquad (1) \\ S_a^d &= \frac{1}{2}\left(S^d - SP_a^d\right) \end{aligned}$$

Where, n^i is the number of cases in decision class i, $n_p$is the number of cases that has symbolic value p for criteria a, and $\mathrm{n}_\mathrm{p}^\mathrm{i}$is the number of cases from decision class i that has symbolic value p for criteria a.

Step2: Select the attribute with the maximum S_a^d
Step3: Subsequently use the selected attribute to partition the decision table into equivalence classes.
Step4: Repeat the steps from step 1 to step 3 with each equivalence class
Step5: Select the attribute with the maximum $\sum S_a^d$
Step6: Repeat the steps from step 1 to step 5 till $\sum S_a^d = 0$ for all attributes.

2.2 Standard deviation.

The standard deviation (*SD*) is considered as measurement for the weights of the different criteria. The weights of the attributes using (*SD*) are determined by the following steps:
Step1: Create the decision matrix of, *X*

$$X = \left[X_{ij}\right]_{mn} \begin{bmatrix} x_{11} x_{12} \cdots x_{1n} \\ x_{21} x_{22} \cdots x_{2n} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ x_{m1} x_{m2} \cdots x_{mn} \end{bmatrix} \tag{2}$$

Where X_{ij} is the performance value of ith alternative on jth criterion, *n* is the number of parameters and *m* is the number of alternatives.
Step2: Normalize the decision matrix to obtain dimensionless values from various criteria using the following formula:

$$X_{ij}^{S} = \frac{X_{ij} - minX_{ij}}{maxX_{ij} - minX_{ij}} \tag{3}$$

Step3: Evaluation of the (SD) for every criterion using the following formula:

$$SD_j = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (X_{ij}^{S} - \bar{X}_j)^2} \tag{4}$$

where $\mathrm{X_{ij}}$ is the mean of the values of the jth Criteria after normalization and $\mathrm{j} = ,2,3, \ldots, \mathrm{n}$.
Step4: Finally, the weight foe each criterion is computed the following equation:

$$W_J = \frac{SD_j}{\sum_{j=1}^{n} SD_j} \tag{5}$$

2.3 Complex proportional assessment (COPRAS)

Zavadskas et al. developed the method of preference ranking for complex proportional assessment (COPRAS) [18]. This approach considers separate the effect of maximization and minimization parameters on the results of the evaluation. The performance of the alternatives in terms of different criteria and the corresponding criteria weights is taken into account. This approach chooses the best decision, taking into account the optimal and worst solutions. The COPRAS technique was applied in different fields such as material selection, management, construction, economics, etc. [19-22]. The COPRAS technique steps are defined as follows [23]:

Step1: determine the main criteria and define the alternatives.
Step2: Create the decision matrix of, X

$$X = \left[X_{ij}\right]_{mn} = \begin{bmatrix} x_{11} x_{12} \cdots x_{1n} \\ x_{21} x_{22} \cdots x_{2n} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ x_{m1} x_{m2} \cdots x_{mn} \end{bmatrix} \tag{6}$$

Where X_{ij} is the performance value of i^{th} alternative on j^{th} criterion, *n* is the number of parameters and *m* is the number of alternatives.
Step3: Normalize the decision matrix to obtain dimensionless values from various criteria using the following formula, *R*.

$$R = \left[r_{ij}\right]_{mn} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{7}$$

Step4: Calculate the weighted normalized decision matrix, *D*.

$$D = \left[y_{ij}\right]_{mn} = r_{ij} \times w_{j\ (i=1,2,\ldots,m;\ j=1,2,\ldots,n)} \tag{8}$$

Step5: The sums weighted standardized values are determined using the following formulas for beneficial as well as non-beneficial parameters:

$$\begin{aligned} S_{+i} &= \sum_{j=1}^{n} y_{+ij} \\ S_{-i} &= \sum_{j=1}^{n} y_{-ij} \end{aligned} \tag{9}$$

Where $\mathrm{y_{+ij}}$ and $\mathrm{y_{-ij}}$ are the weighted normalized values for the beneficial and non-beneficial attributes, respectively.
Step 6: Calculation the relative importance of each alternative, *Qi* :

$$Q_i = S_i + \frac{S_{-min} \cdot \sum_{i=1}^{m} S_{-i}}{S_{-i} \cdot \sum_{i=1}^{m} (S_{-min}/S_{-i})}, i = 1,2,3, \ldots m \tag{10}$$

