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Research Article

Determination of Optimum Drilling Area for Petroleum Exploration with Adaptive Neuro Fuzzy Inference System (ANFIS)

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Abstract

This paper aimed to determine the optimum drilling area for petroleum exploration based on adaptive neuro fuzzy inference system has been performed. Drilling in petroleum exploration is costly and time consuming and has many problems. Therefore, the determination of drilling points in detailed exploration of petroleum reserves, which takes into account all the complex conditions governing the formation of petroleum reserves and the integration of factors such as source rocks, reservoir rocks, and petroleum traps are of great importance. Therefore, any mistake in determining the location of the excavation is very costly and time-consuming. Therefore, the present study aimed at identifying an optimal drilling area in petroleum exploration using an adaptive neural fuzzy inference system that seeks to reduce the time and cost of exploration. In this regard, the maps were developed using GIS functions. To model maps, this study used adaptive neuro-fuzzy inference system (ANFIS) methods to construct a reliable tool to predict the reservoir properties namely: oil rate, gas rate, cumulative oil, cumulative gas and gas oil ratio that lies within the reservoir and design properties for this study. The proposed approach was tested on an Iranian oil field to determine the potential areas more accurately using well log data. The predicted reservoir properties match the ones generated with an average error as follow; oil rate 13.25%, gas rate 4.32, cumulative oil 11.47%, cumulative gas 8.01%, gas oil ratio 5.41%. Experimental results show that our proposed method can be used to predict any other reservoir parameters using well logs data. So the ANFIS method with R and RSME (0.7651, 0.0298) can predicts optimum drilling area for petroleum exploration accurately.

Keywords*: optimum drilling area, petroleum exploration, adaptive neuro fuzzy inference system*

1. Introduction

In the petroleum engineering field, the adaptive neural fuzzy inference system (ANFIS) had been introduced back in the 1980's when researchers found that it has a huge potential in solving many related problems in the industry in different petroleum engineering segments such as well testing, reservoir characterization, enhanced oil recovery, reservoir stimulation and drilling (Mohammed AlQuisom, 2016).

In petroleum industry, obtaining an accurate estimation of the hydrocarbon in place before exploration or production stages is the most important objective. Therefore, reliable prediction of reservoir characterization is very helpful for evaluation and designing any development plan for production of the field (Chen *et al*, 2013).

In the petroleum exploration activities the main objective is to determine areas where oil and gas were existed. So the basis of any drilling decision is associated to the presence or absence of hydrocarbons in the potential wells of the basin. This evaluation should be results of efforts undertaken by a team of geologists, geochemists, geophysicists and engineers, in trying to get the best picture of the prospects that may be potentially drilled (Ruffo *et al*, 2009).

Moreover, determining and locating factors such as source rocks, reservoir rocks, and oil traps are basis of exploration, there are many problems in various fields with no solution. This is mainly due to no direct access to petroleum reserves in depths. As source rocks are located deep underground, we cannot certainly locate petroleum fields in a region. As a result, it is always probable to face a dry well after spending over hundred million dollars to drill an exploration well (Bott & Carson, 2007).

Therefore, determining the best possible areas to achieving seismic data is highly costly and determining the best areas for drilling exploration wells has particular importance, so incorrect or careless in determining the best areas imposes large costs or may be time consuming for the exploration project. The basic problem is how to determine the place of possible areas within the target zone in less possible

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time and with minimum possible exploration and production costs (Haris *et al*, 2017).

In addition, the same field production maps were modeled and integrated utilizing the artificial neural system. The main goal of such expert system was to predict the reservoir properties in term of cumulative oil and gas for a total of two years. The obtained data was compared to the actual field data; it shows a close relationship between both of them. These results were used then to approximate the placement of new infill drilling with the aid of the surface maps (Bansal, 2011). Fuzzy control algorithms and especially ANFIS have been widely used to predict process, on the other hand, they use a non-linear approach to create a model, so when faced with the problems and non-linear data, these networks may express such a data much more accurately as a defined model (Jinlan *et al*, 2007).

One of the neuro-fuzzy systems in which learning algorithm is coincided with integrates approaches is ANFIS system. In recent years, many researches have been carried out to use the ANFIS system for modeling of the exploration engineering (Rabiei and Aranda, 2017)

Adaptive neural fuzzy inference system (ANFIS) is an area of great interest and significance in petroleum exploration and production. Recently, it has made an impact in the petroleum industry, and the application has continued to grow within the industry. The application in petroleum industry has more than 16 years of history with first application dated 1989, for well log interpretation; drill bit diagnosis using neural networks and intelligent reservoir simulator interface (Jalalnezhad and Kamali, 2016).

