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Optimization of Direction and Length of Horizontal Wells in Oil Field-X Using Fuzzy Substractive Clustering and Fuzzy Logic Methods

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Abstract

This study discusses an optimization model to obtain the optimal direction and length of horizontal wells in the oil field X. In the common practice in oil industries, the optimal direction and length are obtained from a trial and error method through a considerably time consuming reservoir simulation runs. Employing the basic reservoir properties data of the porosity, permeability, oil saturation, and location of each grid of the available reservoir model, Fuzzy Subtractive Clustering is used to classify grids. Furthermore, Fuzzy Logic optimization model is built to find the optimal direction and length of the horizontal well. Determination of the optimal direction and length is based on the oil recovery represented by a recovery factor that does not have any simple relationship with the basic reservoir properties data, but, through a reservoir simulation model that basically calculates fluid flows in porous media performances using a finite different formulation of the governing equation, i.e., the diffusivity equation. The filed case discussed in this study is one with the drilling starting point already known. The results of the study show that the methods of Fuzzy Subtractive Clustering and Fuzzy Logic are effective in determining the optimal direction and length simultaneously without running the reservoir simulation.

Keywords: fuzzy logic, fuzzy subtractive clustering, horizontal well, recovery factor

1. Introduction

In oil industry business, well placement is one of the most important activities as the cost of drilling wells is a major invesment cost whether during the exploration or exploitation stage. In doing so, oil companies maximize their oil recovery in as short time as possible by drilling wells as few as possible, since this could be the most economical. This maximum recovery corresponds directly to the horizontal well placement that is influenced by subsurface charactersitics, i.e, rock and reservoir fluid properties, the amount of oil volume, and reservoir pressure. For a known starting point such as from a platform, the horizontal well placement requires its direction and length to produce the maximum amount of oil. Thus, determining the optimum direction and length of horizontal wells is a crucial problem in the exploitation of an oil field. However, the longer the horizontal wells are, the greater the cost required, even though it does not necessarily mean that the oil production increases. The conventional method of trial and error procedure that is commonly used in practice takes a considerable amount of work and time for large and complex reservoirs. For this reason, the objective of this study is to determine the optimal direction and length of the horizontal wells simultaneously without using a reservoir simulator. Determination of the optimal direction and length is based on the oil recovery or the Recovery Factor, that is, a ratio between the volume of oil produced to the surface and an initial volume of oil in the reservoir, namely, Original Oil In Place. The greater the oil recovery factor is, the more the oil obtained from the reservoir.

There are numerous applications of fuzzy logic in peteroleum enginering papers that will be discussed in the following covers field development, production engineering and petrophisical andproperties estimation. We start with the area of field development. To find an optimal placement of a development well, various data of geophysical, geological, or engineering attributes that have varying degrees of confidence shoul be considered into account. Saggaf (2002) is to integrate a multitude of fragmented pieces of knowledge derived from various input sources to come up with a single number at each location in the field that is indicative of the reservoir potential at that particular location. To solve the problems of single or integral attributes that are capable of indicating oil and gas or not, Li al al (2013) propose a multi-attribute fusion method based on fuzzy logic, applying the fuzzy theory to fuzzy attributes, with the help of membership function to quantify the fuzzy problem, calculating weight factors through fuzzy nearness matrix, and eventually obtaining a quantitative comprehensive result. Futhermore, Popa (2013) presents a new approach for identification and placement of horizontal wells using fuzzy logic. In addition to the large number of wells identified, the methodology focused the asset team on high potential areas and offered an objective approach to deal with imprecise and uncertain reservoir information. A Fuzzy Logic approach was considered to deal with the imprecise information and aggregate multiple variables with suitable membership functions. The Fuzzy Inference System (FIS) using the Mamdani model incorporated knowledge rules developed by the asset team. Previously, Ebrahimi and Sajedian (2010) developed a prediction method using fuzzy logic for Inflow Performance Relationship (IPR) of horizontal oil wells.

