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Application of Bayesian decision making tool in detecting oil-water contact in a carbonate reservoir

A. Mollajan[1*], H. Memarian[1], B. Tokhmechi[2]

1. School of Mining Engineering, University College of Engineering, University of Tehran, Tehran, Iran
2. School of Mining, Petroleum & Geophysics Engineering, University of Shahrood, Shahrood, Iran

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**Corresponding author: a.mollajan@alumni.ut.ac.ir (A. Mollajan).*

Abstract
Defining Oil-Water Contact (OWC) is essential for detail petrophysical evaluations and reservoir volumetric calculations. This paper presents Bayesian decision making tool as a sophisticated technique in OWC detecting from well log data. The proposed method is applied to data related to three wells of an oil field of the Southwestern Iran. The method's performance is evaluated based on well testing reports and also through comparisons with the results of conventional approach based on permeability prediction. Results indicate that the proposed method is more accurate than conventional approach and may improve the results about 5% on average. In addition, using this method, any variation of water saturation (S_w) log and reservoir fluid types may be detectable.

Keywords: *Oil-Water Contact, Petrophysical Evaluation, Well Log Data, Bayesian Decision Making Tool, Iran.*

1. Introduction

Determining Oil-Water Contact (OWC) is a challenging issue in the characterization of the carbonate reservoirs and important for detailed petrophysical calculations. Gravity segregation of fluids puts oil on top of water in most reservoirs. The OWC is commonly a bounding surface or transition zone that above which gradually oil occurs and below which gradually water occurs [1]. The reservoir's vertical interval can be subdivided by fluid type to account for differences in the average fluid saturation as follow:

a. Clean oil production zone: located at the top of the transition zone. Perforations above this depth should produce mostly oil.
b. Transition zone: is a region where water is produced along with oil. Perforations below this point will produce oil with some water. Water saturation in this zone may still be quite low and may pass economic cutoffs.
c. Water production zone: This zone is located at the base of the transition zone and is the top of Free Water Level (FWL). Perforations below this point will produce 100% water.

The OWC may usually be picked on the resistivity and permeability logs in a clean, porous reservoir [2]. However, top of transition zone may be masked by shaliness, changes in pore geometery, and residual oil. In general, there are two methods for fluids detection: direct and indirect approaches. In direct methods such as well testing, reservoir fluids are identified through the reservoir liquid observation; while in indirect methods, those fluids will be detected by interpretation of geophysical data [3-10].

In this paper, we are going to develop a decision making tool based on Bayes theorem algorithm for detecting OWC in a carbonate reservoir from well log data. The presented method can be utilized in several applications of reservoir characterization.

2. Methodology

2.1. Conventional method

The position taken by each of reservoir fluids inside an oil trap is directly related to the reservoir's permeability. The studies show that oil moves through a path in which it has higher relative permeability than water [11]. Consequently, if permeability (K) is plotted versus depth, the OWC can be picked on the permeability log where pemeability reaches its lowest values. In contrast to permeability log, the water saturation log reaches its highest value. Based on the above issues, conventionally, detecting the OWC will be possible by following the bellow steps [11]:

a. Estimating water saturation log
b. Calculating the permeability through the wells
c. Determining OWC by applying proper cut off values on K and S_w.

2.2. Bayesian decision making

The Bayesian decision making tool is an effective probabilistic algorithm, assigns the most likely class to a given data. Bayes' formula allows us to express the probability of a particular class given an observed x as ([12, 13]):

$$P(w_i|x) = \frac{P(x|w_i).P(w_i)}{P(x)} \quad (1)$$

Where w_i, with i =l,...,n denotes the n different classes. $P(x|w_i)$ is "priory knowledge" of a particular class before having observed any x. Also, $P(w_i|x)$ known as "posterior probability", can be estimated from the training data [12]. For the case of n=2, in order to make a right decision about assigning the depth under study to an appropriate corresponding class, the logic of decision making could be represented as follows:

If $P(w_1|x)\times P(w_1) > P(w_2|x)\times P(w_2) \rightarrow w_1$ is optimum decision

If $P(w_2|x)\times P(w_2) > P(w_1|x)\times P(w_1) \rightarrow w_2$ is optimum decision

2.3. Back– Propagation artificial neural network

Multi-layer Perceptron (MLP) is an effective type of neural networks frequently used in different fields of engineering as well as science. This type of neural networks consists of three layers; namely input layer, output layer and hidden layer(s). One of the most paramount issues related to ANN is learning. In this regard, Back-propagation is the common supervised learning method used for the training of feed-forward multi-layer networks [14].