It has been suggested in solving many problems in the petroleum industry, seismic pattern recognition, reservoir characterization, permeability and porosity prediction, prediction of PVT properties, drill bits diagnosis, estimating pressure drop in pipes and wells, optimization of well production, well performance, portfolio management and general decision making operations and many more can be used (Jahani-Keleshteri and Bahadori, 2017).

Drilling operation activities on adaptive neural fuzzy inference system (ANFIS) have evolved over the years giving flexibility in selection, monitoring, diagnosing, predicting, and optimizing, thus impact in overall efficiency and profitability cannot be highlighted (Ameri Shahrabi *et al*, 2015).

Therefore this paper study and analyzes the successful application of adaptive neural fuzzy inference system (ANFIS) techniques as related to one of the major aspects of the petroleum industry, drilling capturing the level of application and trend in the industry. A summary of various papers and reports associated with adaptive neural fuzzy inference system applications and it limitations will be highlighted. This analysis is expected to contribute to further development of this technique and also determine the neglected areas in the field.

2. Area of study

The area of research is the South Pars Region. Pars Special Economic Energy Zone (Asalouyeh) was established in 1998 in accordance with the resolution of the thirty-ninth session of the Supreme Council of the Free Industrial and Trade Zones in order to exploit the oil and gas resources of the South Pars region and to carry out economic activities in the field of oil, gas and petrochemicals in the range of coastal line of Asalouyeh and Naiband have been established in an area of 30,000 hectares.

South Pars Energy Special Economic Zone is located in the east of Bushehr province at the geographical location of 27 degrees and 49 minutes north and 52 degrees 59 minutes east, on the border of the Persian Gulf in 300 kilometers east of Bushehr port and 420 kilometers west of Bandar Lengeh and 570 kilometers west of Bandar Abbas and about 100 kilometers of the South Pars gas field located in the Persian Gulf. The Pars Special Economic Energy Zone covers an area of approximately 10,000 hectares, approved by the Cabinet of Ministers and the Supreme Council of Free Industrial -Trade Zones, from the west to the village of Shirino, from the south to the Persian Gulf, from the north to the continent of the Zagros Mountains and from the east to village of Chah Mobarak is limited (Karbassii *et al*., 2014).

3. Methodology and implementation

3.1 Adaptive neuro-fuzzy inference systemstructure (ANFIS)

In general, a fuzzy system consisted of fuzzy-making processes, fuzzy foundation law, and fuzzy and non-fuzzy output engine. In the fuzzy step, each component of input data, convert into a membership degree. In the classic set, membership functions is two members set zero and one, while the range of fuzzy membership functions is closed between zero and one. Direct perception, inference, genetic algorithms and neural networks are such ways that can be identified membership function of variables. Commonly artificial neural networks to optimize fuzzy membership functions used. This method is called adaptive neuro fuzzy inference system following is introduced.

Adaptive neuro-fuzzy inference system (ANFIS) first time in 1993 by Zhang (1997, 1993) was introduced. The system of neural networks and fuzzy logic algorithms for designing nonlinear mapping between input and output space is used. The system of fuzzy system language power with numerical strength of neural network in modeling of complex processes is very powerful. The more complex training algorithm that uses a combination of gradient method for reducing and minimizing squares, introduction and implementation and rapid learning system equivalent to the fuzzy inference algorithm is discussed. If a fuzzy inference system with two inputs x and y and one output z presented. The first order Sugeno fuzzy model with two if-Then fuzzy law can be expressed as follows:

$$Rule1: if\ x = A_1\ and\ y = B_1\ then\ z_1 = p_1x + q_1y + r$$
$$Rule2: if\ x = A_2\ and\ y = B_2\ then\ z_2 = p_2x + q_2y + r$$

The first layer (input): each node i of this layer, membership values that belong to each of the appropriate fuzzy sets, using the membership function produced.

$$O_{1,i} = \mu_{A_i}(x) \quad for\ i = 1,2 \quad or \quad O_{1,i} = \mu_{B_{i-2}}(y) \quad for\ i = 3,4$$

Where x (or y) node input ith and A_i (or B_{i-2}) is language tags (like "small" or "large") are related to the node. $Q_{1,i}$ is membership of fuzzy set (A1, A2, B1, B2) and determines the degree to which input variable x (or y) correspond to the A quantity. Usually membership functions A, B by bell functions is expressed:

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}}$$

The second layer (membership functions input): This layer is composed of Π node as an input signal and the output is multiplied. for example:

$$O_{2,i} = w_i = \mu_{A_i}(x)\,\mu_{B_i}(y) \qquad for\ i = 1,2$$

In other words, the operator layer "and" used.