In the area of production engineering, fuzzy logic theory can be used to build evaluators to help an engineer select an optimal stimulation candidate and an optimal stimulation method, diagnose the formation damage, evaluate the conditions of potential barriers for fracture treatments, and select fracture fluids. The fuzzy logic evaluators described can be applied to study, evaluate, and determine the best methods to improve productivity in oil and gas wells or injectivity in water wells (Siong and Holditch, 19XX). A solution for oil or gas fields having multilayer reservoirs and production contributions from individual reservoir layers is required. For the fields' reservoir simulation modeling and production evaluation/prediction, fuzzy Logic can be applied to investigate the pattern of the relationships between production contributions of layers in commingle wells and rock petrophysical data as well as other relevant geological/engineering data (Widarsono et al, 2005)

In the research area of petrophysical properties estimation, quite a lot of papers have been published, and, to mention a few, are as discussed in the following. Errors or fuzziness of a particular litho-facies type that can give any well log reading, though some are more likely than others, have been measured and used to improve the litho-facies prediction. A proposed technique by Cuddy (2000) showed differentiation among rock types, and the method used basic log data sets such as gamma ray and porosity instead of depending on new logging technology to predict permeability. Lim and Kim (2004) used Fuzzy curve analysis based on fuzzy logics for selecting the best related well logs with core porosity and permeability data. Neural network is used as a nonlinear regression method to develop transformations between the selected well logs and core measurements. Fuzzy ranking algorithm can be used to select inputs best suited for predicting the desired output. Furthermore, Taghavi (2005) conducted a study to predict permeability from well log data for a heterogeneous carbonate reservoir in the upper part of the Sarvak Formation (mid-Cenomanian to early Turonian) in an Iranian oil field, and the results from the study show that fuzzy logic yields better results than the other two methods. Then, (Aminzadeh and Brouwer, 2006) used neural networks in conjunction with fuzzy logic to high-grade prospects containing hydrocarbon saturated reservoirs and to formulate general rules of thumbs derived from rock physics data and interpreter's knowledge and experience. Abdulraheem et al (2007) used fuzzy logic modeling to estimate permeability from wireline log data in a Middle Eastern carbonate reservoir by making correlation coefficients the criteria for checking whether a given wireline log is suitable as an input for fuzzy logic modeling. The coefficients are enhanced if they are evaluated with respect to the logarithm of core-based permeability values of the given well. It is also observed that the Subtractive Clustering technique gives better predictions of permeability when compared with the Grid Partitioning technique.

Based on the above literature studies, this study gives a contribution to the field development area in which the idea is new and the approach completely different from the previous conventional methods to optimize the horizontal well production. In oil industry practices, experts use a reservoir simulation method to produce oil recovery performances after obtaining a reservoir model constructed from a geological model. The reservoir simulation runs a reservoir simulator, usually a finite difference formulation of the governing fluid flow in porous media governing equation, namely, diffusivity equation. This governing equation requires geological and reservoir model and data. The process of reservoir simulation involves initialization, history matching past production data, if any, and forecasting future performances of some development scenarios such as vertical infill well and horizontal well placements. The approach of the proposed method of this study is to obtain the best reservoir performance, i.e., oil recovery, from an optimal horizontal well placement by substituting complex and tedious calculations of the conventional method using a reservoir simulation technique with the application of the fuzzy theory to relate directly the basic reservoir properties to the ultimate target of the horizontal well placement, i.e., oil recovery. Therefore, the importance of this study is in finding a new short cut, that is still reliable by applying the fuzzy logic optimization. Thus, this proposed method is hoped to have a great practical implication to the effort of finding the best horizontal well placement.

2. Method and Materials

Oil Field X is modeled in a two-dimensional grid. This research works on one layer. In this layer there are 48 × 27 grids with the size of 340 ft × 340 ft per grid. Each grid has a value of porosity (ϕ), permeability (k), and oil saturation (S_o). Figure 1 shows maps of porosity and permeability of the field.

The grids reviewed in this study are only those at $10 \le s \le 35$ and $15 \le t \le 27$ with *s*as a coordinate index of *x* and *t* as a coordinate index of *y*. This is because the grids outside the coordinates do not have a good oil saturation value (unproductive areas). The following is the limitation of the research problems.

1. Calculation is based on three factors, ie. ϕ, *k* and S_o.
2. Each grid of the horizontal well passes has one perforation.
3. The existing well is considered no longer in production.
4. The case reviewed is one with a coordinate of (18,22) as a starting point of drilling.
5. The rate ofproductionis is assumed as 80 STB/day.

As the productive areas are scattered and there are similarities in the grid values, grouping of data was conducted. Reservoir grids were grouped by their locations and quality in order to obtain information on reservoir areas that contain good and bad qualities. In each group, one central point will be chosen of the group. These central points will be considered as candidates for the end points of the horizontal wells.

The metodology of this research is outlined in Figure 2, starting with gathering data of porosity, permeability and oil saturation from a reservoir model, and then followed by data clustering using fuzzy substructive clustering, objective function construction, optimal direction and length determination using fuzzy logic, and validation using reservoir simulator.

