# SPE 164747

# Hydraulic Unit estimation from predicted permeability and porosity using artificial intelligence techniques

Syed Shujath Ali, M. Enamul Hossain*, Md. Rafiul Hassan, and Abdulazeez Abdulraheem; King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia



This paper was prepared for presentation at the 2013 North Africa Technical Conference & Exhibition held in Cairo, Egypt 15 - 17 April 2013.



## Abstract

Rock classification or assigning a type or class to a specific rock sample based on petrophysical characteristics is a fundamental technique to reduce the uncertainty in prediction of reservoir properties due to heterogeneity. One of the popular approaches is to classify a reservoir rock from the fundamentals of geology and the physics of flow at pore network scale. In this approach, rocks of similar fluid conductivity are identified and grouped into classes. Each grouping is referred to as a hydraulic flow unit (HU). HUs are estimated for the uncored section of the wells from wire line log data received from field using three popular artificial intelligence (AI) techniques such as (i) Adaptive Network Fuzzy Inference Systems (ANFIS); (ii) Functional Networks; and (iii) Support Vector Machines. HUs can either be predicted directly from wire line log data as a classification model or can be estimated indirectly from predicted permeability and porosity. In the present study, HUs were predicted employing both approaches. The comparison of the two approaches shows that it is a better practice to estimate HUs by directly relating them to well logs. Calculation of HUs from predicted permeability and porosity results in inferior accuracy. This is due to the accumulation of errors during the estimation of permeability and porosity. The Knowledge of HUs acquired from well logs can significantly help in determining ultimate hydrocarbon recovery, optimal well placement, and well stimulation. Thus, the finding of this research will impact the economy of the development and operations of a field.

**Keywords:** permeability; Kozney-Carman model; porosity; artificial intelligence; reservoir management.

## Introduction

Estimation of permeability in uncored but logged wells is a generic problem common to all reservoirs. Traditional approaches for estimation of permeability utilize mathematical functions and correlations to establish relationships between the well logs and the core data. Permeability calculation by HU concept offers an improved estimation over traditional regression based average relationships. HU concept has widely been used in reservoir characterization and management (Amaefule et al., 1993; Abbaszadeh et al., 1996; Elkewidy, 1996; Al-Ajmi et al., 2000, Nooruddin and Hossain 2011). The concept relates the geological control properties of a rock such as tortuosity, cementation between grains, and the structure of the grains (grain size, grain shape, sorting and packing) to the petrophysical properties such as porosity, permeability, and capillary pressure.

Numerous studies have been conducted on this topic and the results show an improved reservoir characterization by classifying reservoir rock into HUs. Gardner and Albrechtsons (1995) observed a significant improvement in the reservoir description through the refinement of permeability model using HU concept. Svirsky et al. (2004) were able to resolve the challenges in Siberian Oil field using the concept of hydraulic flow units (HUs). Guo et al. (2007) showed that hydraulic flow concept proved to be an effective technique for rock-typing in clastic reservoirs in South America. Shenawi et al. (2009) developed generalized porosity-permeability transforms based on hydraulic unit technique with excellent accuracy for carbonate reservoirs in Saudi Arabia. Orodu et al. (2009) expressed a satisfactory estimation of permeability from HUs,

*Corresponding authors: Dr. M. Enamul Hossain, Department of Petroleum Engineering, College of Engineering Science, King Fahd University of Petroleum & Minerals, Dhahran 31261, KFUPM Box: 2020, Kingdom of Saudi Arabia. Tel: + 96638602305 (O), Fax: +96638604447. Email: menamul@kfupm.edu.sa, dr.mehossain@gmail.com.

considering high reservoir heterogeneity, availability of less number of cored wells and poor well log response correlation to permeability. Shahvar et al. (2010) observed an enhanced prediction of relative permeability by discretizing reservoir rock based on hydraulic flow units for a carbonate reservoir in Iran. Recently, Nooruddin and Hossain (2011) developed a porosity-permeability model employing new parameters with conventional Kozney-Carman model. They used 30,000 data points of an exisiting Middle East field. The resuls show an excellent agreement with the data.