The third layer (law): each node in this layer is a fixed node N is labeled.

The i-th node have the ability to fire law ith to the ability to fire calculated and for convenience, the outputs of this layer is called the ability to normalized fire.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1+w_2} \quad , \quad i = 1,2$$

The fourth layer (membership function output): nodes this layer match function nodes:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i)$$

Where $\overline{W}_i$ third layer is output and p_i, q_i, r_i is parameters set. These layer parameters are like the parameters set of Tully fuzzy model.

The fifth layer (output): This layer is called fixed node Σ, overall output is calculated by adding up all input signals. So in layers defuzzification process, the results of any fuzzy law convert to defuzzification output.

$$O_{5,i} = \textstyle\sum_{i=1} \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

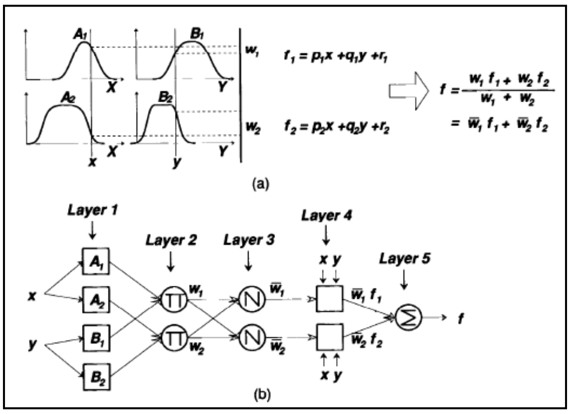

Figure 1: Sugeno first order fuzzy model with two fuzzy law and ANFIS equivalent system

Neuro-fuzzy model allows fuzzy systems on parameters education issues use adaptive returns training algorithm. The downward sloping algorithm error, the error correction parameters are distributed to the inputs. In this method, using the error retarder algorithm, the error value is distributed to the inputs and the parameters are corrected. This training method is exactly the same as the post-propagation technique used in artificial neural networks. The neuro-fuzzy network structure is observed in Figure 1, the total output (f) as a linear combination of parameters written as follows:

$$f = \frac{w_1}{w_1+w_2}f_1 + \frac{w_2}{w_1+w_2}f_2 = \bar{w}_1(p_1x + q_1y + r_1) + \bar{w}_2(p_2x + q_2y + r_2)$$
$$= (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 +$$
$$(\bar{w}_2 y)q_2 + (\bar{w}_2)r_2$$

The implementation of a fuzzy system is done in a way that will have the ability to learn. Then parameters values obtained using the least squares error method. By combining these techniques and error retardation method, creating a blended learning method that works as follows:

In both training when moving forward, the nodes output are calculated as normal until the fourth layer and the resulting parameters are calculated by methods such as least square error are calculated.

In the following, after calculating the error in the afterward return, the error ratio is distributed over the conditional parameters and corrected by using the error retardation method are corrected.

3.2 Evaluation criteria for classification and accuracy of classification

The criteria used in this study to obtain classification accuracy, is confusion matrix or cross matrix. The following equation was used to calculate the classification accuracy (Vogel *et al*, 2015):

$$\%ACC = \frac{\sum_{i=1}^{M} n_{ii}}{N} * 100$$

In this regard, M is the number of classes and N is the number of total signs and n_{ii} confusion matrix elements are disturbed.

3.3 Oil Potential Data Modeling

The first and the most important step in data preparation for ANFIS modeling is classifying input data into two sets: learning set and testing and validation set. Test data set must be representative of the main data set. Here, 70% of the main data sets for each input variable (460 ×359 matrices) were randomly selected as neural network training data, 15% as testing data, and 15% as validation data. A key problem in neural network modeling is to find the optimal number of neurons. In this study, the number of network layers and neurons in the hidden layer were experimentally changes from the smallest possible size to the largest possible size. In each case, the error between the desired output and the real output was calculated.

ANFIS models were developed in MATLAB environment. The inputs and outputs were then defined and categorized as training, testing and validation data. In the next step, network was trained and finally error was calculated based on the network output. The transfer functions for hidden layer and output layer were sigmoid and linear functions, respectively. The minimum error threshold was set to 0.005. Weights of neurons in case of minimum error for testing data were selected as final weights.