The method used to classify the data is Fuzzy Subtractive Clustering, which is based on the size of the density of the data points in a variable. The basic concept of Fuzzy Subtractive Clustering is determining regions in variables that have high density relative to the surrounding points (Chiu, 1994). If a point has a high density, this means that the point has a value proximity to the other surrounding points. Each data has potential D*i* based on its proximity to the other data. *Di* can be calculated using equation (Chiu, 1994):

$$D_i = \sum_{k=1}^{n} e^{-\sum_{j=1}^{m} \frac{\|x_{ij}-x_{kj}\|^2}{\left(r/2\right)^2}}, \tag{1}$$

with $\| X_{ij}\text{-}X_{kj} \|$ being the distance between X_i and X_k for data type *j* and the radius (influence range) *r*. The radius is a vector that will determine how strong the influence of the cluster center at each variable is.

After the density of each point is obtained, the point with the highest density will then be selected as the candidate for the cluster center. For example, V_j is chosen as the center point of the cluster, while D_c is the size of the density. Then the value of the density at each point is reduced by using this equation: (Chiu, 1994)

$$D_k^* = D_k - D_C e^{-\sum_{j=1}^{m} \frac{\|v_j-x_{ij}\|^2}{\left(r_b/2\right)^2}}, \tag{2}$$

with D_k^* being the density of the newer *k-th* and D_k the older one, and r_b a positive constant that indicates a radius that results in reduced size of the density of the points. The point with the largest density will be selected as the next cluster center. This process goes on until a sufficient number of clusters are obtained. Figure 3 shows the sceme of this selection.

