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Research Article

Optimal Selection of Stimulation Wells Using a Fuzzy Multicriteria Methodology

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Choosing the most appropriate wells for stimulation is one of the greatest challenges affecting reservoir production and economic development. In this paper, an integrated fuzzy decision-making methodology is developed to choose the most appropriate stimulation wells based on a number of criteria. The presented approach is able to determine the final decision priorities for multiple candidate wells considering uncertainty, incomplete information, and the large number of factors involved. The proposed modelling framework works as a stepwise procedure to fuse several different methods with combined benefits. The analytic hierarchy process (AHP) method is adopted to build the factor framework. Grey theory is introduced to determine the influence weights of factors, and combined with the fuzzy logic concept, these values are used to rank candidate wells. A field application shows that the presented method is able to identify the wells with the highest potential for enhanced production.

1. Introduction

The availability of energy is a critical factor for the development of economies and societies. Notably, China has attempted to decrease its dependence on imported energy to increase its standard of living. China has become the largest crude oil importer worldwide over the past two decades [1]. The International Energy Agency (IEA) predicts Chinese net oil imports to reach 13.1 million barrels per day in 2030 [2, 3]. As part of an effort to meet the national energy needs, China has turned to the previously neglected region of Africa. Although domestic oil and natural gas reserves are plentiful in China, production has been restricted by the lack of means of selecting the most economically suitable wells for stimulation [4–7]. Selecting among candidate wells for stimulation is a complex process involving several different criteria and experts with different backgrounds [8–15]. In addition, policies for selecting among candidate wells generally have a number of objectives that should be stated clearly. It is also essential that the following questions be considered: What are the criteria or factors that should be taken into account? What standards are to be applied when choosing candidate wells? Which of the candidate wells are most appropriate for stimulation?

Several major factors are involved in this process, including geological factors, well reserves, and hydraulic fracturing and construction parameters [16]. The relationship between being a good candidate well for stimulation and these parameters is highly nonlinear and complex [17, 18]. Many approaches have been developed for candidate well selection, including neural networks, support vector machines, deep learning, the analytic hierarchy process (AHP), and the tree-like structure technique (Sellitto M. A., 2018). However, each method has its inherent limitations. Neural networks are based on identifying statistical patterns and do not consider the knowledge on the underlying physical processes associated with fracturing. Consequently, neural networks require a large amount of high-quality data, and errors in these data can lead to inaccurate results [19]. The AHP method provides a

framework for making pairwise comparisons and derives ratio scales from a set of paired comparisons by making numerical trade-offs to arrive at a conclusion [20]. One deficiency of the AHP method is that it is unable to operate in the presence of fuzzy or incomplete comparisons [21, 22]. Another deficiency is that when one removes or introduces a new criterion in the AHP, it may cause an inversion of priorities in some circumstances.

There is no doubt that stimulation well selection is a problem fraught with error, uncertainty, and fragile correlations between datasets [18]. These uncertainties come from the challenge of designing and building sensors to measure complex geological factors as well as well reserves in hostile environments [23]. It is obvious that the variations used in neural networks and the AHP method are simplifying hypotheses in consideration of extreme or mean values, which cannot deal with the uncertainties associated with vague or imprecise information. Fuzzy logic is better able to tackle system uncertainty and fuse subjective perceptions into evaluations than are the methods discussed above [24, 25]. Different from classical logic, which is based on crisp sets of "true and false," fuzzy logic views problems as a degree of "truth," or "fuzzy sets of true and false." The fuzzy set concept allows us to express uncertainty in a different way from classical probability theory based solely on the randomness concept. The key point in fuzzy logic is to find a membership function to transform fuzzy scales into crisp scales for the computation of a single parameter, the fuzzy probability. Grey system theory is an interdisciplinary scientific area that was first introduced by Deng [26] that requires a limited amount of data to estimate the behaviour of unknown systems and obtains an unbiased as well as consistent point estimator. It is widely employed to determine the influence weights of factors [27]. Combined with grey theory, these fuzzy possibilities can be combined harmonically to provide a combined fuzzy possibility [23, 28].

All in all, choosing a stimulation well involves multiple criteria and multiple expert group decision-making problems. A single tool or discipline cannot provide all the information necessary for the complete characterization of a good candidate well, but by integrating geological, geophysical, petrophysical, drilling, and reservoir simulation data, as well as the relevant concepts, appropriate results can be obtained [29]. Hence, a fuzzy multicriteria decision-making approach is necessary to accommodate different perspectives and provide a supportive framework with appropriate alternatives. These issues are addressed in the remainder of this paper, which is organized as follows: Section 2 proposes a new hierarchical approach and evaluation criteria to overcome the identified shortcomings and select the most appropriate wells for stimulation. Section 3 describes the implementation of the proposed method for choosing among alternative wells for stimulation. Section 4 summarizes the conclusions.

2. Mathematical Models

2.1. Determining the Factor Hierarchical Structure. According to the Gas Research Institute, the greatest benefit for the petroleum industry lies in the selection of candidate wells for stimulation [30]. Selecting target stimulation wells from huge numbers of producing wells in a reservoir is a difficult task involving different domains, attributes, and features. Xiong and Holditch [31] used nine fuzzy variables to assess candidate wells for hydraulic fracturing. Yang [5] studied the process of selecting candidate wells and considered nine influential factors to rank the wells. Yin and Wu [32] studied a range of multiattribute decision-making alternatives using seven parameters. Zoveidavianpoor [6, 33] considered eight drivers to choose the most suitable wells for fracturing. The selection criteria identified in these studies are listed in Table 1.

Some of the parameters identified in Table 1 are not always available, such as the skin factor, recovery percentage of reserves, heterogeneity coefficient, fracture width, fracturing effects, and drainage area. Conversely, several significant parameters are not included in Table 1, such as the information from the gamma ray log, density log, and neutron porosity log [33], structure and lithology [34, 35], and hydraulic fracturing and construction data [36].

Because the production following hydraulic fracturing is highly influenced by the reserve capacity, deliverability, and hydraulic efficiency, we use these three main criteria to determine the importance of candidate wells. These criteria are further divided into 14 subcriteria, which are listed in Table 2.

