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Hybridising Human Judgment, AHP, Grey Theory, and Fuzzy Expert Systems for Candidate Well Selection in Fractured Reservoirs

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Academic Editor: Moran Wang

Received: 9 January 2017; Accepted: 24 March 2017; Published: 1 April 2017

Abstract: The selection of appropriate wells for hydraulic fracturing is one of the most important decisions faced by oilfield engineers. It has significant implications for the future development of an oilfield in terms of its productivity and economics. In this study, we developed a fuzzy model for well selection that combines the major objective criteria with the subjective judgments of decision makers. This was done by fusing the analytic hierarchy process (AHP) method, grey theory and an advanced version of fuzzy logic theory (FLT). The AHP component was used to identify the relevant criteria involved in selecting wells for hydraulic fracturing. Grey theory was used to determine the relative importance of those criteria. Then a fuzzy expert system was applied to fuzzily process the aggregated inputs using a Type-2 fuzzy logic system. This undertakes approximate reasoning and generates recommendations for candidate wells. These techniques and technologies were hybridized by using an intercommunication job-sharing method that integrates human judgment. The proposed method was tested on data from an oilfield in Western China and finally the most appropriate candidate wells for hydraulic fracturing were ranked in order of their projected output after fracturing.

Keywords: fractured reservoirs; analytic hierarchy process (AHP); grey theory; fuzzy expert system; candidate wells selection; field application

1. Introduction

Naturally fractured reservoirs represent a significant percentage of oil and gas reservoirs throughout the world [1]. Hydraulic fracturing is a crucial technology for economically developing this type of reservoir. It was found that hydraulic fracturing of existing wells was more economic than infill drilling [2]. In addition, the possibility of future discoveries of giant oil and gas reservoirs in the world is low. Hence, a robust and efficient method for choosing wells for fracturing through the utilization of the available reservoir data would lead to maximizing the recovery rates and efficiency of existing fields. Candidate well selection is the process of choosing wells that have the potential for higher production and better return on investment following the stimulation process [3]. Over the last few decades, a number of studies have investigated the application of a range of decision support and artificial intelligence techniques and technologies in candidate well selection. These range from decision support systems using multivariate nonlinear regression [4–6] to neural networks [7–10], analytical hierarchy process (AHP) [11–16] and fuzzy logic [10,17–20]. Each of these approaches carries with it a set of advantages and limitations. Hence, it would seem natural that some attempts have been made to integrate them in order to obtain the best of all approaches [21–25].

In order to choose the most appropriate wells for hydraulic fracturing, it is advantageous to be able to take into account all known relevant criteria. However, this increases the complexity of the process and may raise the number of parameters beyond the capacity of many conventional methods. Therefore, a way to assess all of the known criteria by combining methods would be very useful [25,26].

Many operators agree that the candidate well choosing process involves a high level of uncertainty and ambiguity [7,21]. Large scale field applications also show that one main factor leading to prominent dissatisfaction is the systems' inability to handle uncertainty [23,27]. Each parameter or selection criterion has its own unique influence on identifying suitable candidate wells for hydraulic fracturing. Determining the relative importance of each one under varying conditions is complicated by confounding factors such as human bias, subjectivity and the complex interrelationships among the various criteria.

AHP [15,28,29] provides a way to deal with these uncertainties by providing a framework for making pairwise comparisons among the criteria and assigning appropriate weights to each factor. However, it is sometimes difficult to make an accurate comparison due to incomplete information or uncertainty about the amount of difference there is between factors. In this situation, there is a need to augment the classical AHP method to be able to operate in the presence of fuzzy or incomplete comparisons [14]. There is also some inherent statistical variation associated with the assessment provided by human decision makers. Hence, in order to reflect this stochastic behavior, it may be useful to apply a probability distribution to impute the values for certain variables.

Some researchers [30,31] highlight that geoscience disciplines, including candidate well selection decisions are subject to multiple sources of uncertainty and contain fuzzy issues. As a statistical technique, fuzzy logic has gained attention as for its ability to cope with uncertainty [18,32] and imprecise linguistic concepts or fuzzy terms [33]. This is particularly true for the newly introduced type-2 fuzzy logic systems (type-2 FLS) [34–36].

In addition to the issues relating to uncertainties, it is also evident that many operators lack the very high level of technical knowledge and analytical skills needed for selecting candidate wells for fracturing [37]. McVey et al. [2,38,39] argue that there is a need to provide a methodology that facilitates selecting the desired well/layer with minimum time and costs and that provides a framework that makes it easier to overcome the difficulties in conventional techniques.

In addition to the large number of objective and measurable factors that inform the selection of wells for fracturing, many oilfield operators possess a wealth of experience, intuition, and judgement that is invaluable for decision making. Therefore, operators' judgement, intuition, and creativity should be an integral element of the candidate well selection process. However, there are no previous examples in the literature, where AHP, grey theory and fuzzy logic have been combined for the purpose of selecting wells for hydraulic fracturing. This paper aims to satisfy this need by implementing such a system and then to measure its performance on a set of wells in Western China.

The remainder of this paper is organised as follows. First, we present an overview of the hybridisation method, which combines human judgement, AHP, grey theory, and fuzzy logic. Each component is then described in more detail. This is followed by an evaluation of the method by testing it in a field application, and then the performance of the presented method is compared against a neural network application. Finally, some conclusions are drawn at the end of the paper.

2. A Hybrid Approach that Combines Human Judgment, AHP, Grey Theory, and Fuzzy Expert Systems for Candidate Well Selection

The problem of selecting the most appropriate well for fracturing is highly complex and involves several interacting variables. In this context, we use a combined method known as judgment incorporated intercommunication hybridisation for addressing the candidate well selection problem. In this method, the overall problem is divided into distinct jobs, with the roles of human decision-makers clarified and defined. These jobs are then assigned to relatively independent and distributed software components that share or exchange data, information and knowledge. The various tasks are carried out synchronously to produce solutions that incorporate human participants' judgement for joint problem solving. The main motivation for designing such integration is to achieve a hybrid of diverse functions and the benefits of different tools in order to deliver improved decision support capabilities for candidate well selection.

The architecture of the hybrid approach is illustrated in Figure 1, where different shapes are used to depict different system elements. The system consists of an AHP component that helps to determine individual strategic factors, a grey theory component that simulates and estimates the relative importance of the relevant factors as well as the fuzzy expert system element that performs intelligent approximate reasoning and recommends candidate wells. The central square-shaped symbol represents human judgment, which links all the elements in an intercommunication job-sharing method.

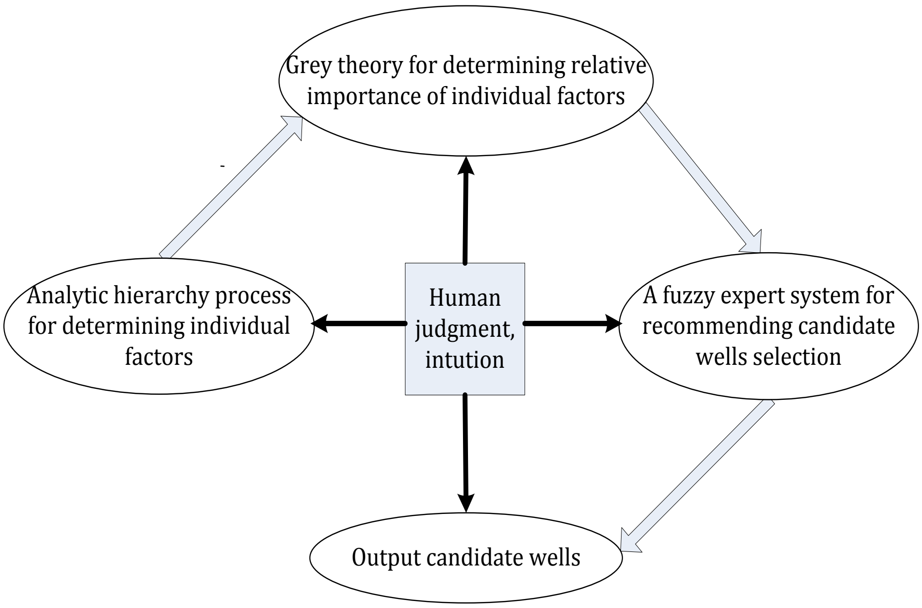


Figure 1. The architecture of the hybrid approach.