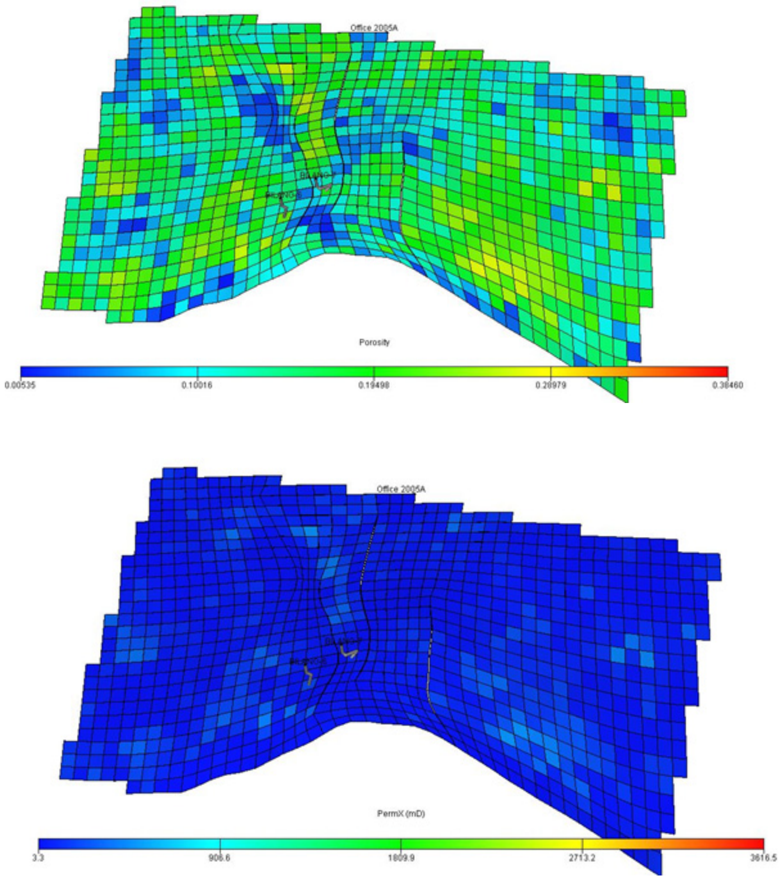

Figure 1. Maps of porosity and permeability of the field

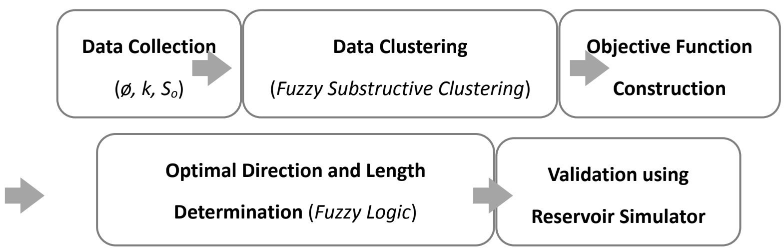

Figure 2. Research methodology

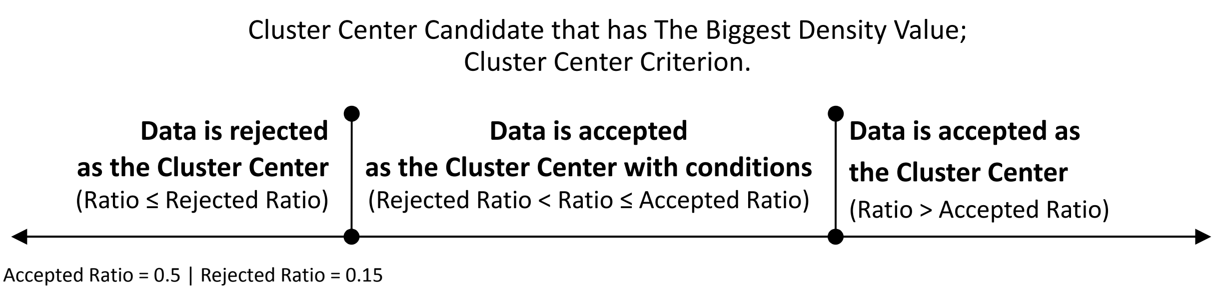

Figure 3. Selection Process. (After Kusumadewi, 2004)

Furthermore, Fuzzy Logic optimization model is built to obtain the optimum direction and length. Fuzzy logic is used to handle the fuzziness (vagueness) in a problem represented by linguistic values. Membership function is a curve that shows the mapping of points of input data into the membership values (Atiaa, 2009). The degree of membership indicates a measurement of existence within a set. In the crisp set, the membership value of a candidate may only be either 0 or 1. However, in the fuzzy set, the membership value of a candidate can range between 0 to 1 (Zadech, 1965). The following are the four components of the fuzzy system (Atiaa, 2009):

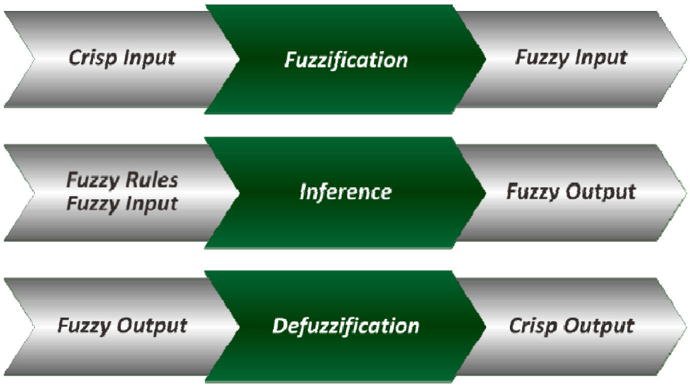

Figure 4. Fuzzy System (Atiaa, 2009)

1. *Fuzzification*: process of converting a crisp input into a fuzzy input.
2. *Fuzzy rules*: rules in the form of logic implications written as "IF x is equal to y THEN y is equal to B" where A and B are linguistic values defined by fuzzy sets.
3. *Inference:* process of combining rules in order to obtain the fuzzy output.
4. *Defuzzification*: process of converting the fuzzy output into a crisp output.

The method used in the process of defuzzyfication is centroid method. In this method, crisp output is obtained by taking the center points (z*) of the fuzzy region. This method is formulated as follows (Li, 2001):

$$z^* = \frac{\int_Z z\mu(z)\,dz}{\int_z \mu(z)\,dz}, \tag{3}$$

with z^* showing the crisp value and $\mu\ (z)$ the degree of membership of a crisp value of z.

As a crisp input of fuzzification, this function is built based on the reference of Ariadji's (2012), as the following:

$$f(x_i, y_i) = \emptyset(x_i, y_i)k(x_i, y_i)S_o(x_i, y_i), \tag{4}$$

with

$f(x_i, y_i)$: the fitness value for the *i-th* direction,

$\emptyset(x_i, y_i)$: the average porosity value for the *i-th* direction,

$k(x_i, y_i)$: the average permeability value for the *i-th* direction, and

$S_o(x_i, y_i)$: the value of the average oil saturation for the *i-th* direction.

The second fitness value is obtained by using geometric average. This is intended to prevent large depreciation of fitness value if one of the three field data has a very small value. The following is the equation.

$$g(x_i, y_i) = \sqrt[3]{\emptyset(x_i, y_i)k(x_i, y_i)S_o(x_i, y_i)}, \tag{5}$$

Through the use of Fuzzy Logic Toolbox in MATLAB, the membership functions are built for the variables of input ($f(x, y)$, ($g(x, y)$) and *output* (*Recovery Factor*) with the category of low, moderate, and high (Figure 5, Figure 6, and Figure 7). Below are three fuzzy rulesformed.