The selection hierarchy for choosing the most suitable candidate wells for stimulation is illustrated in Figure 1.

None of the previous studies used a broader set of selection criteria than that used in our model. This richness in the representation of each well makes it possible to perform analyses with few example cases in building the model. Furthermore, the presented model combines three types of data: crisp, linguistic, and fuzzy data, while the above studies utilized only one data type.

2.2. Weighting Factor Determination. To reflect the real importance of certain parameters in the choice of candidate wells, it is vital to rationally calculate the parameter weights. The factor priorities are determined using grey theory. The application of grey theory consists of a number of substeps, which are detailed below.

2.2.1. Comparative Series. An information series with m components or decision factors can be expressed as x_j. If all information series are comparable, then the m information series can be described by the following matrix [27]:

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_z \\ \vdots \\ x_l \end{bmatrix} = \begin{bmatrix} x_1(1) & \cdots & x_1(j) & \cdots & x_1(m) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_z(1) & \cdots & x_z(j) & \cdots & x_z(m) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_l(1) & \cdots & x_l(j) & \cdots & x_l(m) \end{bmatrix}, \quad z = 1, 2, \ldots, l;\ j = 1, 2, \ldots, m, \tag{1}$$

Table 1: Ranking criteria for candidate well selection.

Authors	Input variables
Xiong and Holditch [31]	Permeability/viscosity ratio, skin factor, net pay thickness, water saturation, formation pressure gradient, wellbore condition, drainage area, formation depth, and porosity
Yang [5]	Formation pressure, permeability, recovery percent of reserves, water saturation, production rate of the well, recovery percentage of reserves, flow coefficient, vertical heterogeneity coefficient, and producing pressure drop
Yin and Wu [32]	Skin factor, permeability, fluidity, water cut, reservoir pressure, fracture width, and fracturing effects
Zoveidavianpoor [6]	Permeability, skin, water saturation, porosity, net pay thickness, drainage area, formation pressure, and formation depth

Table 2: Criteria for the selection of the best candidate well.

Main criteria	C1: reserve capacity	C2: deliverability	C3: hydraulic efficiency
Subcriteria	C11: net pay thickness (TH) C12: porosity (POR) C13: gas saturation (SGT) C14: natural gamma porosity (GR) C15: neutron porosity (NR) C16: density (DEN) C17: sonic (SON)	C21: structure position (SPI) C22: lithology (LTG) C23: lateral resistivity difference (LRDD)	C31: discharge rate (DCR) C32: prepad volume (PRE) C33: slurry volume (SLU) C34: sand volume (SAN)

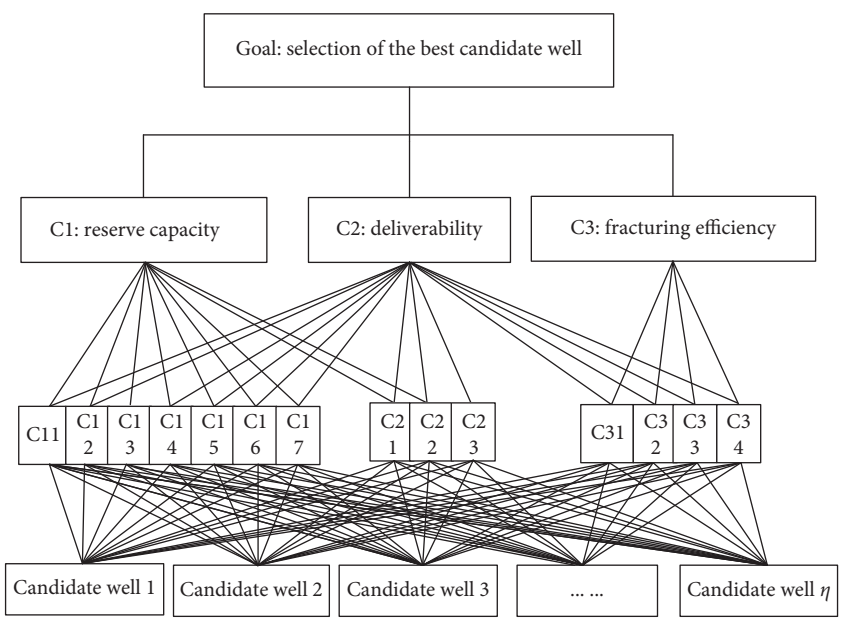


Figure 1: The most appropriate candidate well selection hierarchy.

where $x_z(j)$ denotes the jth factor of sample z and m is the criteria number of each individual well sample under consideration.

2.2.2. Standard Series. A standard series describes the degree of relationship between two series and is expressed as follows:

$$x_0 = \begin{bmatrix} x_0(1) \\ \vdots \\ x_0(z) \\ \vdots \\ x_0(l) \end{bmatrix} = \begin{bmatrix} q_0(1) \\ \vdots \\ q_0(z) \\ \vdots \\ q_0(l) \end{bmatrix}, \quad z = 1, 2, \ldots, l. \tag{2}$$

In our research, a standard series may represent the initial production of all considered sample wells l.

2.2.3. Difference between a Comparative Series and a Standard Series. The difference between the values of the decision factors and the norm of the standard series is determined as

$$D_0 = \begin{bmatrix} \Delta_{01}(1) & \cdots & \Delta_{01}(j) & \cdots & \Delta_{01}(m) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \Delta_{0z}(1) & \cdots & \Delta_{0z}(j) & \cdots & \Delta_{0z}(m) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \Delta_{0l}(1) & \cdots & \Delta_{0l}(j) & \cdots & \Delta_{0l}(m) \end{bmatrix}, \quad z = 1, 2, \ldots, l;\ j = 1, 2, \ldots, m, \tag{3}$$

where $\Delta_{0z}(j) = \|x_0(j) - x_z(j)\|$.