3. The AHP Component

The limitations of human cognition make it difficult to reliably obtain information about a complex system when there is a large volume of data in a range of disparate formats. AHP was developed to assist decision-making when there is a mix of qualitative, quantitative, and sometimes conflicting factors. It has previously been shown to be very effective in making complicated and often irreversible decisions [29,40]. The AHP component of the hybrid approach provides a framework to assist the operators to make reliable judgements when presented with verbal, graphical or numeric data [41]. The results are then passed to the fuzzy expert system, which recommends wells for fracturing.

For the purposes of this study, the factors or criteria to be taken into consideration for selecting wells were obtained from actual field data and have been verified by experts [3,20,42]. These are arranged into three high-level categories: 'reserve capacity', 'deliverability', and 'fracturing efficiency'. These are then subdivided into several factors: 'thickness' (TH), 'porosity' (POR), 'gas saturation' (SGT), 'natural gamma' (GR), 'neutron' (NR), 'density' (DEN), 'sonic' (SON), 'structure position' (SPI), 'lithology' (LTG), 'lateral resistivity depth difference' (LRDD), 'discharge rate' (DCR), 'sand ratio' (SAR), 'prepad ratio' (PADR), and 'sand intensity' (SANDR). This arrangement is shown in Table 1 and illustrated in Figure 2.

Table 1. Criteria taken into account to select the best well.

Main Criteria	C1: Reserve Capacity	C2: Deliverability	C3: Hydraulic Efficiency
Sub criteria	C11: Thickness C12: Porosity C13: Gas saturation C14: Natural gamma C15: Neutron C16: Density C17: Sonic	C21: Structure position C22: Lithology C23: Lateral resistivity depth difference	C31: Discharge rate C32: Sand ratio C33: Prepad ratio C34: Sand intensity

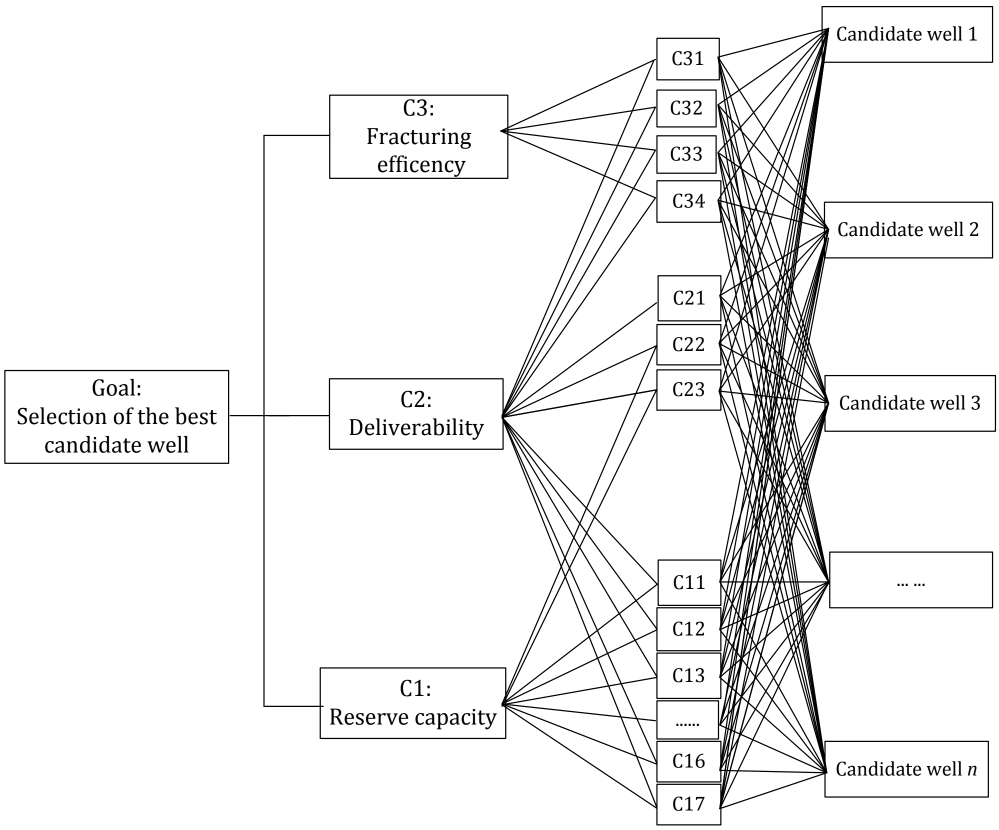


Figure 2. A hierarchy for selection of the most appropriate candidate well.

4. The Grey Theory Component

After the formation of the decision hierarchy, the second stage of the well selection process is to assign weights to the criteria using what is known as grey theory. Grey system theory is an interdisciplinary scientific area that was first introduced by Deng [43]. Its advantage over conventional statistical methods is that grey models only require a limited amount of data to estimate the behavior of unknown systems [44] and obtain an unbiased and consistent point estimator. In grey systems, items such as operation, mechanism, structure, and behavior, are neither deterministic nor totally unknown, but are partially known. System behavior is explored using relational analysis and model construction [44]. The method involves several steps, which are briefly discussed here.

4.1. Determine the Compared and Reference Sequence

In order to use grey theory, the first step is to generate an interval comparative series, which reflects the various criteria to be used for well selection. The decision factors can be represented by r_{zj}, which are the evaluation object factors. Equation (1) shows a generic comparative series comprising l wells with m decision factors represented in the form of a matrix r_{lm}.

$$r = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1m} \\ \vdots & & & & \vdots \\ r_{z1} & \cdots & r_{zj} & \cdots & r_{zm} \\ \vdots & & & & \vdots \\ r_{l1} & \cdots & r_{lj} & \cdots & r_{lm} \end{bmatrix} \quad z = 1,2,\ldots\ldots l;\ j = 1,2,\ldots\ldots m \tag{1}$$

where in m is the number of criteria for each well, l is the number of comparative series samples. The standard series is defined as an objective series that reflects the desired level of all the criteria. Here, this is made up of the 'initial production' (IP) of each well after hydraulic fracturing.

$$r_0 = (r_1, \ldots, r_z \ldots, r_l)^T \quad z = 1,2,\ldots\ldots, l \tag{2}$$

4.2. Dimensionless Processing

For better comparability between factors, it is essential to normalise the comparative series by performing a grey extreme difference transform. By correlating with IP, for the bigger is the better type indexes, the corresponding measured value of r^*_{zj} is:

$$r^*_{zj} = \frac{r_{zj} - \left(r_{zj}\right)_{\min}}{\left(r_{zj}\right)_{\max} - \left(r_{zj}\right)_{\min}} \quad z = 1,2,\ldots\ldots, l;\ j = 1,2,\ldots\ldots, m \tag{3}$$

For the smaller is the better type, the corresponding measured value of r^*_{zj} is:

$$r^*_{zj} = 1 - \frac{r_{zj} - \left(r_{zj}\right)_{\min}}{\left(r_{zj}\right)_{\max} - \left(r_{zj}\right)_{\min}} \quad z = 1,2,\ldots\ldots, l;\ j = 1,2,\ldots\ldots, m \tag{4}$$

where $\left(r_{zj}\right)_{\min}$ represents the minimum value of the jth criteria of all samples l, $\left(r_{zj}\right)_{\max}$ represents the maximum value of the jth feature of all samples l. Then we can obtain a normalized evaluation vector within the range [0, 1].

$$r^* = \left(r^*_{zj}\right)_{l\times m} \tag{5}$$

4.3. Calculation of Grey Relation Coefficient

The difference between the comparative and standard series is calculated using Equation (6) and is known as the grey relation coefficient:

$$\xi_z(j) = \frac{\min\limits_{1\le z\le l}\min\limits_{1\le j\le m} \Delta_z(j) + \rho \max\limits_{1\le z\le l}\max\limits_{1\le j\le m} \Delta_z(j)}{\Delta_z(j) + \min\limits_{1\le z\le l}\min\limits_{1\le j\le m} \Delta_z(j)} \tag{6}$$

where $\Delta_z(j) = \left| r^*_0(j) - r^*_{zj} \right|$, $r^*_0(j)$ is the value of the standard series $r_0(j)$ under dimensionless processing with Equations (3) and (4), r^*_{zj} is the normalized evaluation value, and ρ is an identifier which only affects the relative value of risk without changing the priority, which can be set at 0.5 [45].