1. IF ($f(x, y)$ low) THEN (Recovery Factor low)
2. IF ($f(x, y)$ moderate) THEN (Recovery Factor moderate)
3. IF ($f(x, y)$ high) THEN (Recovery Factor high)

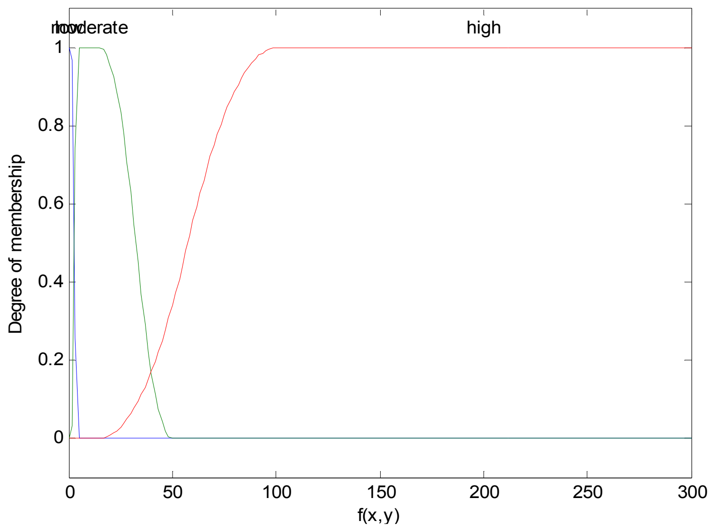

Figure 5. Membership Function $f(x, y)$

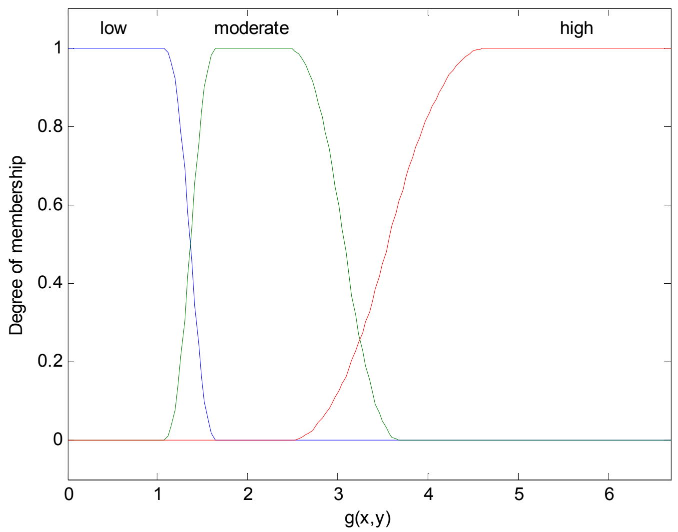

Figure 6. Membership Function $g(x, y)$

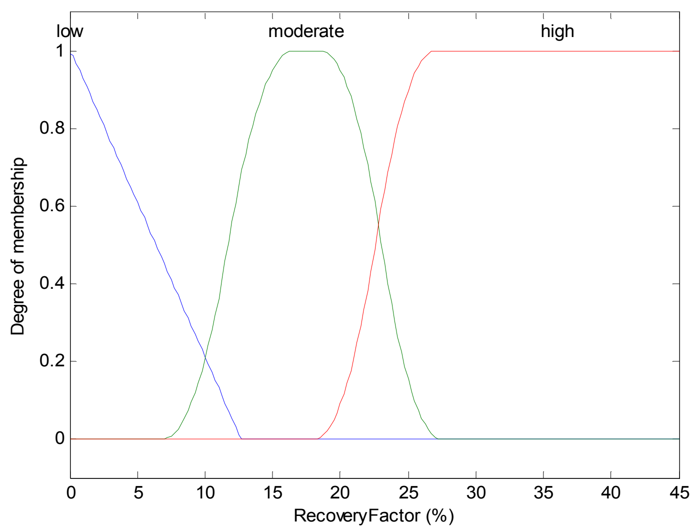

Figure 7. Membership function of recovery factor

3. Results

The simulation for the inputs *f(x ,y)* and *g(x, y)* with different *r* and *q* provides the same optimum end points, but the value of the recovery factor is different. This is because of the differences in the definition of the intervals in each category of the membership function of inputs *f(x, y)* and *g(x, y)*.