3. Data set

To conduct this study, four well logs including DT, LLD, RHOB and NPHI related to three wells of an oil field of Southwestern Iran were used. Permeability and water saturation measured from core analysis and well test reports were also employed to verify the proposed algorithm. In term of Lithology, the formation under study (Sarvak Formation) mainly consists of carbonates. Based on Alavi [15] and Abdollahi fard et al. [16], the formation, deposited in marine environments, consists of shallow marine sediments of the Cenomanian. Table 1 summarizes some characteristics of studied reservoir. The sections in this table are abbreviated as follows:

a) R stands for Reservoir
b) N.R for Non Reservoir
c) M.R for Mid Reservoir

Table1. Some characteristics of reservoir under study.

Section	Remark	Well No.1		Well No.2		Well No.3	
		Porosity (%)	Permeability (md)	Porosity (%)	Permeability (md)	Porosity (%)	Permeability (md)
S_1	R.	9.2	4.6	15.7	16.31	16	16.78
S_2	N.R	5.3	2.14	3.9	2.88	3.6	2.24
S_3	R	28.5	114.06	27.9	107.58	19.5	23.36
S_4	N.R.–M.R.	9.2	4	5.1	3.26	12.4	10.09
S_5	M.R	17.7	8.85	9.4	4.56	10.4	6.38
S_6	N.R	3	2.61	3	2.61	9.4	4.56
S_7	R.	11.5	8.48	19.5	23.36	19.5	23.36
S_8	N.R.– M.R.	8.5	5.64	9.4	4.56	10.5	6.61
S_9	R.	23.8	66.32	16	16.82	22.8	56.50
S_{10}	N.R.	5.4	2.56	4.4	3.04	7.1	3.55
S_{11}	R.	16.1	17.05	18.6	21.65	18.2	20.99
S_{12}	N.R.	4	2.90	4.1	2.95	5.5	3.36

4. Implementing process

The following sections describe the implementation process and results of the employed approaches. It is noted that, to verify the results obtained from both conventional and proposed approaches, well test results were used. For that reason, the reservoir under study was divided into three different classes by a coding system as follows: for intervals which produce water, the zone value is considered 1, if the corresponding interval produces water along with oil then the zone value is 2 and finally if that specific interval produces oil, the zone value is 3.

4.1. Detecting oil-water contact using conventional method

In order to predict the permeability and water saturation logs, two different three-layer MLP neural networks were designed. For S_w predictor, the inputs were four well logs including DT, LLD, RHOB and NPHI and S_w measured from core analysis considered as output. Similarly, permeability was predicted by the help of same logs as inputs and relative K measured from core as output of predictor model. Implementation steps were as follows:

a. Existing wells were divided into two groups: two wells for model construction (including wells 1 and 2); and one for generalization investigation of the model (well No.3).
b. Model construction data set were randomly subdivided into two data sets; namely training data, with 70% of the data points, and testing data with the remaining 30%.

A trial and error approach was utilized since the optimization of the number of neurons in hidden layer still doesn't have a specific rule. In this way, the number of neurons was changed and RMSE was measured. The optimum number of neurons is the one that minimizes the error (Figure 1). In addition, to optimize the weights, a Lenvenberg-Marquardt training method was employed for both water saturation and permeability predictor models. The results of this stage are summarized in Table 2.