4.4. Solution of the Correlation Coefficient

The essence of the correlation analysis is to compare the comparative series and standard series. The correlation between the two sequences will be the average of the two sequences associated with each moment coefficients, namely:

$$\gamma_j = \frac{1}{l}\sum_{z=1}^{l} \xi_z(j) \quad j = 1, 2, \ldots . m \tag{7}$$

4.5. Calculation of the Weighting Factor

Each parameter is given a weight to reflect its overall importance in well selection. The weights are obtained as follows:

$$a_j = r_j / \sum_{k=1}^{m} r_j \quad j = 1, 2, \ldots . m \tag{8}$$

From this, we obtain vector $A = (a_1, a_2, \ldots, a_j \ldots, a_m)$. The degree of relation in the candidate well selection model denotes the relationship between the potential factors and the likelihood of choosing the candidate well. The higher the value obtained from Equation (8), the more influence it has on candidate well selection. Therefore, the increasing order of the degree of relation represents the importance ranking of the criterion.

5. The Fuzzy Expert System Component

Decision makers often find that they are more confident in giving interval judgments rather than fixed value judgments. This is usually due to a desire to express something about the fuzzy nature of the comparison process [46]. The strength of fuzzy logic is its ability to use deterministic tools to quantify uncertainty. The key point in fuzzy logic is to find the appropriate fuzzy rules, which is a membership function employed to transform the fuzzy scales into crisp scales for the computation of a single parameter fuzzy probability. There are several methods of doing this. In this paper, we employ Type-2 fuzzy sets (Interval Fuzzy Sets and Systems) to address this problem.

5.1. Fuzzification of the Individual Factors

The system initially receives inputs for each criterion derived from the human experts using the AHP. The criteria are then converted into fuzzy memberships as listed where Type-2 fuzzy sets and systems membership functions are used. Type-2 fuzzy sets provide a means of dealing with situations where there is uncertainty about the value of the membership function itself. Type-2 fuzzy set logic is a generalization of conventional fuzzy logic (type-1) in the sense that uncertainty is not only limited to the linguistic variables but also is present in the definition of the membership functions [47]. In Type-2, the membership grade is itself a fuzzy set in the range [0, 1]. The use of Type-2 fuzzy sets is now quite widespread [19,48]. For an interval Type-2 Fuzzy Sets and Systems the third-dimension value is the same everywhere, which means that no new information is contained in the third dimension. In this case, we applied a fuzzy rule to each point in the space. This generates n fuzzy rules for the m points. Each of these fuzzy rules was calculated following [3,20,49] as:

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

where d is the value of the criteria; i is the review grade, which is obtained by giving a certain rank to each parameter according to the field engineer and expert's judgement; a, b are parameters calculated as follows. The membership function to determine the level of the same review is:

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

In the formula: d_j represents the value of the j-th criterion; $u_{ji}(d_j)$ is the d_j membership of the review i.

In Equation (11), a is the level of mathematical expectation

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

Here, d_1, d_2 are the intervals of the i-th review level, the upper and lower limit value. The lower limit of the transition point is both a previous review level and the maximum level after a review, so the degree of membership of the transition point is 0.5, i.e.,:

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

and then,

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

It is notable that once the parameter values a, b are determined, the membership function relationships are also determined. While the interval limit values a, b are determined by the i-th review level, which can be obtained from the statistical correlation analysis of mathematical methods.

5.2. Evaluation of Individual Factors

Based on Equations (12) and (13), we can obtain individual criterion in the results of the evaluation of the$j$-th factor in the fuzzy evaluation set.

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

Each fuzzy possibility is now associated with a possible candidate well selection but the fuzzy possibility U_j only reflects one criterion. It is clear that a single criterion only reflects one aspect of the candidate well selection problem so that it cannot reflect the combined effects of all the criteria. Based on Equations (9)–(14), this process is repeated for a second criterion and will give another U_j. This can be repeated for all the criteria. If there are m criteria with n assessment levels the following $m \times n$ fuzzy matrix U can be obtained.

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

5.3. Candidate Well Selection for Hydraulic Fracturing Recommendations

In Equation (15), we have several fuzzy possibilities U_j based on the fuzzy possibilities from the different criteria used in well selection. These fuzzy possibilities will be combined to generate an overall fuzzy possibility. In this paper, we use fuzzy comprehensive evaluation theory [50]. The matrix multiplication summation algorithm, fuzzy evaluation matrix U composite fuzzy weight vector $\boldsymbol{A}$ single factor, considering the contribution of all the factors, the subject being evaluated fuzzy comprehensive evaluation vector, $\boldsymbol{B}$:

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

where b_i is the evaluation index, which is the degree of membership when all criteria are considered. The maximum of b_i is the final result [51].

6. Coupling Human Judgment with the Hybrid Approach

Human judgment 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 to decision-making. In order to integrate human judgment with the hybrid approach, the following guidelines are proposed:

(1) Within the supporting framework of AHP, human experts make judgments about which factors are most significant within the areas of reservoir capacity, deliverability, and construction factors. These can be expressed verbally, graphically or numerically.
(2) Decision makers then decide whether each criterion is either positively or negatively correlated with well output after fracturing. Then grey theory is used to determine the relative importance of the individual factors and assigns a weighting factor to each one. The results are then used for well selection.
(3) There is a further opportunity for 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.

7. Results and Discussion

In order to test the hybridising system in practice, real industrial databases from nineteen different Western Sichuan distinct fractured reservoir wells were acquired. Table 2 shows the data for Well-1 thru Well-19 in terms of the variables chosen earlier namely: ‘thickness’ (TH), ‘porosity’ (POR), ‘gas saturation’ (SGT), ‘natural gamma’ (GR), ‘neutron’ (NR), ‘density’ (DEN), ‘sonic’ (SON), ‘structure position’ (SPI), ‘lithology’ (LTG), ‘lateral resistivity depth difference’ (LRDD), ‘discharge rate’ (DCR), ‘sand ratio’ (SAR), ‘prepad ratio’ (PADR), and ‘sand intensity’ (SANDR).

The objective is to predict the level of ‘initial production’ (IP) after fracturing. The model was estimated using data from wells 1 to 14 then the predictions for wells 15 to 19 were evaluated by comparing the results with the actual values.

7.1. Input Variable Analysis

In order to enable a clearer understanding of the input data, we first perform an analysis of the correlation coefficients between initial production (IP) and each of the input variables. In addition, cross plots are produced to illustrate the results of the statistical analysis. This is depicted in Table 3, Figure 3a,b. One should note that the input variable analysis indicates quite a low correlation with IP. This is because selecting a candidate well for stimulation in fractured reservoirs is a multi-criteria decision making process. Each parameter has its own unique influence on identifying suitable candidate wells and cannot provide all the information needed on its own. However this can be accomplished by the integration of geological and construction information [26,52].

Table 2. Descriptive statistics of wells-1–19.