For example, for *r* = 0.3 and *q* = 1.25, the same optimum end point for the inputs *f(x, y)* and *g(x, y)* was obtained, i.e, the point (11.23) with the length of the well of 1020 ft. Figure 8 shows that the porosity, permeability and oil saturation values for the horizontal wells along this direction are quite homogeneous. However, the recovery factors produced are different. For the input *f(x, y)*, the resulting recovery factor is 18.8%, while for the input *g(x, y)*, the recovery factor produced is 21.67%.

The results obtained using Fuzzy Subtractive Clustering and Fuzzy Logic will be validated using reservoir simulation results. The validation results for the inputs *f(x, y)* and *g(x, y)* can be seen in Table 1 and Table 2, respectively. In addition, visualization of the simulation results can be seen in Figure 9, Figure 10, Figure 11, and Figure 12.

Based on the validation results, for input *f(x, y)*, there are differences in the recovery factor of 2.5% (with 11.26% error) for the value of the parameter *r* = 0.3 and *q* = 1.25. For the value of the parameter *r* = 0.4 and *q* = 1.25, there is a difference in the recovery factor, amounting to 0:32% (1.5% error). This is because the definition of the interval membership functions in the variable of recovery factor is less sensitive.

For the case of point (18.22) as the starting point, the optimum end point is located in an area with a smaller coordinate index of *x* (the area to the left). This area is more productive than the area with a greater coordinate index of *x* (the area to the right). On the right part of the area, the oil saturation value is quite good, but the values of the porosity and permeability are not good.

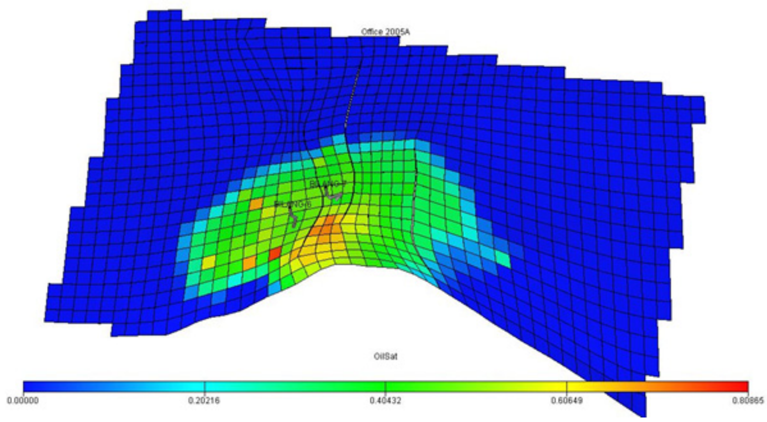

Figure 8. Optimum Direction and Optimum Length with *r* = 0.3 and *q* = 1.25 on the porosity, permeability and oil saturation data