There exist a number of studies that have employed various methods to facilitate HUs for the uncored section of the wells. Flow zone index (FZI) groups the effect of geological properties such as tortuosity, cementation factor, grain size and shape. FZI is an effective indicator of the capability of a rock to permit fluid flow through it. Most of the researchers opted to predict FZI from well log data and then group the predicted FZI as hydraulic units (Al-Ajmi and Holditch, 2000; Soto et al., 2001; Soto and Garcia, 2001, Nooruddin and Hossain, 2011). Some studies aimed to relate HUs directly to well log data (Abbaszadeh et al., 1996; Aminian et al., 2003). In general, a probabilistic approach was employed to tie well logs to HUs (Altunbay et al., 1997; Orodu et al., 2009). As HUs are the functions of permeability and porosity, HUs are indirectly estimated in the present study by making use of the predicted permeability and porosity. Furthermore, the permeability and porosity were predicted from well logs using AI techniques. Three different AI techniques such as (i) Adaptive Network Fuzzy Inference Systems (ANFIS); (ii) Functional Networks (FN) and; (iii) Support Vector Machines (SVM) were tried in order to assess their capabilities in predicting permeability and porosity. Further to these, HUs are also directly predicted from the available well logs using the classification algorithm of SVM. The HUs estimated indirectly from the predicted permeability and porosity were compared to the HUs predicted directly from well logs.

The rest of the paper is organized in the following manner. The first section describes a brief overview of the three computational algorithms used in the present study. The second section gives a brief introduction of the concept of HUs. A description about the data and the performance measures is listed in the following section. Finally, the results and discussion are presented along with the conclusions.

## Computational Intelligence Techniques

A number of approaches have been applied, to the problem of rock typing which includes classification based on lithology, HUs and electrofacies. Delfiner et al. (1987) and Chakrabarty (1996) presented a Bayesian-type statistical approach to determine lithology from well logs (Delfiner et al., 1987); Chakrabarty, 1996). Baldwin et al. (1990) and Rogers et al. (1992) were among the first to apply ANNs to the problem of identification of lithofacies from well logs (Baldwin et al., 1990; Rogers et al., 1992). Later, Saggaf and Nebrija (1999) and Kapur et al. (1998) also proposed the identification of lithofacies from well logs through the use of ANNs (Saggaf and Nebrija, 1998; Kapur et al., 1998). Qi and Carr (2006) estimated lithofacies for a carbonate reservoir using ANN for an oil field in southwest Kansas. More recently, the performance of additional new techniques in classifying rocks has also been tested. Rezaei and Movahed (2008) applied a Fuzzy Logic Model for the determination of lithofacies. Al-Anazi and Gates (2010) demonstrated the superiority of SVM in identifying lithofacies from well log data, and compared to linear discriminant analysis and probabilistic ANNs. Singh (2011) presented an approach of Fuzzy inference system for identification of geological stratigraphy.

In the present study, the more recent computational techniques such as (i) Adaptive Network Fuzzy Inference Systems (ANFISs); (ii) Functional Networks (FNs) and; (iii) Support Vector Machines (SVMs) were employed to predict permeability and porosity and finally estimate HUs. The details of these three algorithms are very well documented in the literature. This section briefly describes each of these three techniques.

### *Adaptive Network Fuzzy Inference Systems (ANFIS)*

ANFIS is the result of coupling between ANN and Fuzzy Logic (FL). ANFIS consists of if–then rules and couples of input–output. Also for ANFIS training, learning algorithms of ANN are used. Jang (1993) implemented Takagi–Sugeno fuzzy rules by ANFIS. ANFIS uses a feed-forward neural network with five layers that is adapted by a supervised learning algorithm (Jang, 1993). The network uses unweighted connections and works with different activation functions in each layer. The learning algorithm modifies the premise parameters of the fuzzy sets according to the training data.