The ANFIS network topology used in this study included numbers of network layers, inputs, outputs, membership functions, and linguistic variables. As previously mentioned, we had 17 inputs and 1 output. Therefore, the parameters of membership functions for each input variable were defined using fuzzy clustering. Weighted average was also used for defuzzification objectives. The number of iterations of the hybrid algorithm (combining back-propagation and least squares algorithms) to correct the model parameters was 300. The target error was set to 0.005.

4. Result

Through this problem, the main target is to be able to predict the reservoir properties generated originally from commercial simulator but this time using the Adaptive neuro-fuzzy inference system (ANFIS).

Table 1: Reservoir properties used in the model

Reservoir Property	Unit	Min	Max
Reservoir Thickness (h)	ft	30	150
Porosity (ϕ)	Fraction	0.1	0.3
Permeability (ki & Kj)	md	5	250
Permeability (kk)	psi	10	150
Reservoir Pressure (P)	1/psi	3000	8000
Rock Compressibility (R_Comp)	%	1.00E-07	1.00E-06
Oil Saturation (So)	%	2	5
Reservoir Temperature (T)	^{0}F	150	250
Gas Density (ρg)	air Density=1	0.6	1.04
Oil Density	API	20	40

The mean average error target is to be adjusted around 5-10%. According to the results obtained the obtained result: oil rate, gas rate, cumulative oil, cumulative gas and gas oil ratio are the most difficult properties to predict accurately due to the fact that the range of data for these properties ranges widely. This made the ANFIS method somehow challenging and time-consuming.

Table 2: Mean error comparison for oil rate and gas rate for different ANFIS structures with different number of layers and neurons

Number of Hidden Layers	Number of neurons	Mean Error	
		Oil Rate	Gas Rate
1	12, 15,18	6.250%	34.214%
2	12,33,35,45	22.278%	14.658%
3	12,12,35,52,51	12.536%	22.171%
4	12,12,33,45,52,51	29.120%	26.689%
5	12,18,33,39,42,43,49	11.101%	5.278%

Table 3: Mean error comparison for cumulative oil and gas for different ANFIS structures with different number of layers and neurons

Number of Hidden Layers	Number of neurons	Mean Error	
		Oil Rate	Gas Rate
1	12, 15,18	15.467%	45.897%
2	12,33,35,45	32.864%	14.665%
3	12,12,35,52,51	41.314%	145.433%
4	12,12,33,45,52,51	21.103%	29.379%
5	12,18,33,39,42,43,49	9.784%	9.665%

Tables 2 and 3 show a detailed comparison between different ANFIS structures with the corresponding error percentage for each reservoir properties. There are some reservoir properties that have low mean error percentage for hidden layers 1, 2, 3, 4 and 5 but overall ANFIS with 5 hidden layers produced the lowest mean error percentage for all the production profiles as it is shown in figure 2.

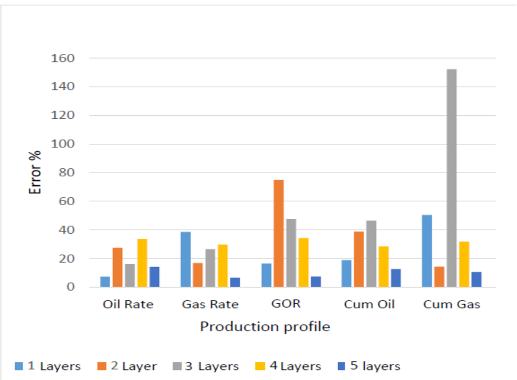

Figure 2: Comparison of ANFIS structures with different number of layers and neurons

All three figures 2 and 3 give us a clear observation that the ANFIS has received appropriate training and has not memorized.

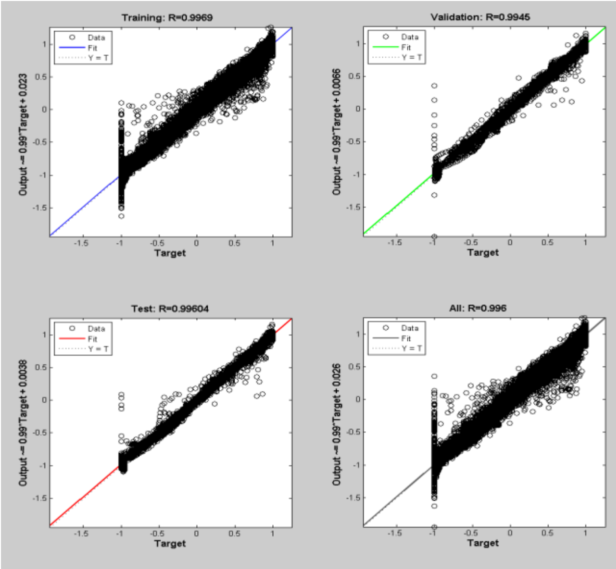

Figure 3: Obtained regression with the trained ANFIS with 5 hidden Layers

Figs 4 and 5 show the structure of the designed model. To assess the accuracy and precision of classified maps, Root Mean Square Error (RMSE) and correlation (R), were calculated.