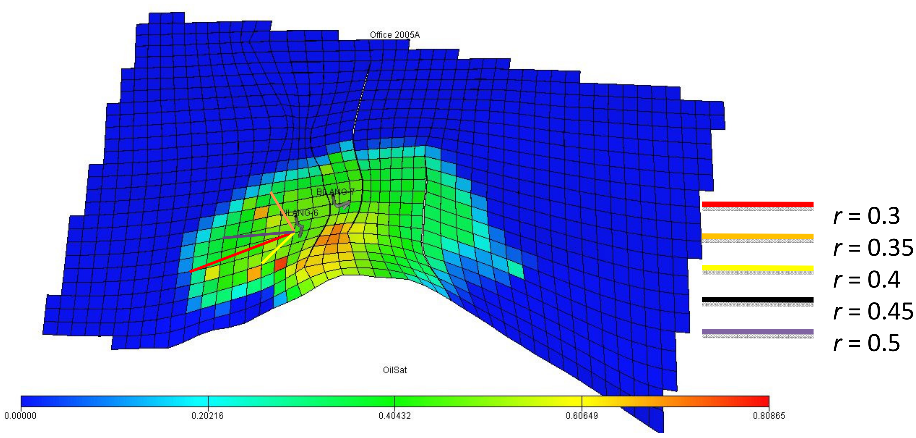

Figure 9. Optimum direction and length for *q* = 1.25

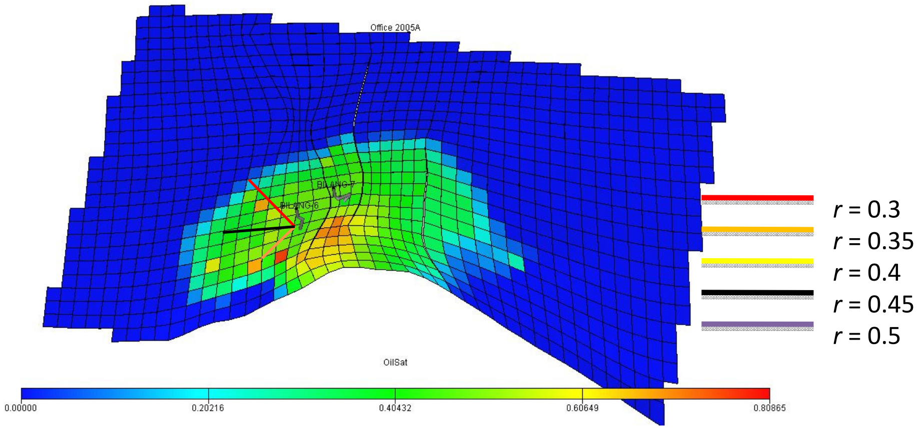

Figure10. Optimum direction and length for q = 1.5

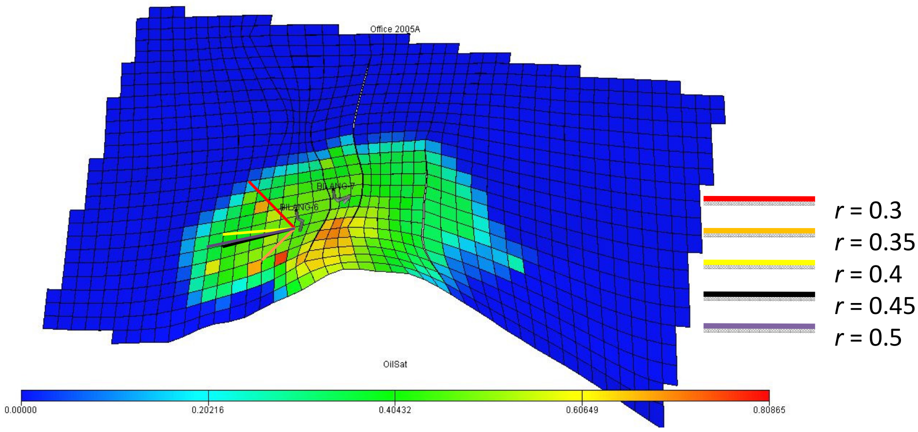

Figure 11. Optimum direction and length for q = 1.75

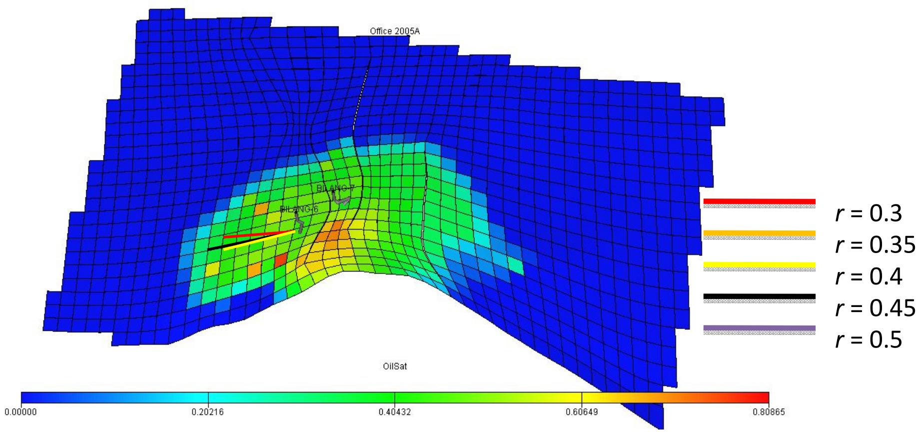

Figure 12. Optimum direction and length for q = 2

Table 1. Results of simulation and validation using a simulator reservoir for *input* $f(x, y)$