Where S_{-min} is the minimum value of S_i.
Step 7: Evaluation of the quantitative utility, U_i

$$U_i = \frac{Q_i}{Q_{max}} .100\% \tag{11}$$

Here, $\mathrm{Q_{max}}$ is the maximum relative importance value. The utility values of the determined

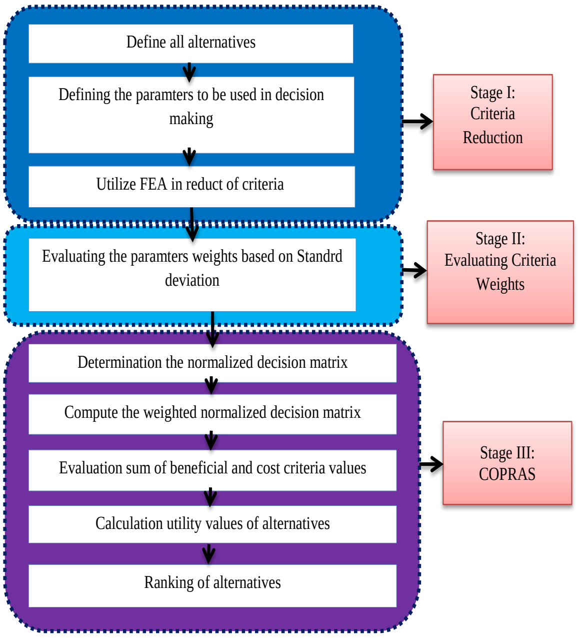

Figure. 1 The schematic structure of the proposed approach

alternatives are between 0 and 100 %. Finally, the most desirable alternative is the maximum utility factor.

3. Proposed methodology

The technique offered is composed of three elementary stages:
1st Stage. Reduction of criteria using FEA algorithm
2nd Stage. Weight computation of reduct parameters using standard deviation method
3rd Stage. Alternatives ranking by using of complex proportional assessment (COPRAS).

The schematic structure of the proposed approach is shown in Fig. 1.

4. Results, validations and discussions

In this section, a practical application is given to validate the performance and the efficiency of the suggested approach for groundwater quality assessment.

4.1 Information system of evaluating groundwater quality

Groundwater quality evaluation problem includes a variety of chemical and physical parameters. Sixteen GW samples were gathered from several GW wells in Jordan [24] as shown in Table 1. For each sample, twelve parameter including hydrogen ion concentration (pH-a1), total dissolved solids (TDS(mg/L)-a2), total hardness (TH(mg/L)-a3), Turbidity (Turb(NTU)–a4), sulfates (SO4(mg/L)-a5), chlorides (Cl(mg/L)-a6), nitrate (NO3(mg/L)-a7), Fluorides (F(mg/L)-a8), sodium (Na(mg/L)-a9), Zinc (Zn(mg/L)-a10), iron (Fe(mg/L)-a11), and Escherichia coli (E. coli(MPN/100mL)-a12) were investigated. These parameters are taken as condition attributes in our approach. In the other hand the water quality index (WQI) is indicated as decision attribute for each sample.

4.2 Discretization and coding of information system

The information system is discretized by transforming the continuous values of the quantitative parameters (a1 – a12), and the degision

Table 1. Groundwater samples information system

W. NO.	Condition parameter												Decision
	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	D
	pH	TDS	TH	Turb	SO4	Cl	NO3	F	Na	Zn	Fe	E.coli	WQI
w1	7.15	446	424	0.3	28	53	45	0.229	25	0.1	0.04	33	274
w2	7.43	424	376	0.1	35	70	61	0.364	41	0.016	0.04	34	287
w3	7.4	671	470	0.2	53	160	33	0.486	99	0.016	0.04	9.4	113
w4	7.81	429	263	0.45	36	68	46	0.411	30	0.03	0.04	3.7	66
w5	7.29	454	407	0.7	32	83	36	0.304	36	0.016	0.04	590	4295
w6	7.4	438	308	0.55	35	74	38	0.338	32	0.03	0.04	6.4	83
w7	7.84	329	218	0.08	9	24	22	0.306	14	0.016	0.04	1.8	44
w8	7.78	464	236	0.4	37	134	2.3	0.709	94	0.016	0.09	1.8	52
w9	7.48	424	290	0.25	60	115	1	1.9	52	0.016	0.04	1.8	55
w10	8.71	262	23	0.45	42	47	7.3	0.124	80	0.016	0.1	1.8	46
w11	7.96	680	283	0.23	37	249	22	0.332	112	0.016	0.04	1.8	60
w12	7.28	1417	861	4.8	605	187	1	1.523	145	0.06	0.11	1.8	96
w13	7.24	565	506	0.1	67	132	16	0.341	73	0.016	0.04	1.9	54
w14	7.82	391	289	0.1	16	59	17	0.256	20	0.016	0.04	3.7	59
w15	7.63	337	267	0.75	39	54	1.9	0.901	23	0.016	0.04	6.4	80
w16	7.61	194	118	0.05	18.9	37	8.18	0.222	21	0.016	0.04	1.9	40