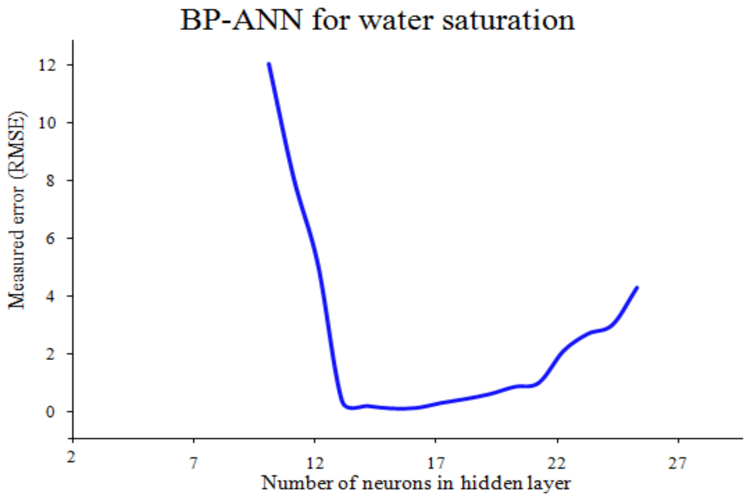
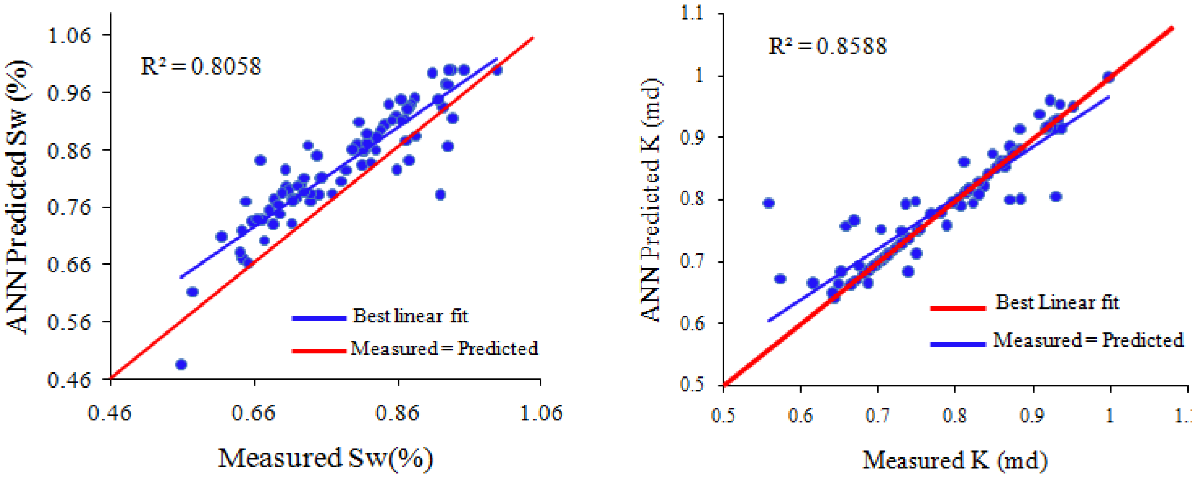


Figure 1. Measured error versus number of neurons for S_w predictor.

Table 2. ANN predictor models explanations.

Model	Transfer function in hidden layer	Transfer function in output	Number of neurons in hidden layer	R^2	RMSE
Water Saturation Predictor	TANSIG	PURELIN	15	0.81	0.12
Permeability Estimator	TANSIG	PURELIN	24	0.89	0.08

Figure 2 shows the determination coefficient (R^2) between predicted and measured water saturation (a) and permeability (b) in well No 3, which is not incorporated in the model development. The value of R^2 for S_w is 0.81 and for relative K is 0.86. The measured RMSE for these parameters are 0.12 and 0.08, respectively.



(a) (b)

Figure 2. Cross plot between measured and predicted S_w (a) and K (b) using ANN model.

As seen, the slope of fitted regression line for both S_w and K is lower than the best linear fit. This means that the models underestimate their target values. Figure 3 displays the plot of permeability and water saturation prediction in well No.3 along with LLD log. As shown in this figure, applying proper cut offs (i.e. limit of 20% water on water saturation log (water bearing zone) and 15 md on permeability) the OWC can be considered at depth of 2789 m. As it is clear in this case, the OWC is mainly dependent on permeability and water saturation cut offs.