r	Number of Group	x_0, y_0	x_u, y_u	Length (ft)	*Recovery Factor* (%)	*Recovery Factor* (%) (Simulator)	Error (%)
q = 1.25							
0.3	44	18,22	11,23	1020	18.7945	21.18	11.26
0.35	31	18,22	16,18	1831	17.4254	21.38	18.5
0.4	23	18,22	16,24	760.2631	21.8127	21.49	1.5
0.45	17	18,22	16,24	760.2631	21.8127	21.49	1.5
0.5	11	18,22	13,21	760.2631	17.4157	21.32	18.31
q = 1.5							
r	Number of Group	x_0, y_0	x_u, y_u	Length (ft)	*Recovery Factor* (%)	*Recovery Factor* (%) (Simulator)	Error (%)
0.3	31	18,22	14,17	2040	18.0532	21.19	14.8
0.35	22	18,22	16,24	760.2631	21.8127	21.49	1.5
0.4	16	18,22	16,24	760.2631	21.8127	21.49	1.5
0.45	11	18,22	13,21	760.2631	17.4157	21.32	18.31
0.5	9	18,22	13,21	760.2631	17.4157	21.32	18.31
q = 1.75							
r	Number of Group	x_0, y_0	x_u, y_u	Length (ft)	*Recovery Factor* (%)	*Recovery Factor* (%) (Simulator)	Error (%)
0.3	25	18,22	14,17	2040	18.0532	21.19	14.8
0.35	15	18,22	16,24	760.2631	21.8127	21.49	1.5
0.4	11	18,22	13,21	760.2631	17.4157	21.32	18.31
0.45	9	18,22	13,22	480.8326	17.3486	21.47	19.2
0.5	8	18,22	12,22	760.2631	17.3585	21.33	18.62
q = 2							
r	Number of Group	x_0, y_0	x_u, y_u	Length (ft)	*Recovery Factor* (%)	*Recovery Factor* (%) (Simulator)	Error (%)
0.3	17	18,22	13,21	760.2631	17.4157	21.32	18.31
0.35	12	18,22	13,21	760.2631	17.4157	21.32	18.31
0.4	10	18,22	13,22	480.8326	17.3486	21.47	19.2
0.45	8	18,22	12,22	760.2631	17.3585	21.33	18.62
0.5	7	18,22	12,22	760.2631	17.3585	21.33	18.62

Table 2. Results of simulation and validation using a simulator reservoir for *input* $g(x, y)$

r	Number of Group	x_0, y_0	x_u, y_u	Length (ft)	*Recovery Factor* (%)	*Recovery Factor* (%) (Simulator)	Error (%)
q = 1.25							
0.3	44	18,22	11,23	1020	21.6703	21.18	2.31
0.35	31	18,22	16,18	1831	17.6619	21.38	17.39
0.4	23	18,22	16,24	760.2631	27.2712	21.49	26.9
0.45	17	18,22	16,24	760.2631	27.2712	21.49	26.9
0.5	11	18,22	13,21	760.2631	17.6243	21.32	17.33
q = 1.5							
r	Number of Group	x_0, y_0	x_u, y_u	Length (ft)	*Recovery Factor* (%)	*Recovery Factor* (%) (Simulator)	Error (%)
0.3	31	18,22	14,17	2040	19.6758	21.19	7.15

0.35	22	18,22	16,24	760.2631	27.2712	21.49	26.9
0.4	16	18,22	16,24	760.2631	27.2712	21.49	26.9
0.45	11	18,22	13,21	760.2631	17.6243	21.32	17.33
0.5	9	18,22	13,21	760.2631	17.6243	21.32	17.33
				q = 1.75			
r	Number of Group	x_0, y_0	x_u, y_u	Length (ft)	*Recovery Factor* (%)	*Recovery Factor* (%) (Simulator)	Error (%)
0.3	25	18,22	14,17	2040	19.6758	21.19	7.15
0.35	15	18,22	16,24	760.2631	27.2712	21.49	26.9
0.4	11	18,22	13,21	760.2631	17.6243	21.32	17.33
0.45	9	18,22	13,22	480.8326	17.3496	21.47	19.19
0.5	8	18,22	12,22	760.2631	17.3934	21.33	18.46
				q = 2			
r	Number of Group	x_0, y_0	x_u, y_u	Length (ft)	*Recovery Factor* (%)	*Recovery Factor* (%) (Simulator)	Error (%)
0.3	17	18,22	13,21	760.2631	17.6243	21.32	17.33
0.35	12	18,22	13,21	760.2631	17.6243	21.32	17.33
0.4	10	18,22	13,22	480.8326	17.3496	21.47	19.19
0.45	8	18,22	12,22	760.2631	17.3934	21.33	18.46
0.5	7	18,22	12,22	760.2631	17.3934	21.33	18.46

4. Conclusion

Fuzzy Logic and Fuzzy Subtractive Clustering are effective methods that can be used to determine the optimum direction and length of the horizontal wells in oil field X. These methods simultaneously generate the direction and length without using a reservoir simulator. In the Fuzzy Subtractive Clustering method, parameters of radius (r) and squash factor (q) affect the number of the groups formed. In the Fuzzy Logic, both of the objective functions constructed provide the same direction and length, but with different output values. Therefore, quite sensitive definintion is required in the membership functions and the interval of the categories in each variable in order that the output obtained be in accordance with the conditions in the field. Economic analysis is also required for further development.

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