2.2.4. Grey Relational Coefficient. The local relationships can be constructed, and the relational coefficient can be expressed as

$$\gamma(x_0(j), x_z(j)) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0z}(j) + \zeta\Delta_{\max}}, \quad z = 1, 2, \ldots, l;\ j = 1, 2, \ldots, m, \tag{4}$$

$$\Delta_{0z}(j) = \|x_0(j) - x_z(j)\|, \tag{5}$$

$$\Delta_{\min} = \overset{\min}{\forall z \in l}\ \overset{\min}{\forall j}\ \|x_0(j) - x_z(j)\|, \tag{6}$$

$$\Delta_{\max} = \overset{\max}{\forall z \in l}\ \overset{\max}{\forall j}\ \|x_0(j) - x_z(j)\|, \tag{7}$$

where $x_0(j)$ is the standard series, $x_z(j)$ is the comparative series, and ζ is an identifier that is generally set to 0.5.

2.2.5. Weighting Factor Determination. Weights are distributed among the parameters to reflect their importance for well selection.

$$a_j = \frac{\gamma(x_0(j), x_z(j))}{\sum_{j=1}^{m} \gamma(x_0(j), x_z(j))}, \quad j = 1, 2, \ldots, m, \tag{8}$$

where a_j represents the weight degree of the jth factor relation for the candidate well and m is the number of factors for the individual wells under consideration.

2.3. Single-Factor Evaluation Model. Consider a problem in which each candidate well has m criteria $(u_j \mid j = 1, 2, \ldots, m)$ and n records in the output $(v_i \mid i = 1, 2, \ldots, n)$. The main objective is to determine which input variables u_j have the most significant impact on the output. A fuzzy rule is used for each point in the space; hence, one can obtain n fuzzy rules for the m points [6, 32]:

$$u_i(d) = e^{-[(d-a)/b]^2}, \tag{9}$$

where d is the value of the evaluation factor, i represents each reviewer's grade, and a and b are indicator parameters.

For the same review, the membership function is determined as follows:

$$u_{ji}(d_j) = e^{-\left[(d_j - a)/b\right]^2}, \tag{10}$$

where d_j represents the value of the jth evaluation factor and $u_{ji}(d_j)$ is the d_j membership of review i.

From formula (10), when $d_j = a$, $u_{ji}(a) = 1$, which indicates the largest membership. Therefore, a represents a level of expectation as follows:

$$a = \frac{(d_1 + d_2)}{2}, \tag{11}$$

where d_1 and d_2 are the maximum and minimum values of the ith review, respectively.

The value at these points is equal to the neighbouring review memberships, and such points are called transition points. The degree of membership of a transition point falls at the midpoint of the range of membership values and is equal to 0.5 for transition points connected to edge points [37]:

$$u_{ji}(d_1) = e^{-\left[(d_1 - d_2)/2b\right]^2} = 0.5. \tag{12}$$

Thus,

$$b = \frac{|d_1 - d_2|}{2\sqrt{\ln 2}}. \tag{13}$$

The membership function relationships can be determined after the parameters a and b are determined. These values represent the ith review level, which can be determined by statistical correlation analysis. The fuzzy evaluation set of the jth factor is as follows:

$$U_j = \left(u_{j1}, \ldots, u_{ji}, \ldots, u_{jn}\right)^T, \quad j = 1, 2, \ldots, m;\ i = 1, 2, \ldots, n. \tag{14}$$

The fuzzy possibility U_j is based on a single parameter and is unable to reflect the combined effects of all factors. With m parameters and n reviews, one can obtain the following matrix:

$$U = u_{ji}(d_j) = \begin{bmatrix} u_{11} & L & u_{1i} & L & u_{1n} \\ M & & & & M \\ u_{j1} & L & u_{ji} & L & u_{jn} \\ M & & & & M \\ u_{m1} & L & u_{mi} & L & u_{mn} \end{bmatrix}, \quad j = 1, 2, \ldots, m;\ i = 1, 2, \ldots, n. \tag{15}$$

2.4. Fuzzy Multicriteria Evaluation. The purpose of this step is to aggregate individual criteria into a group preference for each factor. The fuzzy multicriteria evaluation scores are obtained using a matrix multiplication summation

algorithm. The fuzzy vector B is then formed and combines the contributions of all the factors:

$$B = b_i = (b_1, \ldots, b_i, \ldots, b_n) = A \circ U$$
$$= (a_1, \ldots, a_j, \ldots, a_m) \circ \begin{bmatrix} u_{11} & u_{12} & \ldots & u_{1n} \\ u_{21} & u_{22} & \ldots & u_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ u_{m1} & u_{m2} & \ldots & u_{mn} \end{bmatrix}, \quad (16)$$
$$j = 1, 2, \ldots, m;\ i = 1, 2, \ldots, n,$$

where b_i is the evaluation index, which is the jth factor membership degree of the evaluation object when all input factors are taken into consideration. According to the principle of the maximum membership degree [28], the maximum b_i is used for final decision-making.

2.5. AHP Combined with Fuzzy Multicriteria Evaluation. Human judgement plays a decisive role throughout the process of candidate well selection. Some of the advantages of computer-based models are that they do not suffer from subjective biases and they give consistent results. However, they have limited flexibility in dealing with new conditions. Meanwhile, human operators can be highly adaptable in applying their knowledge and experience but can be inconsistent in their evaluations. Hence, it is desirable to combine the advantages of both approaches in decision-making. The correspondents include geologists, engineers, and managers. They applied their expert judgements in the evaluation as follows [18]:

(1) Within the supporting framework of the AHP, human experts make judgements about which factors are most significant within the areas of reserve capacity, deliverability, and construction factors. These can be expressed verbally, graphically, or numerically.

(2) Decision-makers then decide whether each criterion is positively or negatively correlated with the well output after fracturing. Then, grey theory is used to determine the relative importance of the individual factors and assign a weighting factor to each one. The results are then used for well selection.

(3) There is a further opportunity for the human validation and revision of the membership functions and fuzzy rules. They can also verify that the computer-based selection is consistent with their knowledge and intuition.

3. An Illustrative Application

The case study's objective is to demonstrate how the proposed method works for candidate well selection using fourteen input variables.

3.1. Source Information Analysis. Based on AHP principles and the actual candidate situation, a hierarchy composed of four levels, three main criteria, fourteen subcriteria, and n candidate wells was obtained, as shown in Figure 1. The criteria system is shown in Table 3.