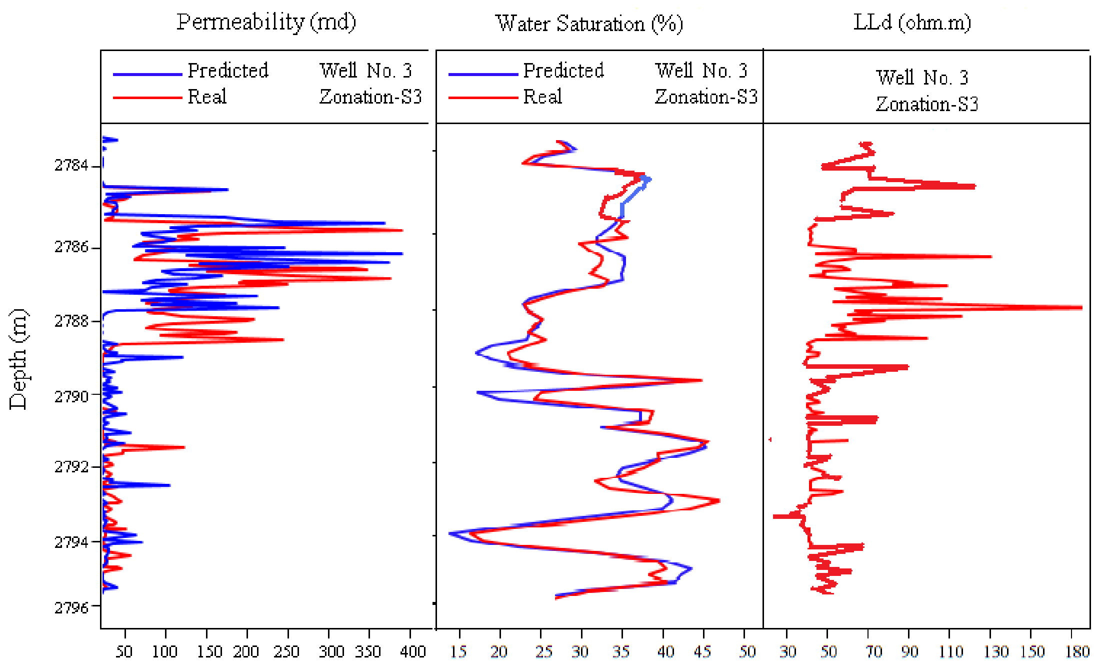


Figure 3. Results obtained from prediction of permeability and water saturation in well No.3.

Similar to the above mentioned steps, the OWC was determined for the two remaining wells. In order to have a quantitative basis for comparing the results of two methodologies, confusion matrix was used. Since the conventional method serves the crisp (sharp) results (a binary coding system of 0 and 1 which indicate water bearing and oil bearing zones, respectively) confusion matrix is a 2×3 in this case, the rows and columns of which represent decision and actual classes, respectively (Figure 4).

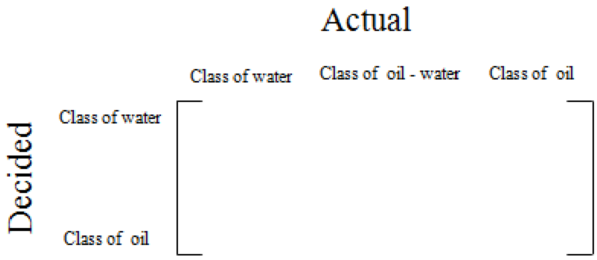


Figure 4. Confusion matrix used for explanation of conventional method's results.

The Classification Correctness Rate (CCR) was also calculated by dividing summation of trace of confusion matrix by number of classes. Table 3 shows the confusion matrices and CCR values of OWC determination using conventional method.

Table 3. Results of conventional method in three studied well.

Well No.	1	2	3
Confusion matrix	$\begin{bmatrix} 0.53 & 0.46 & 0.51 \\ 0.47 & 0.54 & 0.49 \end{bmatrix}$	$\begin{bmatrix} 0.59 & 0.45 & 0.44 \\ 0.41 & 0.55 & 0.56 \end{bmatrix}$	$\begin{bmatrix} 0.62 & 0.46 & 0.48 \\ 0.38 & 0.54 & 0.52 \end{bmatrix}$
Trace of confusion matrix	1.58	1.70	1.68
CCR (%)	52.7	57	56

4.2. Detecting oil-water contact using Bayesian decision making tool

In order to implement the proposed algorithm, the following steps were followed:

a. Water saturation log was estimated from wire line logs using MLP artificial neural network.
b. By implementing two cut offs, one below the limit of 20% water (class of oil) and the other over 55% water (class of water), the studied reservoir was divided into three classes. The class between 20% and 55% water saturation was named oil-water (or mixture zone which is a region where water is produced along with oil).
c. A Bayesian decision making tool was designed to classify the data in each well.

The algorithm was performed in two main stages. At the first attempt, capability of proposed method in identifying different classes was examined in each individual well separately (single well analysis). At the second attempt, the generalization capability of the method was investigated, where input data from two wells were used as training data to identify the classes in the 3th well (multi-well analysis).

4.2.1. Single well analysis

The main idea of this step is examining the capability of the method in detecting the OWC in each well, individually. For this purpose, 70% of data of each well was randomly selected as training data and the Bayesian decision making tool was tested against the rest 30% of the data. Table 4 shows the decisions, made by Bayesian rule on wells under study.