Code Name	Reserve Capacity							Deliverability			Hydraulic Efficiency				Goal
	TH	POR	SGT	GR	NR	DEN	SON	SPI	LTG	LRDD	DCR	SAR	PADR	SANDR	IP
well-1	12.0	9.2	49	70.8	12.6	2.45	72.1	3.42	2.53	0	3.2	21.8	34.3	2.2	4.45
well-2	27.9	9.0	44	69.5	14.5	2.42	71.5	1.70	2.53	0	3.5	25.8	36.9	1.2	1.61
well-3	7.5	7.0	53	69.5	11.5	2.46	69.8	1.70	2.53	−2	3.2	21.8	36.4	3.1	1.20
well-4	15.0	9.6	66	81.0	11.9	2.48	69.5	1.70	2.18	0	3.2	22.2	34.3	2.8	0.64
well-5	36.8	9.7	29	88.0	16.7	2.42	71.5	1.70	2.53	0.5	3.2	23.6	35.8	1.0	0.84
well-6	13.3	9.7	54	87.8	13.4	2.46	71.0	1.70	2.53	0	3.5	23.5	33.1	8.1	1.02
well-7	12.0	9.5	48	70.8	13.3	2.48	70.8	3.42	2.53	0	3.0	20.1	37.4	6.0	5.25
well-8	17.1	5.9	40	60.5	11.4	2.5	67.8	1.70	2.18	1.1	3.5	21.9	34.4	2.4	0.36
well-9	19.9	3.9	65	62.0	6.9	2.54	63.5	3.42	2.53	0	3.5	21.7	30.8	2.6	0.57
well-10	20.5	10.8	24	63.3	14.3	2.55	68.3	1.70	2.53	−0.9	3.6	22	35.2	1.5	8.61
well-11	22.0	9.5	52	61.3	17.5	2.43	71.0	1.70	2.18	1	3.9	22.5	33.3	4.6	6.50
well-12	6.0	6.3	32	82.0	14.8	2.48	68.2	1.70	2.53	0	3.0	16.8	42.9	2.9	0.95
well-13	27.9	9.0	44	69.5	14.5	2.43	71.5	1.70	2.18	0	3.5	25.8	36.9	1.2	1.20
well-14	36.8	9.7	29	88.0	16.7	2.44	71.5	1.70	2.53	0.5	3.2	23.6	35.8	1.0	0.84
well-15	9.0	6.0	38	78.0	9.8	2.51	64.1	1.70	2.53	0	3.1	21.5	29.4	4.4	-
well-16	12.0	8.5	42	64.5	14.5	2.47	66.0	1.70	2.18	1	3.2	20.5	31.3	2.6	-
well-17	6.0	6.3	32	80.8	14.8	2.48	68.2	1.70	2.53	0	3.0	16.8	42.9	2.9	-
well-18	7.5	7.0	53	69.5	11.5	2.47	69.8	1.70	2.53	−2	3.2	21.8	36.4	3.1	-
well-19	13.3	9.7	54	87.8	13.4	2.48	71.0	1.70	2.53	0	3.5	23.5	33.1	8.1	-

Table 3. Correlation coefficient between each of the well variables and initial production.

Parameters	TH	POR	SGT	GR	NR	DEN	SON	SPI	LTG	LRDD	DCR	SAR	PADR	SANDR
Correlation coefficient	0.116	0.288	0.262	0.541	0.127	0.243	0.298	0.036	0.006	0.187	0.113	0.044	0.026	0.655
Slope	0.19	0.727	0.166	−0.228	0.36	−34.38	0.883	0.709	1	−2.01	3.448	0.385	0.219	1.554

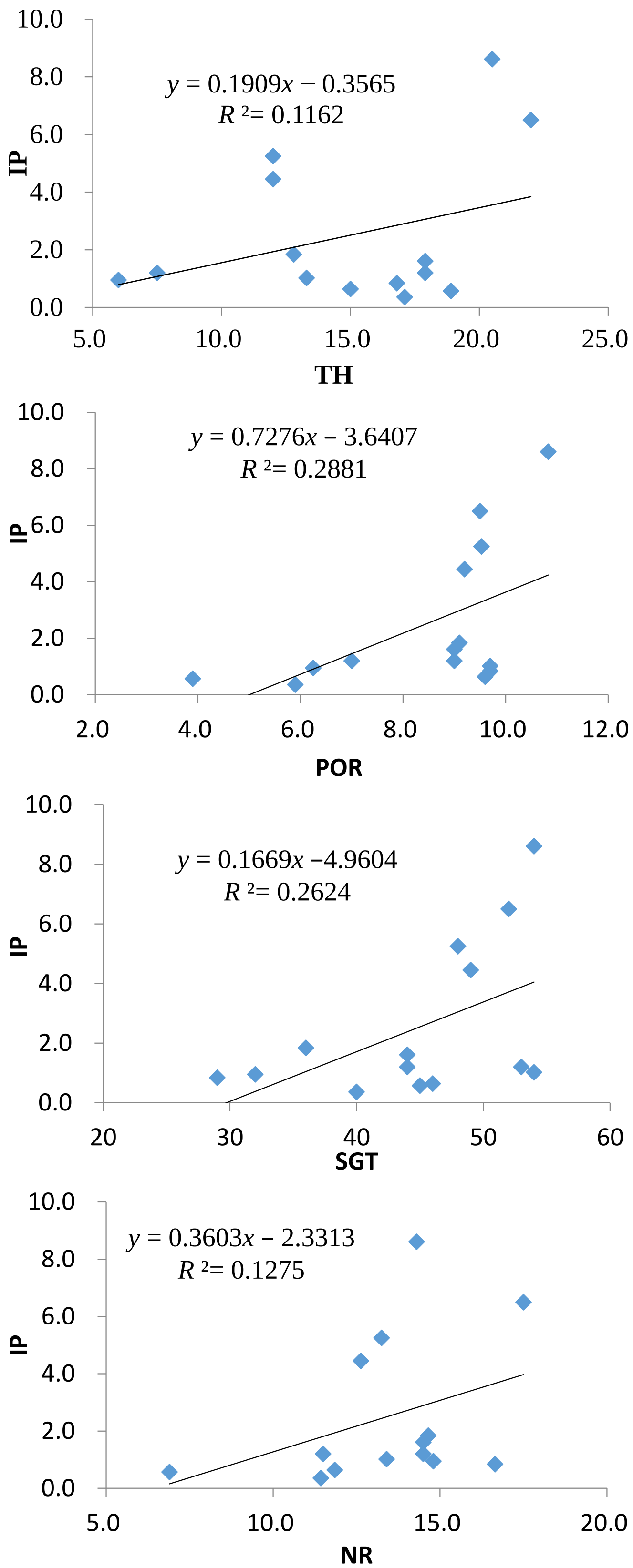
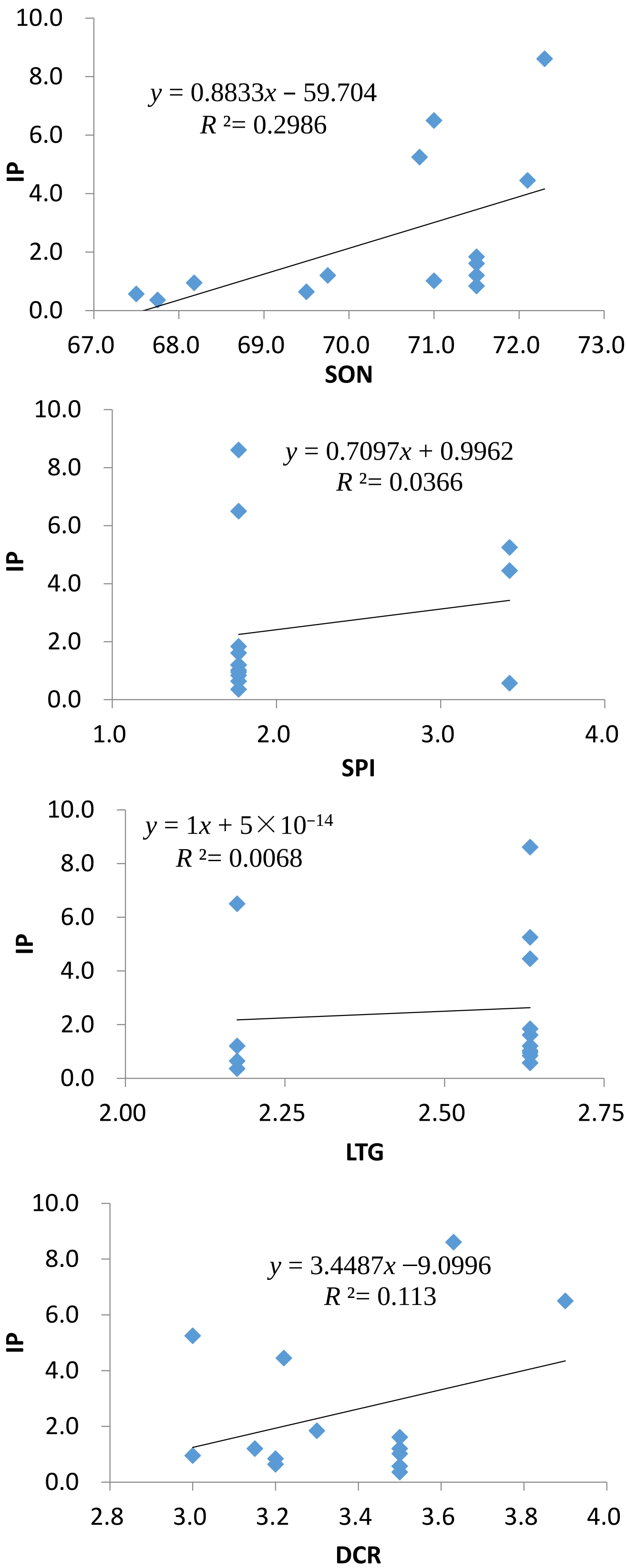