In this study, The ANFIS classifier has six input logs ($x_1$, $x_2$, $x_3$, $x_4$, $x_5$, and $x_6$) and one output ($y$) which is either permeability or porosity. For a first order Sugeno fuzzy model, a typical rule set with the base fuzzy if-then rules can be expressed as:

If $x_1$ is $A_1$ and $x_2$ is $B_1$ and $x_3$ is $C_1$ and $x_4$ is $D_1$ and $x_5$ is $E_1$ and $x_6$ is $F_1$ then

$$f_1 = px_1 + ppx_2 + qx_3 + qqx_4 + sx_5 + ssx_6 + u \tag{1}$$

In Eq. (1), *p, pp, q, qq, s, ss, r, u* are linear output parameters. $A_1$, $B_1$, $C_1$, $D_1$, $E_1$ and $F_1$ are fuzzy linguistic labels. The structure of this ANFIS classifier is formed by using five layer and 256 if-then rules. The first layer is the input layer, the second is the fuzzification layer, the third and the fourth are the fuzzy-rule-evaluation layers, and the fifth is the defuzzification layer.

***Layer-1:*** Every node *i* in this layer is a square node with a node function.

$O_{1,i} = \mu_{Ai}(x_1)$, for $i = 1, 2$
$O_{1,i} = \mu_{Bi}(x_2)$, for $i = 3, 4$
$O_{1,i} = \mu_{Ci}(x_3)$, for $i = 5, 6$
$O_{1,i} = \mu_{Di}(x_4)$, for $i = 7, 8$
$O_{1,i} = \mu_{Ei}(x_5)$, for $i = 9, 10$
$O_{1,i} = \mu_{Fi}(x_6)$, for $i = 11, 12$

where $x_1$, $x_2$, $x_3$, $x_4$, $x_5$, $x_6$ are inputs to node $i$, and $A_i$, $B_i$, $C_i$, $D_i$, $E_i$ and $F_i$ are linguistic label associated with this node function. In order words, $O_{1,i}$ is the membership function of $A_i$, $B_i$, $C_i$, $D_i$, $E_i$ and $F_i$. Usually it is choosen $\mu_{Ai}(x_1)$, $\mu_{Bi}(x_2)$, $\mu_{Ci}(x_3)$, $\mu_{Di}(x_4)$, $\mu_{Ei}(x_5)$ and $\mu_{Fi}(x_6)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as:

$$\mu_i(x_i) = e^{\left[-\frac{x_i - c_i}{a_i}\right]^2} \quad (2)$$

In Eq. (2), $x_i$ is the input and $a_i$, $c_i$ are the parameter set. These parameters in this layer are referred to as premise parameters.

***Layer-2:*** Every node in this layer multiplies the incoming signals and computes the product as output of the corresponding node. The output of each node is fed as input to the following layer in the ANFIS architecture. For instance,

$$O_{2,i} = w_i = \mu_{Ai}(x_1).\mu_{Bi}(x_2).\mu_{Ci}(x_3).\mu_{D}i(x_4).\mu_{Ei}(x_5).\mu_{Fi}(x_6), \qquad i = 1, 2, 3, \ldots, 256 \quad (3)$$

Each node output represents the firing strength of a rule (In fact, other T-norm operators that performs generalized and can be used as the node function in this layer).

***Layer-3:*** Every node 'i' in this layer calculates the ratio of the ith rules firing strength to the sum of all rule's firing strengths as represented in Eq. (4) where, $\overline{w}$ is the normalized firing strength.

$$O_{3,i} = \overline{w} = w_i/(w_1 + w_2 + \cdots + w_{256}), \quad i = 1, 2, 3, \ldots, 256 \quad (4)$$

***Layer-4:*** Every node $i$ in this layer is a square node with a node function

$$O_{4,i} = w_i \,.\, f_i = w_i\,.(p_i x_1 + pp_i x_2 + q_i x_3 + qq_i x_4 + s_i x_5 + ss_i x_6 + u_i), \quad i = 1, 2, 3, \ldots, 256 \quad (5)$$

In Eq. (5), $w_i$ is the output of layer 3, and $\{p_i, pp_i, q_i, qq_i, s_i, ss_i, u_i\}$ is the parameter set. Parameters in this layer are referred to as consequent parameters.