The datasets used in this study came from fourteen gas wells, which were drilled in a complex fractured reservoir located in the Sichuan Basin in West China. The wells were named "well 1" through "well 14." According to geologists, all the wells were drilled in a similar depositional environment. Hence, the properties of one well can be used to infer the properties of other wells. In each well, data for fourteen factors, including geological, drilling, well log, and corresponding initial production information, are available. The input variables used for the analysis were the pay zone thickness (TH), effective porosity (POR), gas saturation (SGT), natural gamma (GR), compensating neutron porosity (NR), rock density (DEN), acoustic time difference (SON), well position in the trap (SPI), lithography (LTG), difference in lateral and vertical resistivity (LRDD), construction rate (DCR), volume of the prepad (PRE), slurry volume (SLU), and sand volume (SAN). These input variables are relatively easy to obtain and are sufficient for estimating the initial production (IP) of each candidate well. To evaluate the performance of the proposed method, wells 15 to 19 were used to test predictions that were made on the basis of the data from the fourteen other wells. The predictions were then verified by comparing the corresponding values with the actual values.

3.2. Input Variable Analysis. We used the sample data in Table 3 (well 1 to well 14) to apply linear regression analysis and determine the effect of each parameter on IP. Based on Figure 2, we found that IP increases with TH, POR, SGT, NR, SON, DCR, PRE, SLU, and SAN and that GR, DEN, SPI, LTG, and LRDD are negatively correlated with IP.

Using this knowledge in combination with the parameters in Table 3, we obtained ratings for all the input variables separately, as shown in Tables 4 and 5. Each input variable is divided into four equally spaced categories with grades "I," "II," "III," and "IV." Grade "I" represents the input variables with the largest positive correlations with IP, and grade "IV" represents those with the smallest correlations, as shown in Tables 4 and 5.

3.3. Fuzzy Weights. The relative importance of each input variable and the corresponding effect on the selection of candidate wells are critical when several possible input variables are considered. In this method, we use a grey theory tool to rank the parameters given in Table 3. Based on equations (1) to (8), we can obtain the reserve capacity, deliverability, and hydraulic efficiency criteria weights as 0.5117, 0.2005, and 0.2878, respectively. Similarly, Table 6 shows each factor weight value for the subcriteria (grade II).

When considering specific criteria weights in the assessment system, one can multiply the main criteria weights by the subcriteria weights. The calculation results show that the most important factors in the sequence are as follows: (1) POR, (2) SLU, (3) NR, (4) TH, (5) SGT, (6) SON, (7) DCR, (8) SAN, (9) GR, (10) SPI, (11) DEN, (12) PRE, (13) LTG, and (14) LRDD.

Table 3: Input data used in the sample case.

Code name	Reserve capacity							Deliverability			Hydraulic efficiency				Goal
	TH	POR	SGT	GR	NR	DEN	SON	SPI	LTG	LRDD	DCR	PRE	SLU	SAN	IP
Well 1	9.0	6.0	38	78.0	9.8	2.51	64.1	1.77	2.63	18.3	3.1	184.2	76.7	39.6	2.4
Well 2	12.0	8.5	42	64.5	14.5	2.47	66.0	1.77	2.18	7.0	3.2	152.2	69.3	31.2	5.1
Well 3	6.0	6.3	32	80.8	14.8	2.48	68.2	1.77	2.63	8.8	3.0	103.6	77.8	17.4	3.0
Well 4	7.5	7.0	53	69.5	11.5	2.47	69.8	1.77	2.63	16.0	3.2	106.7	61.0	23.3	5.2
Well 5	13.3	6.7	44	77.8	13.4	2.48	71.0	1.77	2.63	10.7	3.5	215.1	106.4	50.5	5.8
Well 6	5.8	9.7	54	87.8	13.4	2.46	71.0	1.77	2.63	10.7	3.5	92.8	45.9	20.0	4.0
Well 7	12.0	9.5	48	70.8	13.3	2.48	70.8	3.42	2.63	28.5	3.0	238.8	142.7	48.0	5.3
Well 8	17.1	5.9	40	80.5	11.4	2.5	67.8	1.77	2.18	12.5	3.5	187.4	98.3	41.0	3.4
Well 9	18.9	3.9	45	78.2	6.9	2.54	67.5	3.42	2.63	28.0	3.5	226.5	100.8	49.1	2.6
Well 10	20.5	10.8	54	63.3	14.3	2.4	72.3	1.77	2.63	7.6	3.6	512.5	278.4	112.8	8.6
Well 11	22.0	9.5	52	61.3	17.5	2.43	71.0	1.77	2.18	7.0	3.9	449.8	224.6	101.2	6.5
Well 12	6.0	6.3	32	82.0	14.8	2.48	68.2	1.77	2.63	8.8	3.0	67.9	33.3	21.4	3.0
Well 13	17.9	9.0	44	69.5	14.5	2.43	71.5	1.77	2.18	10.3	3.5	106.9	62.5	21.5	6.7
Well 14	16.8	9.7	29	88.0	16.7	2.44	71.5	1.77	2.63	5.8	3.2	77.8	43.4	16.8	4.8
Well 15	12.0	9.2	49	70.8	12.6	2.45	72.1	3.42	2.63	14.5	3.2	121.1	63.2	26.4	
Well 16	17.9	9.0	44	69.5	14.5	2.42	71.5	1.77	2.63	10.3	3.5	103.3	60.4	21.5	
Well 17	7.5	7.0	53	69.5	11.5	2.46	69.8	1.77	2.63	16.0	3.2	106.7	61.0	23.3	
Well 18	15.0	9.6	46	81.0	11.9	2.48	69.5	1.77	2.18	16.0	3.2	189.2	98.8	42.0	
Well 19	12.8	9.1	36	78.0	14.7	2.42	71.5	1.77	2.63	5.8	3.3	94.8	46.3	20.5	