Table 2. Definition of attribute coding

Attributes		Code				
		I	II	III	IV	V
a1	pH	$a1 \leq 6.5$	$6.5 < a1 \leq 7$	$7 < a1 \leq 7.5$	$7.5 < a1 \leq 8.5$	$a1 > 8.5$
a2	TDS	$a2 \leq 300$	$300 < a2 \leq 500$	$500 < a2 \leq 1000$	$1000 < a2 \leq 2000$	$a2 > 2000$
a3	TH	$a3 \leq 150$	$150 < a3 \leq 300$	$300 < a3 \leq 450$	$450 < a3 \leq 550$	$a3 > 550$
a4	Turb	$a1 \leq 0.05$	$0.05 < a1 \leq 1$	$1 < a1 \leq 5$	$5 < a1 \leq 10$	$a1 > 10$
a5	SO4	$a5 \leq 50$	$50 < a5 \leq 150$	$150 < a5 \leq 250$	$250 < a5 \leq 350$	$a5 > 350$
a6	Cl	$a6 \leq 50$	$50 < a6 \leq 150$	$150 < a6 \leq 250$	$250 < a6 \leq 350$	$a6 > 350$
a7	NO3	$a7 \leq 2$	$2 < a7 \leq 5$	$5 < a7 \leq 20$	$20 < a7 \leq 30$	$a7 > 30$
a8	F	$a8 \leq 0.5$	$0.5 < a8 \leq 1$	$1 < a8 \leq 1.5$	$1.5 < a8 \leq 2$	$a8 > 2$
a9	Na	$a9 \leq 100$	$100 < a9 \leq 200$	$200 < a9 \leq 250$	$250 < a9 \leq 300$	$a9 > 300$
a10	Zn	$a10 \leq .05$	$0.05 < a10 \leq 0.5$	$0.5 < a10 \leq 1$	$1 < a10 \leq 5$	$a10 > 5$
a11	Fe	$a11 \leq 0.1$	$0.1 < a11 \leq 0.2$	$0.2 < a11 \leq 0.3$	$0.3 < a11 \leq 1.5$	$a11 > 1.5$
a12	E.coli	$a1 \leq 1.1$	$1.1 < a1 \leq 2.2$	$2.2 < a1 \leq 10$	$10 < a1 \leq 50$	$a1 > 50$
D	WQI	$D \leq 50$	$50 < D \leq 100$	$100 < D \leq 200$	$200 < D \leq 300$	$D > 300$

Table 3. Coded information system

W. NO.	Condition parameter												Decision
	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	D
	pH	TDS	TH	Turb	SO4	Cl	NO3	F	Na	Zn	Fe	E.coli	WQI
w1	II	II	III	II	I	II	V	I	I	II	I	IV	IV
w2	II	II	III	II	I	II	V	I	I	I	I	IV	IV
w3	II	III	IV	II	II	III	V	I	I	I	I	III	III
w4	III	II	II	II	I	II	V	I	I	I	I	III	II
w5	II	II	III	II	I	II	V	I	I	I	I	V	V
w6	II	II	III	II	I	II	V	I	I	I	I	III	II
w7	III	II	II	II	I	I	IV	I	I	I	I	II	I
w8	III	II	II	II	I	II	II	II	I	I	I	II	II
w9	II	II	II	II	II	II	I	IV	I	I	I	II	II
w10	V	I	I	II	I	I	III	I	I	I	II	II	I
w11	III	III	II	II	I	III	IV	I	II	I	I	II	II
w12	II	IV	V	III	V	III	I	IV	II	II	II	II	II
w13	II	III	IV	II	II	II	III	I	I	I	I	II	II
w14	III	II	II	II	I	II	III	I	I	I	I	III	II
w15	III	II	II	II	I	II	I	II	I	I	I	III	II
w16	III	I	I	II	I	I	III	I	I	I	I	II	I