Table 4. Results of proposed method in three studied well.

Well No.	1	2	3
Confusion matrix	$\begin{bmatrix} 0.29 & 0.38 & 0.33 \\ 0.29 & 0.66 & 0.05 \\ 0.14 & 0.08 & 0.78 \end{bmatrix}$	$\begin{bmatrix} 0.37 & 0.03 & 0.6 \\ 0.12 & 0.80 & 0.18 \\ 0.12 & 0.2 & 0.68 \end{bmatrix}$	$\begin{bmatrix} 0.75 & 0 & 0.15 \\ 0.08 & 0.61 & 0.31 \\ 0.32 & 0.23 & 0.45 \end{bmatrix}$
Trace of Confusion matrix	1.73	1.85	1.81
CCR (%)	58.3	62	60.3

Based on this table, the general accuracy of decision process for class of oil-water (with average accuracy of 69%) and class of oil (with average accuracy of 63.7%) is higher than the class of water and is satisfactory.

4.2.2. Generalization capability of the method

To examine the generalization capability of the proposed method (multi-well analysis), one well was selected as test and data related to the remaining two wells as train. The results are shown in Table 5.

Table 5. Results of generalization investigation.

Test well No. 1		
Training well No.	**2**	**3**
Trace of confusion matrix	1.57	1.7
CCR (%)	52.3	56.7
Test well No. 2		
Training well No.	**1**	**3**
Trace of confusion matrix	1.76	1.61
CCR (%)	58.7	53.7
Test well No. 3		
Training well No.	**1**	**2**
Trace of confusion matrix	1.78	1.57
CCR (%)	59.3	52.3

As it can be seen, the technique is able to identify OWC in other wells and reconstruct the true distribution of reservoir fluids with accuracy between 52.3% and 59.3%. Although CCR in this case (generalization step) is lower than the single well case, it is still worthy of acceptance, regarding the CCR obtained from conventional method. The lower ranges of accuracies belong to the training wells with further data (depth of penetration) from the target well. Figure 5 compares the results obtained from two discussed methodologies in well No. 3, schematically. As shown, there is an appreciable difference between these two approaches, considering the well test results. In this case water producer zones can be considered in depths higher than 2785 m that means OWC is at this depth.