Table 4: Validation results for developed model

	RMSE	R
ANFIS	0.0298	0.7651

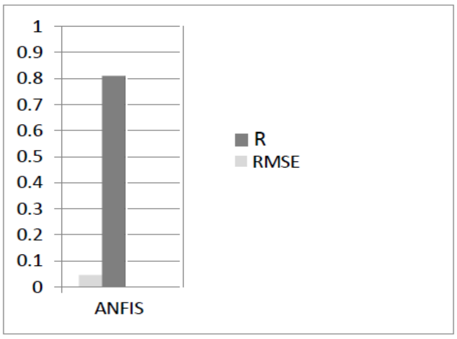

Figure 4: Accuracy of the model

Table 4 and Fig. 4 show RMSE equal to 0.0298 and R equal to 0.7651 outperform ANFIS. It should be noted that in testing step, the closer R to 1 and RMSE to 0, the better the performance.

According to Fig. 5, the oil field marked by oval was fully detected by ANFIS. ANFIS was also able to determine it partly. Gray color on the map represents real oil fields that models failed to identify. Dark color shows areas with no oil field wrongly classified by models as oil potentials. As a result, we can conclude that the ANFIS outperforms accurately.

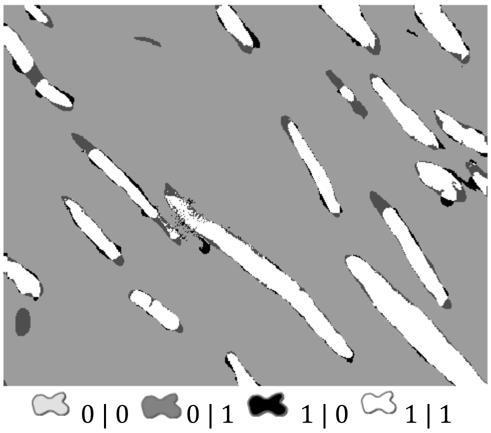

Figure 5: Map of predicted changes by ANFIS. It should be noted that in legend, 1 and 0 represent the presence and the absence of the oil zones, respectively.

Conclusion

In the petroleum industry, the adaptive neural fuzzy inference system (ANFIS) had been used to find traps where oil and gas were existed before exploration or production stages. Then, reliable prediction of reservoir characterization is very helpful for evaluation and designing any development plan for exploration of the field. Petroleum exploration is a very complex process. This study employed neural algorithms to develop a model that can be very helpful in the process of petroleum exploration. Factors affecting petroleum exploration were identified using expert opinions and literature.

So, drilling process considered as one of the most important stages in determining a new reservoir. The reservoir location is so crucial that could affect the productivity of the reservoir if it is done in the wrong way. The location or the depth at which reservoir must be placed at in order to yield a high recovery factor while preserving the natural driving forces, represented by the gas can allowing natural production without the need to use other methods to enhance the recovery at least at early stages of the exploration. Accordingly, the maps were developed using GIS functions. To model maps, this study used adaptive neuro-fuzzy inference system (ANFIS) methods to construct a reliable tool to predict the reservoir properties namely: oil rate, gas rate, cumulative oil, cumulative gas and gas oil ratio that lies within the reservoir and design properties for this study. To this end, after creating models and training them, the final oil reservoirs maps were developed. However, proposed model in this study can be used to predict areas where the general conditions of the region confirm the presence of petroleum resources.

Proposed model also can be utilized for further exploration operations while using explored areas as a guide. Since this model are used in early exploration stages to identify potential areas, and then additional information is provided through precise seismic operations by drilling exploration wells. In this case, the error will be much less. As a result, proposed model help avoiding wasting money by preventing any attempt on low-potential areas and quickly covering large areas. The model developed in the study will predict the reservoir properties for main performance such as oil rate, gas rate, cumulative oil, cumulative gas and gas oil ratio.