***Layer-5:*** The single node in this layer computes the overall output as the summation of all incoming signals to this node

$$o_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (6)$$

***Functional Networks***

Functional Networks (FN) is an extension of Neural Networks which consists of different layers of neurons connected by links. Each computing unit or neuron performs a simple calculation: a scalar, typically monotone, function $f$ of a weighted sum of inputs. The function $f$ associated with the neurons is fixed, and the weights are learned from data using some well-known algorithms such as the least-squares fitting algorithm.

The main idea of FN consists of allowing the $f$ functions to be learned while suppressing the weights. In addition, the $f$ functions are allowed to be multi-dimensional, though they can be equivalently replaced by functions of single variables. When there are several links, say $m$ links, going from the last layer of neurons to a given output unit, we can write the value of this output unit in several different forms (one per different link). Solving this system leads to a great simplification of the initial functions $f$ associated with the neurons.

As shown in Figure 1, an FN consists of a layer of input units which contains the input data (represented by small black circles with its corresponding name), a layer of output units which contains the output data (also represented by small black circles with its corresponding name), and one or several layers of neurons or computing units which evaluates a set of input values coming from the previous layer and sends a set of output values to the next layer of neurons or output units. The computing units are connected to each other, in the sense that output from one unit can serve as part of input to another neuron or to the units in the output layer. Once the input values are given, the output is determined by the neuron type, which can be defined by a function. For example, assume that we have a neuron with $s$ inputs: $(x_1, \ldots, x_s)$ and $k$ outputs: $(y_1, \ldots,$

$y_k$), then we assume that there exist $k$ functions $F_j$; j = 1, …, $k$, such that $y_j = F_j(x_1, \ldots, x_s)$; j = 1, …, $k$.

FN also consists of a set of directed links that connect the input layer to the first layer of neurons, neurons of one layer to neurons of the next layer, and the last layer of neurons to the output units. Connections are represented by arrows, indicating the direction of information flow.

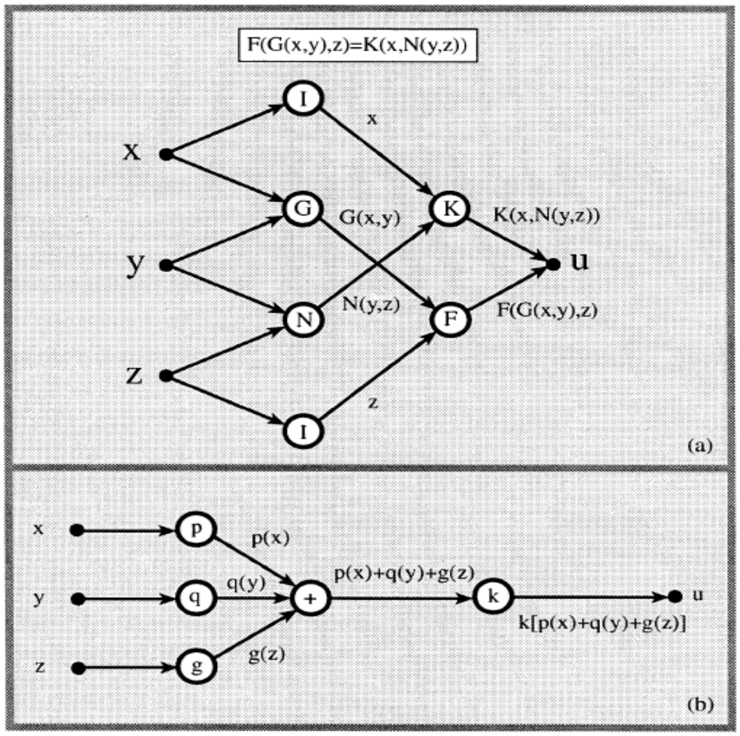


**Figure1 – Illustration of the Generalized Associativity Functional Network: (a) Initial network (b) Equivalent simplified network**

#### *Support Vector Machines (SVMs)*

SVMs are learning systems, that are based on statistical learning theory (SLT) and the principle of structural risk minimization (SRM). In principal, the SVM is a supervised learning system where the training data are mapped into a high dimensional feature space in which an optimal separating hyper-plane between the two classes of the labeled data is obtained using the quadratic programming. The hyper-plane is then pulled back to the input space via inverse algebra and thus it becomes a non-linear decision system to separate/classify the input data (Cortes and Vapnik, 1995).