attribute (D) into qualitative terms. The condition attributes of chemical and physical parameters for groundwater samples are coded into five qualitative terms; (I, II, III, IV, and V). Furthermore, the decision attribute (D) is coded into five qualitative terms; (I (excellent), II (good), III (moderate), IV (poor), and V (very poor)). The definition of attribute coding is shown in Table 2. This coding method is applied as presented in the coded information system of Table 3.

4.3 Groundwater Information system reduction

In this step Feature Extraction Algorithm (FEA) is applied for the coded information system in table III for extracting the reduct. The reduction result obtained as the output of the (FEA) can be written as $\{ a_5, a_7, a_8, a_9, a_{12}\}$. According to the FEA algorithm result the parameters $\{ \mathrm{a}_1, \mathrm{a}_2, \mathrm{a}_3, \mathrm{a}_4, \mathrm{a}_6, \mathrm{a}_{10}, \mathrm{a}_{11} \}$ can be omitted from Table 1 and the reduct Table 4 is obtained.

4.4 Calculation the weights of the assessment parameters by standard deviation

The weights of parameters for GW assessment are determined using the standard deviation. To evaluate the standard deviation, standardization of the range was performed using Eq. (3) to turn different scales and units into specific observable units between different GW assessment parameters to measure their weights. The standard deviation (SD) is then calculated for every assessment parameter using Eq. (4). The next step after determining the standard deviation for all assessment parameters is to

Table 4. Information system reduct

W. NO.	Condition parameter					Decision
	a5	a7	a8	a9	a12	D
	SO4	NO3	F	Na	E.coli	WQI
w1	28	45	0.229	25	33	274
w2	35	61	0.364	41	34	287
w3	53	33	0.486	99	9.4	113
w4	36	46	0.411	30	3.7	66
w5	32	36	0.304	36	590	4295
w6	35	38	0.338	32	6.4	83
w7	9	22	0.306	14	1.8	44
w8	37	2.3	0.709	94	1.8	52
w9	60	1	1.9	52	1.8	55
w10	42	7.3	0.124	80	1.8	46
w11	37	22	0.332	112	1.8	60
w12	605	1	1.523	145	1.8	96
w13	67	16	0.341	73	1.9	54
w14	16	17	0.256	20	3.7	59
w15	39	1.9	0.901	23	6.4	80
w16	18.9	8.18	0.222	21	1.9	40

Table 5. Weights of the GW assessment parameters.

W. NO.	Standardized mean of conditional parameters				
	a5	a7	a8	a9	a12
	SO4	NO3	F	Na	E.coli
w1	0.0319	0.7333	0.0591	0.0840	0.0530
w2	0.0436	1	0.1351	0.2061	0.0547
w3	0.0738	0.5333	0.2038	0.6489	0.0129
w4	0.0453	0.7500	0.1616	0.1221	0.0032
w5	0.0386	0.5833	0.1014	0.1679	1
w6	0.0436	0.6167	0.1205	0.1374	0.0078
w7	0	0.3500	0.1025	0	0
w8	0.0470	0.0217	0.3294	0.6107	0
w9	0.0856	0	1	0.2901	0
w10	0.0554	0.1050	0	0.5038	0
w11	0.0470	0.3500	0.1171	0.7481	0
w12	1	0.0000	0.7877	1	0
w13	0.0973	0.2500	0.1222	0.4504	0.0002
w14	0.0117	0.2667	0.0743	0.0458	0.0032
w15	0.0503	0.0150	0.4375	0.0687	0.0078
w16	0.0166	0.1197	0.0552	0.0534	0.0002
SD_j	0.2322	0.3045	0.2711	0.2922	0.2404
(W_j)	0.17326	0.22714	0.20228	0.21799	0.17933

evaluate their W_j weights, with Eq. (5). The normalized values and the corresponding weights of the assessment parameters are indicated in Table 5.