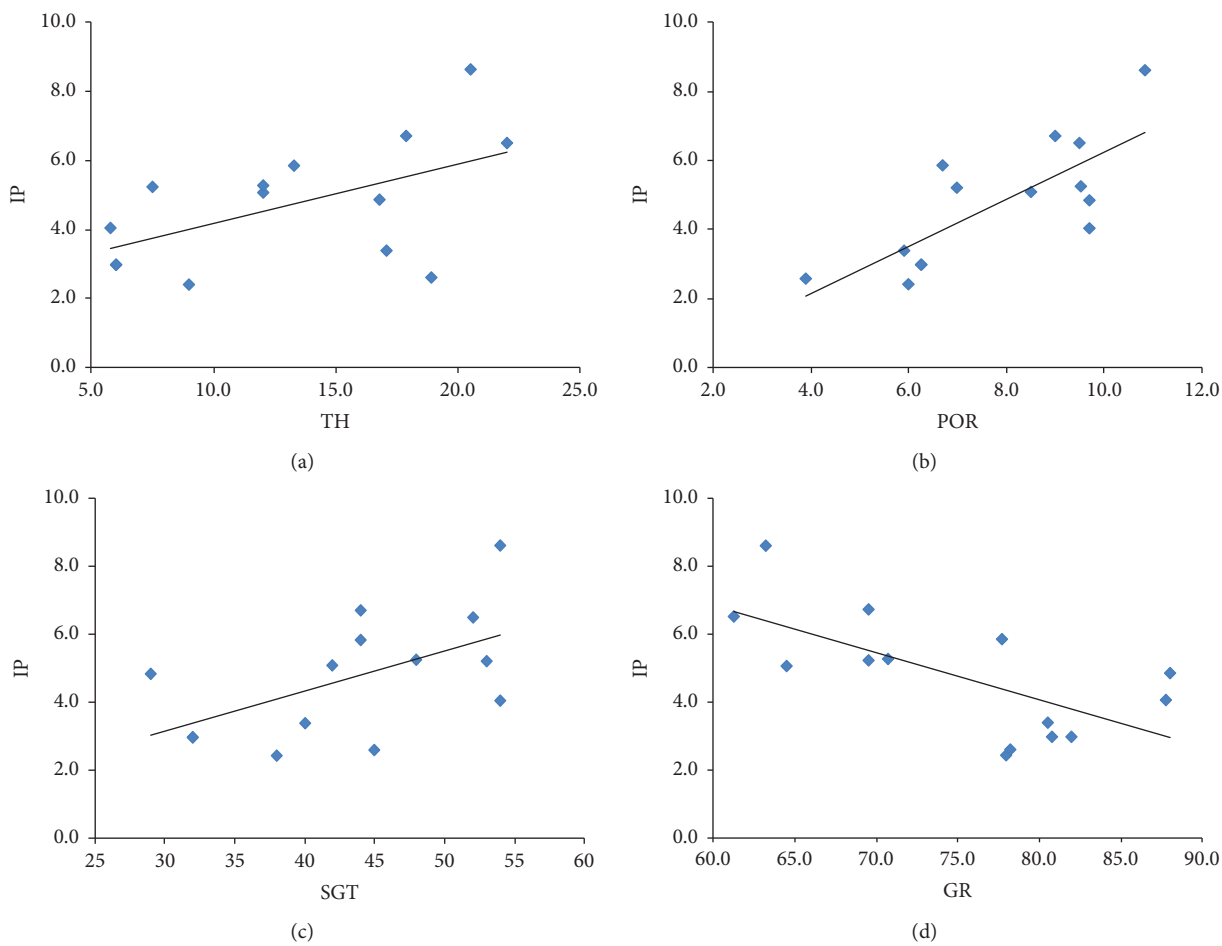
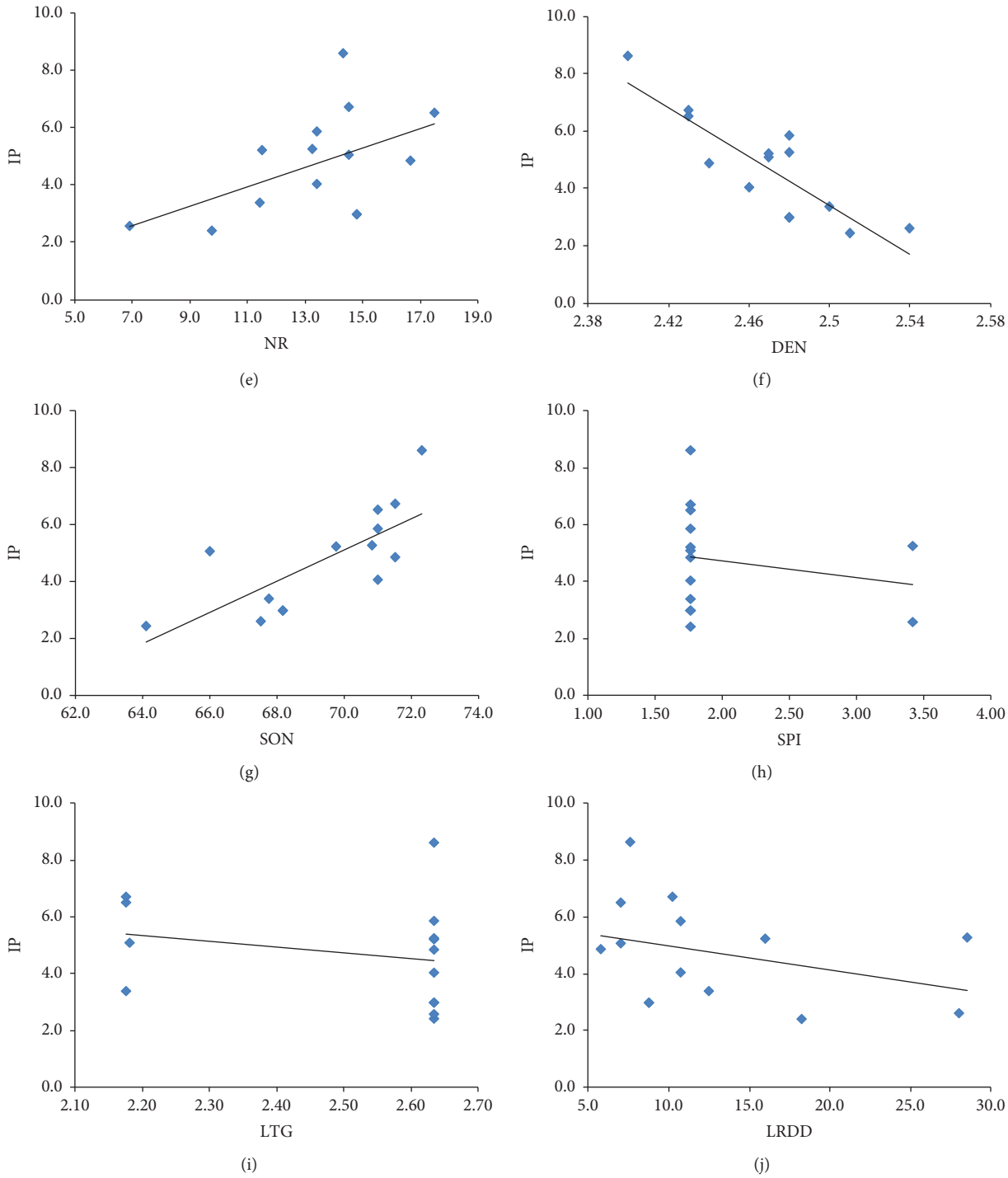