In fact, the input space in SVM is mapped into the high dimensional feature space using a Kernel function *K ()* which is one of the main building blocks of *SVMs*. The kernel trick is a computational short-cut to avoid the implicit definition of feature space mapping (Scholkopf et al., 1997). In order to use the kernel approach we need to create a complicated feature space, then the inner product in that space is to be produced and following this a method to compute that value using the original inputs is to be designed. In other words the kernel function implicitly uses the feature space where the mapping from input space to feature space can be avoided.

### Hydraulic Flow Unit (HU) Theory

The concept of HU is very well documented in the literature (Wyllie and gardner, 1958; Abbaszadeh et. al, 1996). The present section briefly refreshes the theory of HU. A generalized Kozeny-Carman equation (Wyllie and Gardner, 1958) approximating the fluid flow in a porous medium is given by Eq. (7).

$$k = \frac{\varphi_e^3}{(1-\varphi_e)^2}\frac{1}{F_s\tau^2 S_{gv}^2} \tag{7}$$

where $k$ is in µm$^2$ and $S_{gv}$ is in µm$^{-1}$. The effective porosity can be obtained either from core data or appropriate log data. The term $F_s\tau^2 S_{gv}^2$ is a function of geological characteristics of porous media and varies with changes in pore geometry. Thus, this term captures the geological aspect of HUs. Equation (7) can be written as follows:

$$0.031\sqrt{\frac{k}{\varphi_e}} = \frac{\varphi_e}{1-\varphi_e}\frac{1}{\sqrt{F_s}\tau S_{gv}} \tag{8}$$

where, the constant 0.0314 is the conversion factor from μm$^2$ to md. Flow zone indicator (FZI) and reservoir quality index (RQI) are defined as follows:

$$FZI = \frac{1}{\sqrt{F_s}\tau S_{gv}} \tag{9}$$

$$I_{rq} = 0.031\sqrt{\frac{k}{\varphi_e}} \tag{10}$$

Equation (8) can now be written as

$$I_{rq} = \varphi_z * FZI \tag{11}$$

where

$$\varphi_z = \frac{\varphi_e}{1-\varphi_e} \tag{12}$$

FZI can be calculated from Eq. (11) for each of the measurements of permeability and porosity. If $I_{rq}$ vs $\varphi_z$ is plotted on log-log coordinates, data samples with similar FZI values will be located around a single unit slope straight line with a mean FZI value. The mean FZI value is the intercept of a unit-slope line with the coordinate $\varphi_z$ = 1. Samples with significantly different FZI will lie on other parallel unit-slope lines. The basic idea is to identify groupings of data that form the unit-slope straight lines representing similar flow characteristics and hence a distinct hydraulic unit. Permeability of a sample point is then calculated from the respective HU using its mean FZI value and the corresponding sample porosity using the Eq. (13) as:

$$k = 1014(FZI_{mean})^2 \frac{{\varphi_e}^3}{(1-\varphi_e)^2} \tag{13}$$

Shenawi et al. (2009) developed a method to group FZI based on their range to discrete hydraulic unit numbers as given in Eq. (14).

$$HU = Round[2\ln(FZI) + 10.6] \tag{14}$$

## Data Description and Performance Criterion

The present study used a range of data sets available for four wells from a Middle East field. The wells are numbered as Well 1, Well 2, Well 3 and Well 4 respectively. All the wells contain both log and core data. The present study only considered the horizontal wells. Core and log porosity values were plotted with respect to depth in order to check if the data needs any depth shifts. For almost all the wells, the trend/variation of log porosity with depth in general matched with that of core porosity. To ensure that the core and log values are at same depths, the log values were calculated at the core depths using linear interpolation. Five most commonly available logs were selected as input to predict permeability, porosity and HUs. These logs areneutron porosity (NPHI), densilty (RHOB), gamma ray (GR), water saturation (SWT) and acoustic transit arrival time (DT).