4.5 Assessment the available locations of groundwater wells by COPRAS

In COPRAS method, firstly the parameters for groundwater assessment are transformed into dimensionless values using linear normalization procedure, so that all these parameters can be compared. Then, using Eq. (8), the corresponding weighted normalized matrix is constructed, as shown in Table 6.

Table 6. Weighted normalized decision matrix

W. NO.	a5	a7	a8	a9	a12
	SO4	NO3	F	Na	E.coli
w1	0.0042	0.0286	0.0053	0.0061	0.0084
w2	0.0053	0.0387	0.0084	0.0100	0.0087
w3	0.0080	0.0210	0.0112	0.0241	0.0024
w4	0.0054	0.0292	0.0095	0.0073	0.0009
w5	0.0048	0.0229	0.0070	0.0087	0.1509
w6	0.0053	0.0241	0.0078	0.0078	0.0016
w7	0.0014	0.0140	0.0071	0.0034	0.0005
w8	0.0056	0.0015	0.0164	0.0228	0.0005
w9	0.0090	0.0006	0.0439	0.0126	0.0005
w10	0.0063	0.0046	0.0029	0.0194	0.0005
w11	0.0056	0.0140	0.0077	0.0272	0.0005
w12	0.0912	0.0006	0.0352	0.0352	0.0005
w13	0.0101	0.0102	0.0079	0.0177	0.0005
w14	0.0024	0.0108	0.0059	0.0049	0.0009
w15	0.0059	0.0012	0.0208	0.0056	0.0016
w16	0.0028	0.0052	0.0051	0.0051	0.0005

Then, the sums of weighted normalized values are calculated using Eq. (9), for both maximizing parameters (S_{+i}) and minimizing parameters (S_{-i}). Subsequently, relative significance (priority) of each GW well was obtained by using Eq. (10). Finally, by using Eq. (11), quantitative utility for each alternative was calculated upon which the final ranking was obtained (Table 7).

Table 7. Sum of the weighted normalized values, relative significance, utility values and ranking of the groundwater wells

W. NO.	S_{+i}	S_{-i}	Q_i	U_i	Rank
w1	0	0.0711	0.038473	26.39825	14
w2	0	0.1627	0.016809	11.53313	15
w3	0	0.0667	0.040994	28.12821	13
w4	0	0.0524	0.052216	35.82801	9
w5	0	0.1944	0.014072	9.655704	16
w6	0	0.0549	0.049815	34.18062	11
w7	0	0.0249	0.10969	75.26369	2
w8	0	0.0337	0.081076	55.6299	4
w9	0	0.0464	0.058984	40.47148	6
w10	0	0.0263	0.104124	71.44464	3
w11	0	0.0467	0.058518	40.15208	8
w12	0	0.0666	0.041038	28.15829	12
w13	0	0.0351	0.077815	53.39239	5
w14	0	0.0466	0.058646	40.2399	7
w15	0	0.0526	0.051989	35.67238	10
w16	0	0.0188	0.145741	100	1

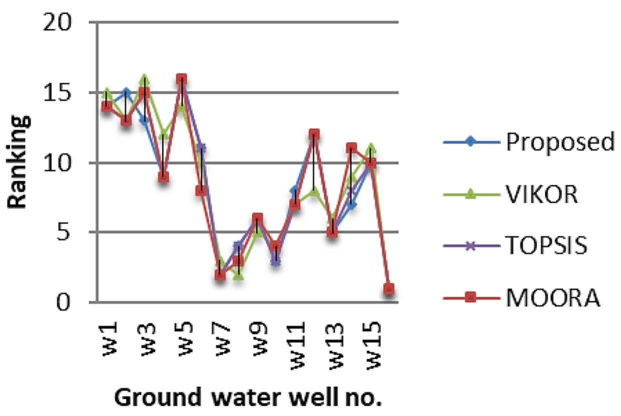

Figure. 2 Comparative rankings of suggested method with other MCDM techniques

4.6 Comparison between the proposed method and comprehensive evaluation techniques

To evaluate the validity and strength of the suggested methodology, the ranking results were also compared with the previously investigated optimization approaches such as: MOORA [6], VIKOR [5] and TOPSIS [4]. The results of rankings of various approaches are presented in the Fig. 2.