Figure 3. *Cont.*



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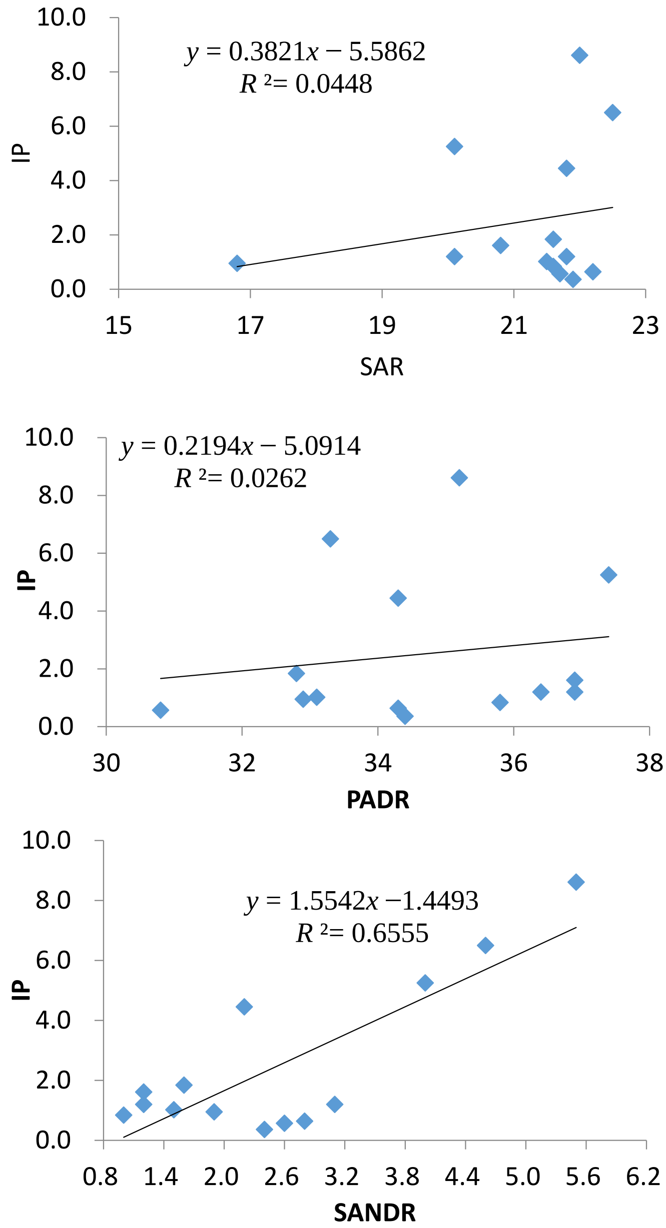

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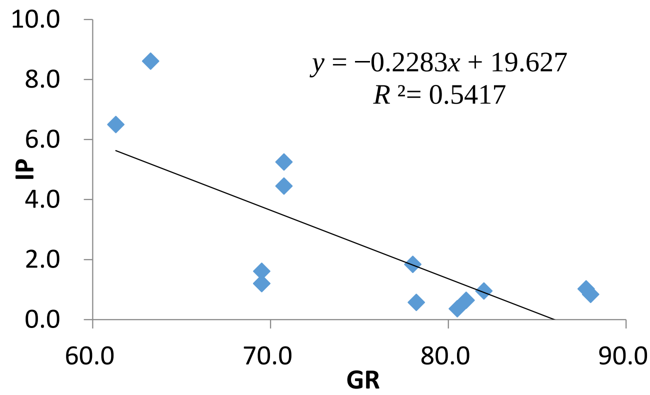

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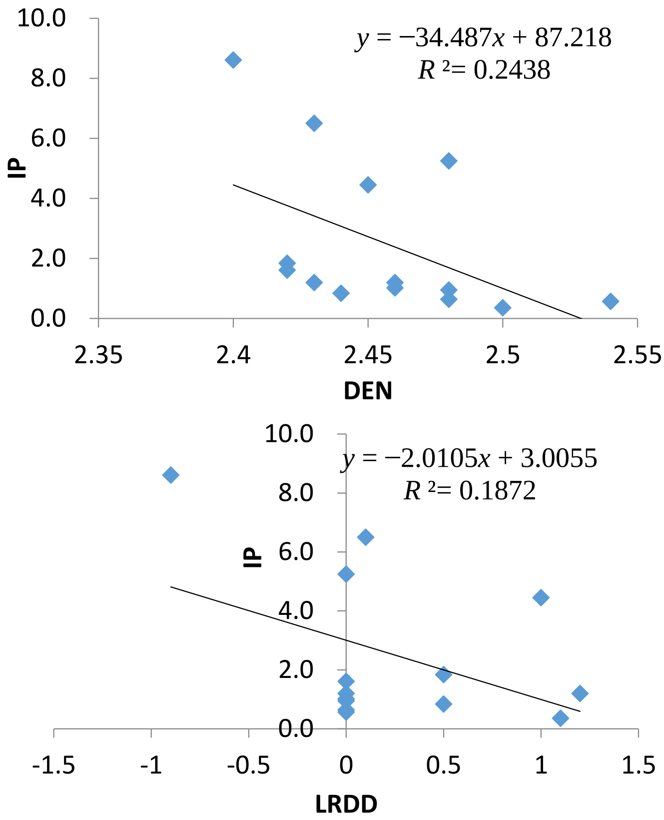

(**b**)

Figure 3. (**a**) Positive slope parameters crossplots between initial production and inputs; and (**b**) negative slope parameters crossplots between initial production and inputs.

An R-squared determination coefficient is used to determine whether two variables are related, and if so, how strongly. The coefficient ranges from +1, indicating a perfectly reliable relationship, to 0, indicating no relationship at all. Here we use the R-squared determination to show how each of the parameters is related to initial production. These are shown in Table 3.

Another important parameter is the slope, which reflects how each parameter varies with initial production (IP). If the slope is positive, IP increases with the parameter. If it is negative, initial production decreases with the parameter. In this sense, we can see that parameters TH, POR, SGT, NR, SON, SPI, LTG, DCR, SAR, PADR, and SANDR are positively correlated with IP, Figure 3a, whereas the remaining input variables: GR, DEN, and LRDD are negatively correlated, Figure 3b.

7.2. Ranking the Input Variables

Our strategy for testing the hybrid model was to build a version using only data for wells 1–well 14. Then use the model to predict the initial output for wells 15–well 19. We divided each input variable into four review grades "I", "II", "III", and "IV" with equal difference. For the variables that are positively correlated with IP, review grade "I" represents the larger value of the input variables under consideration. While for the input variables that are negatively correlated with IP, review grade "I" represents the smallest value of the input variables under consideration. This is illustrated in Tables 4 and 5.

Table 4. Reserve capacity factor grade level.