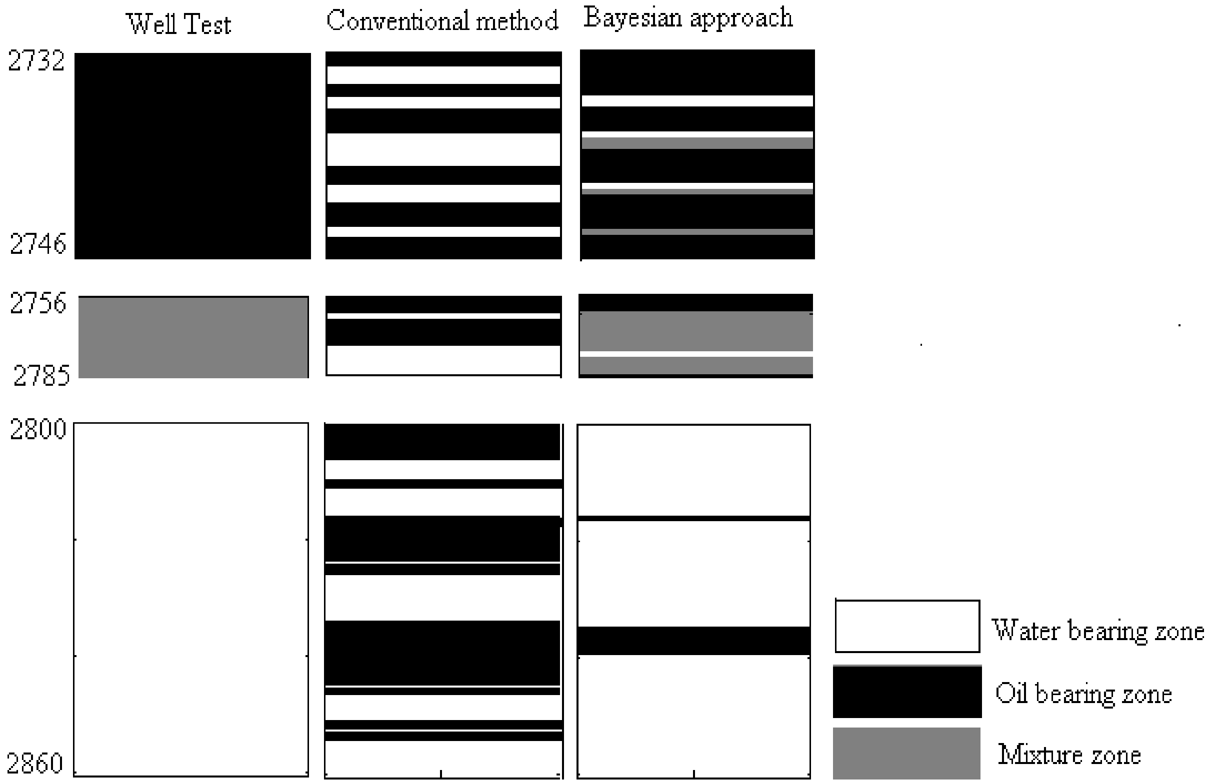


Figure 5. Results of detecting OWC through two different approaches in well No.3.

5. Discussion

A comparison of the two presented methodologies reveals that the most important advantage of the new method is that by employing Bayesian algorithm, all S_w variations are detectable and it helps to have a more actual image of reservoir under study. In contrast to Bayesian method, conventional methods can only find one major contact between two reservoir fluids and divide reservoir crisply into two (or three in case of existing gas) class of fluids, as a result. Therefore, transition zone as one important section in an oil column is not recognizable by conventional methods. According to Figure 5, the conventional method overestimates in detecting oil bearing zones and classifies nearly all the mixture zone as oil bearing zone. Considering the CCRs values of both conventional and Bayesian approaches discloses that, Bayesian method can improve the results up to 4.97%. Besides, based on outputs of Bayesian method shown in Figure 5, overall, the transition zone can be considered in range from about 2760 m to 2785 m.

6. Conclusions

Detecting reservoir fluid contact is one of the primary tasks in reservoir characterization and determining hydrocarbon in place. It also plays an important role in determining net pay zones and depth in which perforation operation must be done. This paper presents a new approach based on Bayes theorem and compares its performance with conventional ones. Conventional methods are usually suffering some difficulties in finding OWC. Because OWC is actually a transition zone and considering a sharp line as OWC is far from reality. Using well logs related to three wells of a carbonate reservoir, the proposed algorithm was performed in two stages: Single well and multi-well analysis. It has been shown that the suggested method can effectively model all S_w variations and specify transition zone. Besides, the accuracy of reservoir fluid type identification has been improved about 5% in comparison to employed conventional approach.

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به‌کارگیری ابزار تصمیم‌گیر بیزی در شناسایی مرز تماس آب- نفت در یک مخزن کربناته

امیر ملاجان[۱*]، حسین معماریان[۱]، بهزاد تخم‌چی[۲]

۱- دانشکده مهندسی معدن، پردیس دانشکده‌های فنی، دانشگاه تهران، ایران

۲- دانشکده مهندسی معدن، نفت و ژئوفیزیک، دانشگاه شاهرود، ایران

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* نویسنده مسئول مکاتبات: a.mollajan@alumni.ut.ac.ir

چکیده:

تعیین مرز تماس آب- نفت برای ارزیابی‌های پتروفیزیکی و محاسبات حجمی مخزن ضروری است. این مقاله ابزار تصمیم‌گیر بیز را به‌عنوان تکنیکی خبره برای شناسایی مرز تماس آب- نفت با استفاده از داده‌های چاه‌نمودار معرفی می‌کند. روش پیشنهادی بر روی داده‌های مربوط به سه چاه از میدانی در جنوب غرب کشور پیاده‌سازی شده است. کارایی روش پیشنهادی با استفاده از گزارش‌های آزمایش چاه و نیز مقایسه با روش سنتی تخمین تراوایی مورد ارزیابی قرار گرفته است. نتایج حاکی از آن است که این روش دقیق‌تر از روش سنتی جواب داده و دقت آن به‌طور متوسط تا ۵ درصد بالاتر است. علاوه بر این، روش ارائه شده قادر است تغییرات درجه اشباع آب را مدل‌سازی کرده و نوع سیال مخزنی را تشخیص دهد.

کلمات کلیدی: مرز تماس آب- نفت، ارزیابی پتروفیزیکی، داده‌های چاه‌نمودار، ابزار تصمیم‌گیر بیزی.