The results do not show much difference between the proposed method and the other MCDM methods except in the rankings of the middle rated alternatives. It can be observed that GW well 16 received the highest attention by all methods, hence may be regarded as the most appropriate. The results indicate that the suggested approach is consistent with the other techniques. The suggested approach is not only improve decision-making process in selecting the best alternative but also in dealing with datasets with a large number of input variables, FEA can obviously minimize the parameters of input space and calculation difficulty. A considerable amount of time is saved at the same time.

5. Conclusions

The assessment of GW quality is one of the key issues in water resources management. In this research, a methodology based on FEA combined with COPRAS Method and SD for GW assessment is introduced. Twelve parameter including hydrogen ion concentration (pH), total dissolved solids (TDS), total hardness (TH), Turbidity (Turb), sulfates (SO4), chlorides (Cl), nitrate (NO3), Fluorides (F), sodium (Na), Zinc (Zn)), iron (Fe), and Escherichia coli (E. coli) were investigated to evaluate GW quality. First, FEA was used to perform attribute reduction of parameters for water assessment. Then, the parameter weights were computed using SD. Finally, COPRAS for evaluating GW quality rankings was successfully employed. The results reveal that sulfates (SO4), nitrate (NO3), Fluorides (F), sodium (Na), and Escherichia coli (E. coli) are the main parameters for GW quality assessment. Furthermore, the optimal concentrations of physicochemical parameters: (SO4), (NO3), (F), (Na), and (E. coli) are 18.9(mg/L), 8.18(mg/L), 0.222(mg/L), 21(mg/L), 1.9(MPN/100mL), respectively. To validate the suggested approach output, three MCDM analytical techniques, including MOORA, VIKOR, and TOPSIS, are being compared. It demonstrates that the computed values for the proposed model are close to the methods MOORA, VIKOR, and TOPSIS. Hence, the suggested model is considered to be an effective evaluation method for ranking groundwater wells. We can, therefore, conclude that FEA combined with COPRAS Method and SD approach is powerful in the optimization of GW parameters. Moreover, the proposed approach provides a generic method that can be extended to various selection difficulties that include complexity and a variety of performance indicators. Compared to other MCDM methods, the results derived from the proposed model are reasonable and reliable to implement.

Conflicts of Interest

The author declare no conflict of interest.

References

[1] P. Piroozfar, S. Alipour, S. Modabberi, and D. Cohen, “Hydrogeochemical investigation and water quality assessment in the Sarough watershed, Takab mining district”, *Geosciences*, Vol. 106, pp. 13-28, 2018.

[2] T. Subramani, S. Krishnan, and P. K. Kumaresan, “Study of groundwater quality with GIS application for Coonoor Taluk in Nilgiri district”, *International Journal of Modern Engineering Research*, Vol. 2, No. 3, pp. 586–592, 2012.

[3] A. D. Gorgij, O. Kisi, A. A. Moghaddam, and A. Taghipour, “Groundwater quality ranking for drinking purposes, using the entropy method and the spatial autocorrelation index”, *Environmental Earth Sciences*, Vol. 76, No. 7, pp. 269–277, 2017.

[4] F. Lei, G. Wei, H. Gao, J. Wu, and C. Wei, “TOPSIS Method for Developing Supplier Selection with Probabilistic Linguistic Information”, *International Journal of Fuzzy Systems*, Vol. 22, pp. 749–759, 2020.

[5] Y. Suh, Y. Park, and D. Kang, “Evaluating mobile services using integrated weighting approach and fuzzy VIKOR”, *PLoS ONE*, Vol. 14, No. 6, pp. 1–28, 2019.

[6] S. K. Shihaba, N. Z. Khanb, P. Mylac, S. Upadhyayd, Z. A. Khanb and A. N. Siddiqueeb, “Application of MOORA method for multi optimization of GMAW process parameters in stainless steel cladding”, *Management Science Letters*, Vol. 8, pp. 241-246, 2018.

[7] S. M. Shaban and A. M. AbdEl-latif, “Integration of Evaluation Distance from Average Solution Approach with Information Entropy Weight for Diesel Engine Parameter Optimization”, *International Journal of Intelligent Engineering and Systems*, Vol. 13, No. 3, pp. 101 – 111, 2020.

[8] M. A. Baghapou and M. R. Shooshtarian, “Extending a Consensus-Based Fuzzy Ordered Weighting Average (FOWA) Model in New Water Quality Indices”, *Iranian Journal of Health, Safety & Environment*, Vol. 4, No. 4, pp. 824–834, 2017.