For this model, the optimum ANFIS structure was found to have 5 hidden layers that contained a total of 558 neurons. The predicted reservoir properties match the ones generated with an average error as follow; oil rate 13.25%, gas rate 4.32, cumulative oil 11.47%, cumulative gas 8.01%, gas oil ratio 5.41%. Results obtained by validation revealed that ANFIS can predict optimum drilling area for petroleum explorations accurately. Experimental results show that our proposed method can be used to predict any other reservoir parameters using well logs data. So the ANFIS method with R and RMSE (0.7651, 0.0298) can predict optimum drilling area for petroleum explorations more accurately.

The results of ANFIS show that the accuracy of the ANFIS model is generally very high. This method does not depend on specific well location but also depend on GIS functions and can be used worldwide for two reasons. First, a well-known drilling parameter is selected which does not depend on a specific location or formation. The second reason comes from ANFIS properties which train and test the system by using its own available data and not by predetermined values from other wells. Finally, increasing development of GIS technology along with ANFIS model and wide applications of GIS- based ANFIS model in different sectors of petroleum industry in the future could lead to reduced exploration costs and higher efficiency in sectors of the petroleum industry. It can be concluded that a GIS-based ANFIS model can be useful in providing valuable information from raw data to model petroleum reservoirs. The fact is that GIS has been less noted in petroleum industry than mining industry.

References

Mohammed AlQuisom (2016). Development of an artificial neural network based expert system to determine the location of horizontal well in a three-phase reservoir with a simultaneous gas cap and bottom water drive. The Pennsylvania State University, the Graduate School, John and Willie Leone Family Department of Energy and Mineral Engineering. Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science.

Jin-Hong Chen, Ayaz Mehmani, Baoyan Li, Daniel Georgi, Guodong Jin (2013). Estimation of Total Hydrocarbon in the Presence of Capillary Condensation for Unconventional Shale Reservoirs. Society of Petroleum Engineers. SPE Middle East Oil and Gas Show and Conference, 10-13 March 2013, Manama, Bahrain.

Paolo Ruffo, Livia Bazzana, Alberto Consonni, Anna Corradi, Andrea Saltelli and Stefano Tarantola (2009). Hydrocarbon exploration risk evaluation through Uncertainty and Sensitivity analyses techniques. Ispra (VA), Italy.

A Haris, T Mulyawan and A Riyanto (2017). Drilling exploration design controlled by pore pressure prediction from 2D seismic and well data: case study of South Sumatra Basin. Southeast Asian Conference on Geophysics . Earth and Environmental Science 62(2017)

Bansal, Y. (2011). Forecasting the Production Performance of Wells Located in Tight Oil Plays Using Artificial Expert Systems. University Park: The Pennsylvania State University

Jinlan Liu, Yin Bai, Bin Li: A New Approach to Forecast Crude Oil Price Based on Fuzzy Neural Network", in the proceeding of FSKD, pp 273-277,2007.

Peyman Rabiei, Danie Arias-Aranda (2017). An Adaptive Network-based Fuzzy Inference System for predicting organizational commitment according to different levels of job satisfaction in growing economies. SAGE Journals. First Published June 28, 2017. pp 222-246

Mohammad Javad Jalalnezhad and Vahid Kamali(2016). Development of an intelligent model for wax deposition in oil pipeline. Journal of Petroleum Exploration and Production Technology. March 2016, Volume 6, Issue 1, pp 129–133

Zahra Jahani-Keleshteri, Alireza Bahadori. (2017) An accurate model to predict viscosity of heavy oils. *Petroleum Science and Technology* 35:4, pages 371-376

Mohammadjavad Ameri Shahrabi , Iman Rahimzadeh Kivi , Mohammadreza Akbari , Anoush Safiabadi (2015). Application of adaptive neuro-fuzzy inference system for prediction of minimum miscibility pressure. International Journal of Oil, Gas and Coal Technology. Volume 7, Issue 1. pp 22-37

Karbassii, A.R.; Nabi-Bidhendi, Gh.R.; Bayati, I., 2014. Environmental geochemistry of heavy metal in a sediment core off Bushehr, Persian Gulf, Iran Journal of Environment Health science Engineering, 2: 255-260.

J., S. Haddadin, B. Jarosiewicz, J. Simeral, D. Bacher, L. Hochberg, J. Donoghue, and P. Van Der Smagt, "An assistive decision-and-control architecture for force-sensitive hand–arm systems driven by human–machine interfaces," The International Journal of Robotics Research ,vol. 34, no. 6, pp. 763–780, 2015