Figure 2: Continued.



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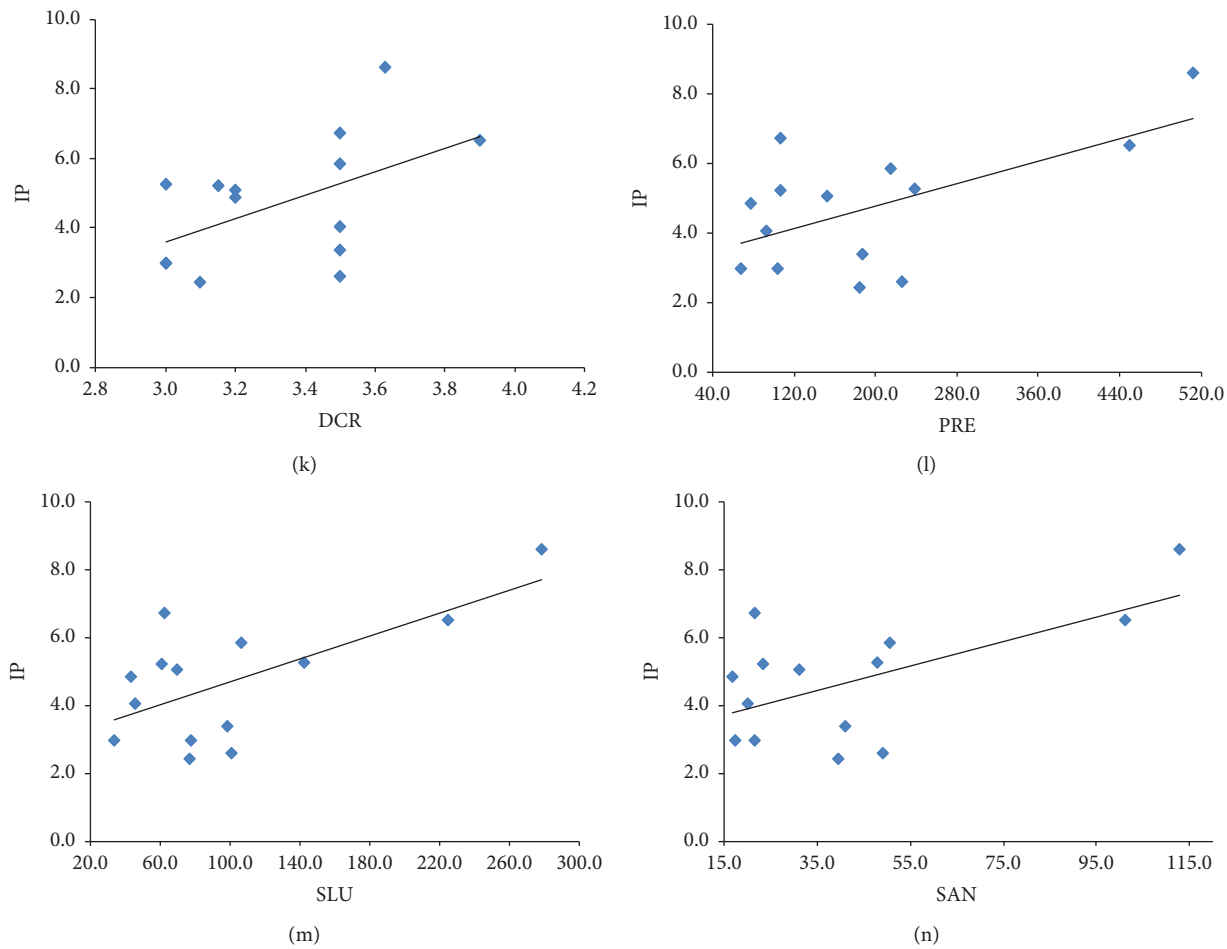

Figure 2: Testing the initial production relationship data with input variables.

Table 4: Review grades of reserve capacity factor.

Review grade	TH	POR	SGT	GR	NR	DEN	SON
I	22.00–17.94	10.83–9.09	54.00–47.75	61.29–67.97	17.5–14.84	2.39–2.43	72.29–70.25
II	17.94–13.89	9.09–7.36	47.75–41.50	67.97–74.64	14.84–12.19	2.43–2.47	70.25–68.20
III	13.89–9.84	7.36–5.63	41.50–35.25	74.64–81.32	12.19–9.54	2.47–2.50	68.20–66.15
IV	9.84–5.79	5.63–3.90	35.25–29.00	81.32–87.99	9.54–6.89	2.50–2.54	66.15–64.10

Table 5: Review grades of deliverability and hydraulic efficiency factors.