Grade Level	TH	POR	SGT	GR	NR	DEN	SON
I	22–18	10.83–9.09	54.00–47.75	61.29–67.97	17.5–14.84	2.39–2.43	72.29–71.09
II	28–14	9.09–7.36	47.75–41.5	67.97–74.64	14.84–12.19	2.43–2.47	71.09–69.89
III	14–10	7.36–5.63	41.5–35.25	74.64–81.32	12.19–9.54	2.47–2.50	69.89–68.69
IV	10–6	5.63–3.90	35.25–29.00	81.32–87.99	9.54–6.89	2.50–2.54	68.69–67.49

Table 5. Factor grade level.

Grade Level	Deliverability			Hydraulic Efficiency			
	SPI	LTG	LRDD	DCR	SAR	PADR	SANDR
I	3.41–3	2.63–2.51	(−0.91)–(−0.38)	3.89–3.67	22.5–21.07	37.39–35.75	5.5–4.37
II	3–2.59	2.51–2.4	(−0.38)–0.14	3.67–3.44	21.07–19.64	35.75–34.1	4.37–3.25
III	2.59–2.18	2.4–2.28	0.14–0.67	3.44–3.22	19.64–18.22	34.1–32.45	3.25–2.12
IV	2.18–1.76	2.28–2.17	0.67–1.19	3.22–2.99	18.22–16.79	32.45–30.8	2.12–1

In this methodology, we utilise a grey theory tool that has proven to be very efficient in ranking the input parameters. In this specific study, we dealt with fourteen wells with fourteen drivers for each well. Based on the data listed in Table 2, we used Equations (1)–(7) to calculate each criterion correlation coefficient, the results of which are shown in the fourth column of Table 6. This is followed by applying Equation (8) to estimate the main criteria weights. For example, the sum of the weights for reservoir capacity is (4.2434). This was divided by the sum of all the values of the parameters (9.3188) to obtain the value of 0.4554. We find the main criteria weights (first-grade) for reserve capacity, deliverability, and hydraulic efficiency are 0.4554, 0.2416, and 0.3030 respectively. Also, we can obtain the sub-criteria weights (second-grade) for each of the factors listed in Table 6.

Table 6. Factor grade level.

Main Criteria Weights		Sub Criteria Weights		
Factors	Weights	Factors	Correlation Coefficient	Weights
Reserve capacity	0.4554	TH	0.5925	0.1396
		POR	0.6374	0.1502
		SGT	0.6339	0.1494
		GR	0.5709	0.1345
		NR	0.6110	0.1440
		DEN	0.5958	0.1404
		SON	0.6018	0.1418
Deliverability	0.2416	SPI	0.7975	0.3541
		LTG	0.7023	0.3119
		LRDD	0.7521	0.3340
Hydraulic efficiency	0.3030	DCR	0.6950	0.2462
		SAR	0.7023	0.2487
		PADR	0.6982	0.2473
		SANDR	0.7280	0.2578

By using the data from Table 2 and the method described in Equations (1)–(8), the weights of the drivers in respect of their influence on IP were calculated. These are ranked on a scale from 0 to 1, shown in Figure 4. In this example SPI is highest ranked driver, followed by LRDD, POR, SGT, SANDR, NR, SAR, LTG, SON, PADR, DCR, DEN, TH, and GR. The finding that SPI is the most important factor suggests that if a large portion of gas is produced from the wells located in a higher structure position this indicates that higher initial production is likely after fracturing. This is consistent with the structure-lithology of the region under investigation. In this type of reservoir, high IP implies plenty of natural fractures and the consequence is consistent with the real situation.

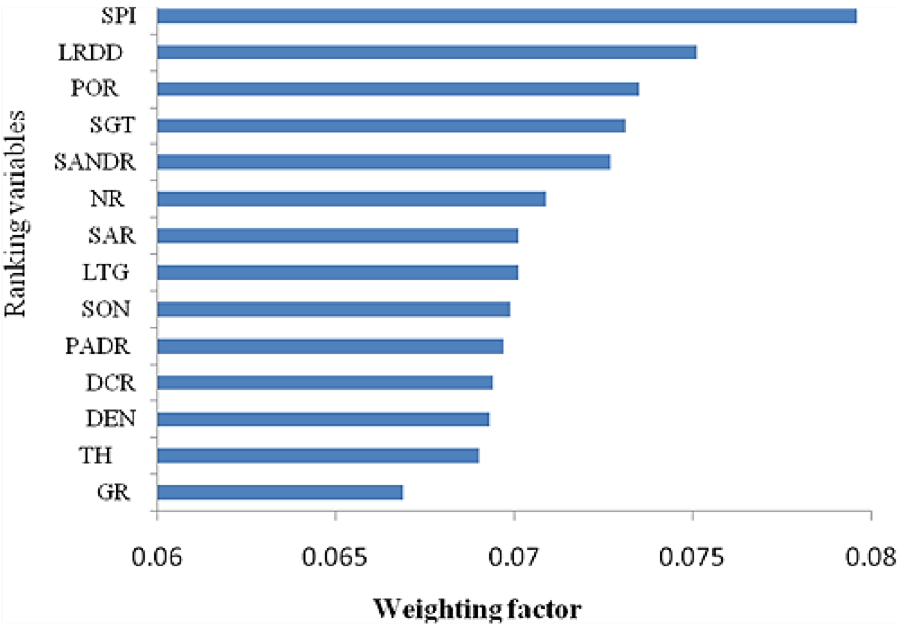

Figure 4. Ranking input drivers. Ranking scale is from 0 to 1.

7.3. Single Criteria Assessment

A fuzzy model is used to reflect uncertainties presented as inexact intervals for a number of system parameters. Due to the prevalence of the normal distribution, supported by the central limit theorem and observation, it is the best distribution to use in most cases [7]. Here we use Interval Type-2 Fuzzy Sets and Systems [19,48] to calculate the membership function. Taking the parameters of well-15 as an example, applying Equations (9)–(16) gives the results shown in Table 7.

From these results, a single factor can be obtained corresponding to each factor fuzzy evaluation set. From the preceding analysis, there are fourteen terms of evaluation parameters and four level review grades. This is described in the following 14×4 fuzzy matrix U:

$$U = \begin{bmatrix} 0 & 0.0002 & 0.2102 & 0.8409 \\ 0 & 0.0102 & 0.7969 & 0.2434 \\ 0 & 0.0444 & 0.9901 & 0.0863 \\ 0 & 0.0612 & 1 & 0.0633 \\ 0 & 0.0039 & 0.6229 & 0.3849 \\ 0 & 0.002 & 0.1458 & 0.8409 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0.0019 & 0.5309 \\ 0.4545 & 0.0006 & 0 & 0 \\ 0.0165 & 0.8627 & 0.1981 & 0.0001 \\ 0 & 0 & 0.0483 & 0.9987 \\ 0.8957 & 0.1691 & 0.0001 & 0 \\ 0 & 0 & 0 & 0.0065 \\ 0.5371 & 0.4633 & 0.0017 & 0 \end{bmatrix} \quad (17)$$

Table 7. Measured data of well-15.

Membership Grade	TH	POR	SGT	GR	NR	DEN	SON	SPI	LTG	LRDD	DCR	SAR	PADR	SANDR
	9.0	**6.0**	**38**	**78.0**	**9.8**	**2.51**	**64.1**	**1.77**	**2.63**	**0.0000**	**3.1**	**21.5**	**29.4**	**4.4**
I	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.4545	0.0165	0.0000	0.8957	0.0000	0.5371
II	0.0002	0.0102	0.0444	0.0612	0.0039	0.0020	0.0000	0.0000	0.0006	0.8627	0.0000	0.1691	0.0000	0.4633
III	0.2102	0.7969	0.9901	1.0000	0.6229	0.1458	0.0000	0.0019	0.0000	0.1981	0.0483	0.0001	0.0000	0.0017
IV	0.8409	0.2434	0.0863	0.0633	0.3849	0.8409	0.0000	0.5309	0.0000	0.0001	0.9987	0.0000	0.0065	0.0000