[9] Y. J. He, D. Wang, and G. L. Wang, “Fuzzy Comprehensive Evaluation on North-China Groundwater Quality”, *Advanced Materials Research*, Vol. 610-613, pp. 2729-2733, 2012.

[10] A. D. Gorgij, J. Wu and A. A. Moghadam, “Groundwater quality ranking using the improved entropy TOPSIS method: a case study in Azarshahr plain aquifer, east Azerbaijan, Iran”, *Human and Ecological Risk Assessment: An International Journal*, Vol. 25, No. 1-2, pp. 176–190, 2019.

[11] H. Haider, A. Ghumman, I. S. Al-Salamah, and H. Thabit, “Assessment Framework for Natural Groundwater Contamination in Arid Regions: Development of Indices and Wells Ranking System Using Fuzzy VIKOR Method”, *Water*, Vol. 12, No. 2, pp. 423–447, 2020.

[12] A. Organ and E. Yalçın, “Performance Evaluation of Research Assistants By Copras Method”, *European Scientific Journal*, Vol. 12, pp. 102–109, 2016.

[13] L. I. Peiyue, W. U. Jianhua, and Q. Hui, “Groundwater quality assessment based on entropy weighted osculating value method”, *International Journal of Environmental Sciences*, Vol. 1, No. 4, pp. 621–630, 2010.

[14] Z. W. Li, Y. Fang, G. Zeng, J. B. Li, Q. Zhang, Q. S. Yuan, Y. M. Wang, and F. Y. Ye, “Temporal and spatial characteristics of surface water quality by an improved universal pollution index in red soil hilly region of South China: A case study in Liuyanghe River watershed”, *Environmental Geology*, Vol. 58, pp. 101–107, 2009.

[15] S. S. Mahapatra, M. Sahu, R. K. Patel and B. N. Panda, “Prediction of Water Quality Using Principal Component Analysis”, *Water Quality Exposure and Health*, Vol. 4, pp. 93–104, 2012.

[16] V. K. Jena and D. Sinha, “Ground water quality assessment by multivariate factor analysis”, *Research Journal of Chemistry and Environment*, Vol. 21, pp. 21–25, 2017.

[17] G. Borowik, J. Jankowski, and K. Kowalski, “Fast algorithm for feature extraction”, In: *Proc. of SPIE 9662, Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2015*, Wilga, Poland, pp. 9662 3T, 2015.

[18] E. K. Zavadskas, A. Kaklauskas, Z. Turskis, and J. Tamošaitien, “Selection of the Effective Dwelling HouseWalls by Applying AttributesValues Determined at Intervals”, *Journal of Civil Engineering & Management*, Vol. 14, No. 2, pp. 85–93, 2008.

[19] P. Chatterjee, V. M. Athawale, and S. Chakraborty, “Materials selection using complex proportional assessment and evaluation of mixed data methods”, *Materials and Design*, Vol. 32, No. 2, pp. 851–860, 2011.

[20] L. Uzsilaityte and V. Martinaitis, “Search for optimal solution of public building renovation in terms of life cycle”, *Journal of Environment Engineering and Landscape Management*, Vol. 18, No. 2, pp. 102–110, 2010.

[21] L. Tupenaite, E. K. Zavadskas, A. Kaklauskas, Z. Turskis, and M. Seniut, “Multiple criteria assessment of alternatives for built and human environment renovation”, *Journal of Civil Engineering and Management*, Vol. 16, No. 2, pp. 257-266, 2010.

[22] E. K. Zavadskas, A. Kaklauskas, F. Peldschus, and Z. Turskis, “Multi-Attribute Assessment of Road Design Solutions by Using the COPRAS Method”, *Baltic Journal of Road and Bridge Engineering*, Vol. 2, No. 4, pp. 195–203, 2008.

[23] P. Chatterjee and S. Chakraborty, “Gear Material Selection using Complex Proportional Assessment and Additive Ratio Assessment-based Approaches: A Comparative Study”, *International Journal of Materials Science and Engineering*, Vol. 1, No. 2, pp. 104-111, 2013.

[24] M. N. Ibrahim, “Assessing Groundwater Quality for Drinking Purpose in Jordan: Application of Water Quality Index”, *Journal of Ecological Engineering*, Vol. 20, No. 3, pp. 101-111, 2019.