Review grade	Deliverability			Hydraulic efficiency			
	SPI	LTG	LRDD	DCR	PRE	SLU	SAN
I	1.76–2.18	2.17–2.28	5.75–11.43	3.89–3.67	512.5–401.33	278.39–217.11	112.75–88.76
II	2.18–2.59	2.28–2.40	11.43–17.12	3.67–3.44	401.33–290.17	217.11–155.83	88.76–64.77
III	2.59–3.00	2.40–2.51	17.12–22.81	3.44–3.22	290.17–179.01	155.83–94.55	64.77–40.78
IV	3.00–3.41	2.51–2.63	22.81–28.50	3.22–2.99	179.01–67.85	94.55–33.27	40.78–16.80

Figure 3 shows that the input variable weights vary between 0 and 1. Clearly, POR is found to be the highest-ranked driver in this example.

3.4. Single-Criterion Candidate Well Selection. Table 7 provides the fuzzy scores of fourteen evaluation parameters with four review grades for well 15 using equations (10) to (14). Based on the maximum membership degree principle, the rating of input variable TH is closest to review grade "III," so we can say that the TH (net pay thickness) of well 15 is grade "III." POR is grade "I." As previously mentioned, the candidate well selection results are affected by all the relevant criteria, and it is essential to combine the factors to tackle the task in a comprehensive way.

Table 6: Factor criteria weights.

Main criteria weights		Subcriteria weights		
Factor	Weight	Factor	Correlation coefficient	Weight
Reserve capacity	0.5117	TH	0.7086	0.1445
		POR	0.7373	0.1503
		SGT	0.6936	0.1414
		GR	0.6714	0.1369
		NR	0.7324	0.1493
		DEN	0.6688	0.1364
Deliverability	0.2005	SON	0.6929	0.1413
		SPI	0.6705	0.3489
		LTG	0.6614	0.3441
		LRDD	0.5900	0.3070
Hydraulic efficiency	0.2878	DCR	0.6852	0.2484
		SAR	0.6662	0.2415
		PADR	0.7354	0.2666
		SANDR	0.6719	0.2436

PADR is the ratio of the prepad fluid volume to the injected fluid volume. SANDR is the ratio of the prepad sand volume to the slurry volume.

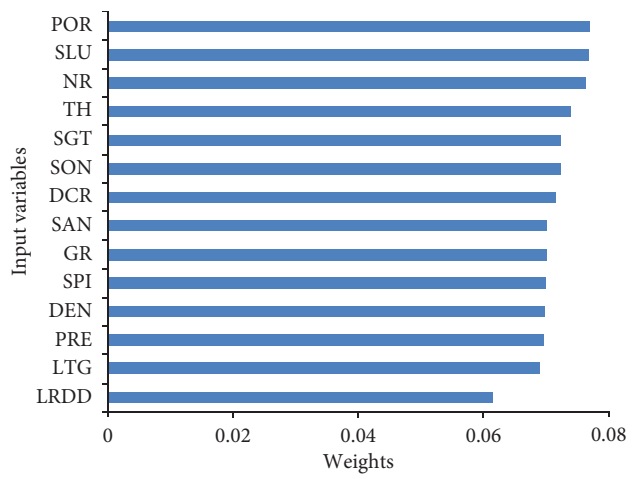

Figure 3: Ranking the input drivers between 0 and 1.

Table 7: Input values of well 15 and the fuzzy scores.

Input variables	Value	Fuzzy scores			
		I	II	III	IV
TH	12.0	0.0000	0.0625	1.0000	0.0625
POR	9.2	0.5892	0.4145	0.0011	0.0000
SGT	49	0.7792	0.2570	0.0003	0.0000
GR	70.8	0.0976	0.9810	0.0389	0.0000
NR	12.6	0.0074	0.7340	0.2923	0.0005
DEN	2.45	0.0625	1.0000	0.0230	0.0002
SON	72.1	0.6319	0.0043	0.0000	0.0000
SPI	3.42	0.4665	0.0016	0.0000	0.0000
LTG	2.63	0.0000	0.0000	0.0006	0.4545
LRDD	14.5	0.0497	0.9957	0.0775	0.0000
DCR	3.2	0.0000	0.0028	0.5000	0.5000
SAR	121.1	0.0000	0.0000	0.0556	0.9988
PADR	63.2	0.0000	0.0000	0.0587	0.9997
SANDR	26.4	0.0000	0.0000	0.1019	0.9766

Table 8: Measured data and single-criterion fuzzy scores of wells.

Input variables	Well 16					Well 17					Well 18					Well 19				
	Value	Fuzzy scores				Value	Fuzzy scores				Value	Fuzzy scores				Value	Fuzzy scores			
		I	II	III	IV		I	II	III	IV		I	II	III	IV		I	II	III	IV
TH	**17.9**	0.4657	0.5350	0.0024	0.0000	**7.5**	0.0000	0.0000	0.0299	0.9576	**15.0**	0.0131	0.8409	0.2102	0.0002	**12.8**	0.0001	0.1696	0.8950	0.0185
POR	**9.0**	0.4300	0.5733	0.0030	0.0000	**7.0**	0.0003	0.2490	0.7896	0.0098	**9.6**	0.8881	0.1735	0.0001	0.0000	**9.1**	0.5080	0.4920	0.0019	0.0000
SGT	**44**	0.0349	0.9727	0.1058	0.0000	**53**	0.7258	0.0069	0.0000	0.0000	**46**	0.1851	0.8744	0.0161	0.0000	**36**	0.0000	0.0051	0.6701	0.3445
GR	**69.5**	0.2291	0.8162	0.0115	0.0000	**69.5**	0.2291	0.8162	0.0115	0.0000	**81.0**	0.0000	0.0029	0.5674	0.4349	**78.0**	0.0000	0.0612	1.0000	0.0633
NR	**14.5**	0.3353	0.6818	0.0054	0.0000	**11.5**	0.0002	0.2013	0.8528	0.0141	**11.9**	0.0008	0.3571	0.6551	0.0047	**14.7**	0.4288	0.5744	0.0030	0.0000
DEN	**2.42**	0.8409	0.2102	0.0000	0.0000	**2.46**	0.0131	0.8409	0.1458	0.0020	**2.48**	0.0002	0.2102	0.9259	0.0625	**2.42**	0.8409	0.2102	0.0000	0.0000
SON	**71.5**	0.9654	0.0329	0.0000	0.0000	**69.8**	0.2370	0.8040	0.0106	0.0000	**69.5**	0.1240	0.9513	0.0283	0.0000	**71.5**	0.9654	0.0329	0.0000	0.0000
SPI	**1.77**	0.0000	0.0000	0.0020	0.5333	**1.77**	0.0000	0.0000	0.0020	0.5333	**1.77**	0.0000	0.0000	0.0020	0.5333	**1.77**	0.0000	0.0000	0.0020	0.5333
LTG	**2.63**	0.0000	0.0000	0.0009	0.5000	**2.63**	0.0000	0.0000	0.0009	0.5000	**2.18**	0.6288	0.0072	0.0000	0.0000	**2.63**	0.0000	0.0000	0.0009	0.5000
LRDD	**10.3**	0.7778	0.2584	0.0003	0.0000	**16.0**	0.0089	0.7751	0.2602	0.0003	**16.0**	0.0089	0.7751	0.2602	0.0003	**5.8**	0.5122	0.0021	0.0000	0.0000
DCR	**3.5**	0.0112	0.8534	0.1910	0.0003	**3.2**	0.0000	0.0014	0.3798	0.6231	**3.2**	0.0000	0.0014	0.3798	0.6231	**3.3**	0.0000	0.0331	0.9498	0.1363
SAR	**103.3**	0.0000	0.0000	0.0209	0.9131	**106.7**	0.0000	0.0000	0.0255	0.9391	**189.2**	0.0000	0.0041	0.6298	0.3789	**94.8**	0.0000	0.0000	0.0125	0.8320
PADR	**60.4**	0.0000	0.0000	0.0451	0.9909	**61.0**	0.0000	0.0000	0.0477	0.9938	**98.8**	0.0000	0.0034	0.5980	0.4071	**46.3**	0.0000	0.0000	0.0101	0.7954
SANDR	**21.5**	0.0000	0.0000	0.0347	0.9721	**23.3**	0.0000	0.0000	0.0528	0.9975	**42.0**	0.0000	0.0098	0.7894	0.2492	**20.5**	0.0000	0.0000	0.0272	0.9467