7.4. Comprehensive Evaluation

A single factor fuzzy evaluation cannot reflect the combined effects of all the factors. Therefore, in order to obtain comprehensive results, the matrix multiplication summation algorithm, fuzzy evaluation matrix U, and composite fuzzy weight vector $\boldsymbol{A}$ single factor (Figure 4) is used to consider the contribution of all the factors. This gives the fuzzy comprehensive evaluation vector $\boldsymbol{B}$:

$$\begin{aligned}
\boldsymbol{B} &= (b_1, \ldots b_i, \ldots, b_n) = AU \\
&= \begin{bmatrix} 0.0691 & 0.0735 & 0.0732 & 0.0669 & 0.0709 & 0.0694 & 0.0700 & 0.0797 & 0.0702 & 0.0751 & 0.0694 & 0.0702 & 0.0698 & 0.0727 \end{bmatrix} \\
&\begin{bmatrix} 0 & 0.0002 & 0.2102 & 0.8409 \\ 0 & 0.0102 & 0.7969 & 0.2434 \\ 0 & 0.0444 & 0.9901 & 0.0863 \\ 0 & 0.0612 & 1 & 0.0633 \\ 0 & 0.0039 & 0.6229 & 0.3849 \\ 0 & 0.002 & 0.1458 & 0.8409 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0.0019 & 0.5309 \\ 0.4545 & 0.0006 & 0 & 0 \\ 0.0165 & 0.8627 & 0.1981 & 0.0001 \\ 0 & 0 & 0.0483 & 0.9987 \\ 0.8957 & 0.1691 & 0.0001 & 0 \\ 0 & 0 & 0 & 0.0065 \\ 0.5371 & 0.4633 & 0.0017 & 0 \end{bmatrix} \\
&= \begin{bmatrix} 0.1348 & 0.1188 & 0.2849 & 0.2839 \end{bmatrix}
\end{aligned} \tag{18}$$

where b_i corresponds to the membership grade I, II, III, and IV. For well-15, its membership of grades I, II, III, IV are 0.1348, 0.1188, 0.2849, and 0.2839 respectively. As grade III has the highest value, it can be said that well-15 belongs to grade III for candidate well selection. There is an initial production of 0.78×10^4 m^3/d after hydraulic fracturing, which is consistent with the estimate made using the hybrid approach. Similarly, the IP of the other four wells was calculated to verify the plausibility of the results shown in Table 8. The wells with a higher grade are consistent with higher daily production after construction. This demonstrates that, despite the complexity of the problem, the proposed approach was able to capture the underlying relationship that exists between the input parameters and initial production (IP) after fracturing, based on all the available data. The actual field application of many wells using this technique has proven reliable and able to determine the most appropriate wells for hydraulic fracturing.

Table 8. Descriptive statistics of well-15–19.

Code Name	Reserve Capacity						Deliverability				Hydraulic Efficiency				Membership Function	IP
	TH	POR	SGT	GR	NR	DEN	SON	SPI	LTG	LRDD	DCR	SAR	PADR	SANDR		
well-15	9.0	6.0	38	78.0	9.8	2.51	64.1	1.70	2.53	0	3.1	21.5	29.4	4.4	III	0.78
well-16	12.0	8.5	42	64.5	14.5	2.47	66.0	1.70	2.18	1	3.2	20.5	31.3	2.6	IV	0.62
well-17	6.0	6.3	32	80.8	14.8	2.48	68.2	1.70	2.53	0	3.0	16.8	42.9	2.9	III	0.95
well-18	7.5	7.0	53	69.5	11.5	2.47	69.8	1.70	2.53	−2	3.2	21.8	36.4	3.1	II	2.02
well-19	13.3	9.7	54	87.8	13.4	2.48	71.0	1.70	2.53	0	3.5	23.5	33.1	8.1	II	3.73

7.5. Comparison of the Presented Method with Other Approaches

In comparison with other approaches that are traditionally used for well selection, such as linear regression, nonlinear regression, AHP, conventional fuzzy logic, and a BP (backpropagation) neural network, the hybrid method has a number of advantages. Firstly, since the evaluation of candidate wells for fracturing involves a large number of parameters involving complex nonlinear relationships linear regression is clearly unsuitable. Non-linear regression approaches such as, for example, quadratic regression requires a much larger sample of data to be able to fit the function between the input parameters and IP. In addition, the functional form of the relationship must be specified in advance but we do not have a method of determining precisely what it is. Secondly, in the process of selecting a well for fracturing, it is necessary to specify a set of weights which indicate the extent of the influence each element has on the performance of the fractured well. While AHP is able to provide the weights, this is based solely on the conductors' experience and subjective judgment, which, as we noted earlier, is subject to a range of biases and inconsistencies. Also, a neural network model trained by backpropagation only makes the inputs and outputs available for inspection while the internal workings are hidden. Finally, the conventional fuzzy logic algorithm can only assess a single criterion at a time, which precludes a comprehensive evaluation of all the parameters simultaneously.

The hybrid approach presented here combines the advantages of human judgment, AHP, grey theory, and fuzzy expert systems for well selection, which not only provides the final results but also reveals each parameter's effect on the outcome.

In order to test the accuracy of the predictions provided by this method, the results are compared against those generated by a well-trained neural network. As this implements non-linear, non-parametric regression, it forms a general benchmark for evaluation.

7.5.1. BP Neural Network Optimization

Applying the BP (back propagation) neural network forecasting process to achieve a good prediction effect, we need to set the parameters for the network structure, specifically including the hidden layer nodes *S*, node transfer function *TF*, training function *BTF*, network learning function *BLF*, performance analysis function *PF*, input processing function *ITF*, output processing functions *OPF* etc. In addition, we also need to optimize the training times and rates repeatedly to achieve the best results.

In this test, we use the newff function to create the BP neural network through repeatedly changing each function parameter in the newff function. When the mean squared error of the BP neural network training results, compared against the actual value, reaches a minimum, this indicates the best parameters for the newff function.

A range of combinations of node transfer functions and training functions were tested, for example, we compared six different kinds of newff function composition. The other values of the remaining parameters are as follows: the number of training iterations is 100,000, the training rate is 0.01 and the learning accuracy is 0.000001.

Table 9 shows the value of different combinations of transfer functions and function prediction mean square difference after training. From Table 9, we can see that the combination of different transfer functions TF and training functions *BTF* give different average mean squared errors, the smaller the variance, the better the accuracy. As can be seen from the table: in combination [tansig, trainlm], the average value of the minimum mean square deviation obtained was (0.44), so we chose the [tansig, trainlm] combination. Also, the same neural network structure can also be obtained in other functions to eventually determine the best newff to create functions: newff (inputn, outputn, 5, {'tansig'}, 'trainlm', 'learngdm', 'mse').

Table 9. Different combination of transfer functions and function prediction mean square difference between training.

Newff Function	Code Name														Average Mean Squared Error
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
[tansig, traingd]	0.40	0.82	1.49	0.82	0.07	1.45	0.92	1.23	1.13	3.68	1.14	1.08	0.49	0.80	1.11
[purelin, traingdx]	0.28	0.27	0.23	0.03	0.13	1.64	0.08	3.78	5.65	0.39	0.95	0.98	0.03	0.72	1.08
[logsig, traingda]	1.22	0.07	0.63	0.84	0.66	0.47	1.89	1.04	1.62	4.54	2.91	0.11	0.44	0.11	1.18
[tansig, trainlm]	0.00	0.73	0.00	0.00	0.00	0.00	0.00	2.98	0.00	0.00	0.00	1.66	0.00	0.76	0.44
[hardlim, traingdm]	0.87	0.04	0.14	0.73	0.2	1.2	1.43	1.63	2.22	4.99	3.89	3.13	0.14	0.5	1.51
[hardlims, traingda]	0.33	0.11	2.34	0.38	0.25	0.82	0.23	1.28	1.14	2.9	3.06	7.35	0.69	0.46	1.52

7.5.2. Comparison with BP Neural Networks

Table 10 presents a comprehensive evaluation of the results based on the four membership grades V = {I, II, III, IV} of the presented model using fuzzy mathematical theory. When using the BP neural network model to train IP values on test samples 1–14, the actual IP values are almost the same as the ones obtained by prediction. However, the IP values of wells 15–19 greatly differ from the actual IP values. In particular, the relative error of the IP value for sample 16 reached 55%. In the application of the presented model to test the IP value of samples 1–14 samples, based on the principle of maximum membership grade, leads to more accurate comprehensive evaluation results and predict the IP of 15–19 prediction samples).

Table 10. Comparison of both the Presented Model and Neural network model.

Remarks	Code Name	Presented Model		Neural Network Prediction IP	Actual IP
		Membership Grade	Fuzzy Evaluation		
Test samples	well-1	[0.2317 0.3585 0.1451 0.1916]	II	4.44	4.45
	well-2	[0.2399 0.4256 0.1557 0.1401]	II	1.60	1.61
	well-3	[0.1189 0.2775 0.2427 0.2639]	II	1.17	1.20
	well-4	[0.1935 0.3346 0.3083 0.1731]	II	1.64	1.64
	well-5	[0.2538 0.2763 0.2403 0.2011]	II	1.83	1.84
	well-6	[0.2235 0.3357 0.1529 0.1943]	II	1.02	1.02
	well-7	[0.2077 0.3855 0.2778 0.0894]	II	5.22	5.25
	well-8	[0.1022 0.2481 0.2706 0.3461]	IV	0.34	0.36
	well-9	[0.1984 0.2134 0.2493 0.0986]	III	0.51	0.57
	well-10	[0.3035 0.2790 0.0777 0.0932]	I	8.61	8.61
	well-11	[0.3512 0.1618 0.0945 0.1036]	I	6.48	6.50
	well-12	[0.0669 0.1340 0.2736 0.4056]	III	1.25	0.95
	well-13	[0.2548 0.4121 0.1865 0.1054]	II	1.22	1.20
	well-14	[0.2591 0.2333 0.0810 0.2366]	II	0.97	0.84
Prediction samples	well-15	[0.1348 0.1188 0.2849 0.2839]	III	1.08	0.78
	well-16	[0.1710 0.2669 0.2346 0.2733]	IV	1.37	0.62
	well-17	[0.0345 0.0949 0.3515 0.3480]	III	1.34	0.95
	well-18	[0.1193 0.2444 0.2985 0.2259]	III	2.40	2.02
	well-19	[0.2046 0.2332 0.2300 0.1389]	II	3.30	3.73

From Table 10, we find that when predicting the IP values, the presented model outperforms the neural network model on some key measures. For example, the proposed method puts the best well (well 19) in grade II. Wells 15, 17, and 18 are mid-range and are all placed in grade III. The well with the lowest IP is in grade IV. All these results are consistent in terms of the ordering of well output after fracturing.

Meanwhile, the neural network correctly assigns positions 1 and 2 to wells 19 and 18 but it mixes up the order of the others. Well 16 in particular is ranked third by the neural network when it should be ranked fifth, with the lowest output. Hence, in terms of ordering the wells by their post fracturing output, which is critical for selecting the best wells for fracturing, the proposed method gives more reliable results than the neural network benchmark. It can also be noted that this is in an environment where the wells have a similar geology, which is where the neural network can be expected to perform well.

7.6. Discussion

The selection of a candidate well for hydraulic fracturing in fractured reservoirs is a complex multi-criterion decision process, which involves quantitative evaluation of parameters in isolation as well as their combined influence. In addition, error, uncertainty and fragile correlations between data-sets are intrinsic to this environment due to the challenge of designing and building sensors to measure complex formations in hostile environments [7], and that uncertainty in data may be due to fuzziness rather than chance [53]. For fracture treatments that are performed in fields where large databases are available, statistical multivariate techniques and neural networks are usually used to choose the candidate wells for hydraulic fracturing. Regression analysis also offers appealing solutions. However, their main drawback is the need to identify all the factors and then establish a linear or nonlinear model that best represents the interactions among them. This becomes unwieldy when the number of parameters is very large. In addition, regression analysis is poor at extrapolating and predicting values outside the range of the conditioning data-set [54]. Neural networks are also promising because, unlike regression analysis techniques, it is not necessary to specify structural relationships between the input and output data. Neural networks have the ability to infer general rules, extract patterns from a set of examples and recognize input output mappings from complex multi-dimensional field data. These properties give the neural networks the ability to interpolate between typical patterns or data and generalize their learning in order to extrapolate to a region beyond their training domains. However, using neural networks for identification purposes is more useful when a large amount of data is available. In addition, neural network models cannot deal with uncertainty in data due to fuzziness [55]. Furthermore, all the above mentioned methods rely on there being a statistical correlation between fracture performance and the field variables. In some cases, no such relationship exists and this results in a poor selection of the best candidate wells for fracturing [56]. The Analytic Hierarchy Process (AHP) [28] is a nonlinear framework, which is based on deductive and inductive reasoning. It makes it possible to consider several factors simultaneously and allow for interdependence and feedback among variables. However, one of the difficulties associated with the AHP method is that operators must assign a specific number, within a scale from 1 to 9, to the pair-wise comparisons in order to enable the priority vector to be computed. In AHP, when two factors are equally important, a scale value of 1 is assigned to the comparison. Weak to moderate intensities in the difference in importance of a factor, score from 2 to 4. More highly critical differences score from 5 to 8 while 9 would indicate a high level of importance of one alternative over the other. The corresponding reciprocals 1, 1/2, 1/3, ..., 1/9 are used to make a comparison in the opposite direction. However, this is restrictive in cases where the expert is unsure as to the magnitude or direction of the comparison or they do not have sufficient information to make a comparison. This makes classical AHP unsuitable for use when choices are fuzzy or there is incomplete information.

So far, all the above approaches make use of simplifying assumptions such as consideration of extreme or mean values, or the application of safety factors and cannot deal adequately with the uncertainties associated with vague or imprecise information in the objective and constraint functions [57]. The process of selecting candidate wells is inherently error prone with uncertainty and unstable correlations between parameters. This is due in part to the challenge, in petro-physics, of designing and building sensors to measure complex formations in hostile environments [7] and that uncertainty in data may be due to fuzziness rather than chance [53]. Fuzzy logic has the ability to deal with human error and uncertainty in systems to a greater extent than any methods discussed above [58]. This paper presented a fuzzy model for well selection, which is done by fusing the analytic hierarchy process (AHP) method, grey theory and an advanced version of fuzzy logic theory (FLT). It undertakes approximate reasoning and generates recommendations for candidate wells. In addition, these techniques and technologies are hybridized by using an intercommunication job-sharing method that integrates human judgment. The presented approach is able to reduce uncertainty caused by mathematical approximations and the prediction results will become more accurate as more construction data is collected. Field application shows that in the application of the proposed methodology, the best candidate wells are determined for stimulation and achieve promising production.

8. Conclusions

Choosing the best candidate wells for hydraulic fracturing in a complex and dynamic geological environment has never been an easy task. This paper applies and tests a novel hybrid approach that would be the first to hybridise human judgment, AHP, grey theory, and a fuzzy expert system to support the process of candidate well selection. Various techniques and functional components are combined using an intercommunication job-sharing hybridisation method, which also incorporates human judgment. A field study was also conducted to evaluate the hybrid approach with a model based on data from 14 hydraulic fracturing wells and five wells for testing. The results demonstrate the feasibility of this approach and find a close relationship between the model's recommendations and what was observed in the field.

Acknowledgments: This work was funded by the National Natural Science Foundation of China (project No. 51504203, 51525404), and by Open Fund (PLN1515) of State Key Laboratory of Oil and Gas Reservoir Geology and Exploitation (Southwest Petroleum University), a special fund from China's central government for the development of local colleges and universities—the National First-level Discipline in the Oil and Gas Engineering Project (Project No. 20150727), and Scientific Research Starting Project of Southwest Petroleum University (Project No. 2014QHZ004).

Author Contributions: Fanhui Zeng conceived and designed the experiments; Fanhui Zeng and Xiaozhao Cheng performed the experiments; Fanhui Zeng and Xiaozhao Cheng analyzed the data; Fanhui Zeng, Xiaozhao Cheng, Jianchun Guo, Liang Tao and Zhangxin Chen wrote the paper. Authorship must be limited to those who have contributed substantially to the work reported.

Conflicts of Interest: The authors declare no conflict of interest.

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