Table 9: Rating and ranking of other wells.

Candidate alternatives	Fuzzy scores				Rating	Ranking	IP (10^4 m^3/d)
	I	II	III	IV			
Well 15	0.1621	0.3121	0.1519	0.3176	IV	4	4.62
Well 16	0.3274	0.3556	0.0028	0.0028	II	2	6.74
Well 17	0.1244	0.2567	0.1902	0.3555	IV	5	3.21
Well 18	0.1730	0.3007	0.3443	0.1674	III	3	5.84
Well 19	0.2689	0.1204	0.2525	0.2436	I	1	7.25

3.5. Fuzzy Multicriteria Candidate Well Selection. The fuzzy comprehensive evaluation vector B, which considers the contributions of all the factors, is derived a follows:

$$\begin{aligned} B &= A \circ U \\ &= \begin{bmatrix} 0.0739 & 0.0749 & 0.0705 & 0.0682 & 0.0744 & 0.0680 & 0.0704 & 0.0681 & 0.0672 & 0.0599 & 0.0696 & 0.0677 & 0.0747 & 0.0683 \end{bmatrix} \\ &\quad \circ \begin{bmatrix} 0.0000 & 0.0625 & 1.0000 & 0.0625 \\ 0.5892 & 0.4145 & 0.0011 & 0.0000 \\ 0.7792 & 0.2570 & 0.0003 & 0.0000 \\ 0.0976 & 0.9810 & 0.0389 & 0.0000 \\ 0.0074 & 0.7340 & 0.2923 & 0.0005 \\ 0.0625 & 1.0000 & 0.0230 & 0.0002 \\ 0.6319 & 0.0043 & 0.0000 & 0.0000 \\ 0.4665 & 0.0016 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.0006 & 0.4545 \\ 0.0497 & 0.9957 & 0.0775 & 0.0000 \\ 0.0000 & 0.0028 & 0.5000 & 0.5000 \\ 0.0000 & 0.0000 & 0.0556 & 0.9988 \\ 0.0000 & 0.0000 & 0.0587 & 0.9997 \\ 0.0000 & 0.0000 & 0.1019 & 0.9766 \end{bmatrix}, = \begin{bmatrix} 0.1621 & 0.3121 & 0.1519 & 0.3176 \end{bmatrix}, \end{aligned} \tag{17}$$

where b_i reflects the value set of grades "I," "II," "III," and "IV." Equation (17) shows that the fuzzy scores of well 15 for grades "I," "II," "III," and "IV" are 0.1621, 0.3122, 0.1519, and 0.3176, respectively. According to the maximum membership degree principle, the rating of the well is closest to grade "IV," so we can say that candidate well 15 belongs to review grade "IV." Similarly, the results for the other four wells are shown in Table 8.

Finally, all the candidate well fuzzy scores and ranking results are listed in Table 9. "Well 19," which has the maximum fuzzy score values closest to review grade "I," is determined to be the best candidate for hydraulic fracturing. The ranking of the candidate wells can be summarized in the following order: well 19, well 16, well 18, well 15, and well 17. The field application shows that the wells with high fuzzy scores consistently have high initial production levels after hydraulic fracturing.

4. Conclusions

Appropriate well selection for stimulation is one of the most important decisions taken by oilfield engineers, and it incorporates geological parameters, construction parameters, and economic effects. Uncertainty is an inherent condition in the candidate well selection decision-making process. This paper presents a modified fuzzy AHP multiple-criteria decision-making approach developed to choose the most appropriate stimulation wells based on a number of criteria. The proposed methodology allows hydraulic fracturing data to be used in a flexible way by exploiting linguistic terms,

fuzzy numbers, precise numerical values, and ranges of numerical values. The main advantage of the method introduced in this paper is that it requires a relatively small number of samples to identify the wells most likely to benefit from a fracture treatment without human interference. Notably, the method uses the available data for each well, including the reservoir parameter information, fracture treatment information, and production history, to find the most promising candidate well. A field application shows that the presented model based on the proposed complex evaluation system provides satisfactory candidate wells with high production levels. This study is based on actual field data, and there are no a priori assumptions or simulated data used in the verification of the method. This approach provides well-structured comprehensive information at different levels to aid in decision-making.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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