Average absolute error (AAE) was used to evaluate the measure of error for permeability and porosity prediction and percentage of correct classification (PCC) was used as a performance criterion for HU classification. PCC is given by Eq. (15) as:

$$PCC = \frac{Number\ of\ correct\ HU\ classification}{Total\ number\ of\ data\ points} \tag{15}$$

## Results and Discussion

### *Hydraulic Unit Estimation Using Predicted Permeability and Predicted Porosity*

HUs are regions in the reservoir exhibiting similar flow properties with FZI quantizing the measure of this flow property. Thus, Eq. (14) displays HU as a function of FZI. FZI in turn is a function of permeability and porosity as seen from Eq. (11). For the uncored section of wells and wells for which core data does not exist, permeability and porosity needs to be predicted first. In the present section permeability and porosity are predicted from well log data and finally the HUs are estimated making use of Eqs. (10) – Eqs. (14).

Table 1 compares the prediction of permeability and porosity and the resulting HUs using ANFIS, SVM and FN. The accuracy of prediction for permeability and porosity are measured by calculating AAE. It is clear that the error in permeability and porosity is the least when SVM was used as the predictive algorithm. This is reflected in a relatively better percentage of correct classification for HU estimation. Comparison between the predicted and core permeability plotted against an arbitrary depth, for the four wells using SVM algorithm is shown in Figure 2. A similar comparison for porosity is shown in Figure 3. Figure 2 shows a good match between the predicted and core permeability for all the four wells. An excellent match between the predicted and core porosity was obtained as seen in Figure 3. However, the accuracy of permeability is more critical when compared to porosity. Considering the percentage of correct classification of HUs none of the four wells could exceed an accuracy of more than 50%. HUs are a function of ratio of permeability to porosity. Although, an excellent performance in predicting porosity is abtained, as shown in Table 1, the accuracy of calculated HUs are low, indicating that the error in predicted permeability seem to play a critical role in lower HU classification accuracy. Figure 4 shows a plot of permeability vs porosity with identified HUs based on core data. The boundaries of each HU are marked by black lines as shown in Figure 4. The effect of error in the predicted permeability on the accuracy of HU classifaction is analyzed considering a fixed instance of porosity. For example, the samples containing 15% porosity is shown in Figure 4 where it is marked with a red verticle line. It is noted that each HU is associated with a range of permeability values at that porosity value (15%). All the HUs groups are separated by the red color horizontal lines where the permeability ranges increase with the increase of HU number. HU7 represents approximately the permeability ranges from 0.08 to 0.18 mD, and the rest of the HUs show as 0.18 to 0.55 mD for HU8, 0.55 to 1.8 mD for HU9, 1.8 mD to 4 mD for HU10, 4 to 10 mD for HU11, 10 to 29 mD for HU12, 29 to 75 mD for HU13 and 75 to 400 mD for Hu14. Most of the available data fall on the HU8, HU9, HU10 and HU11 where the combined permeability ranges are between 0.18 to 10 mD. However, the average error obtained in predicting permeability (as shown in Table 1) is much more than 10 mD except for Well2. It was observed that an average absolute error of approximately 4.5 mD is obtained for Well2 even though the error is beyond the permeability range of an individual HU. This might explain the reason for low classification accuracy (less than 50%) in predicting HUs.

**Table 1 – Performance of permeability and porosity predictions and HU classification performance for four wells**

| | ANFIS | | | SVM | | | FN | | |
|---|---|---|---|---|---|---|---|---|---|
| **Well Name** | **AAE (K)** | **AAE ($\phi$)** | **PCC** | **AAE (K)** | **AAE ($\phi$)** | **PCC** | **AAE (K)** | **AAE ($\phi$)** | **PCC** |
| Well1 | 26.53 | 0.02 | 22.22 | 23.44 | 0.001 | 50.00 | 26.27 | 0.03 | 16.67 |
| Well2 | 4.61 | 0.02 | 31.82 | 4.32 | 0.004 | 45.45 | 5.16 | 0.02 | 38.64 |
| Well3 | 26.06 | 0.02 | 38.46 | 25.56 | 0.003 | 39.74 | 26.04 | 0.02 | 41.67 |
| Well4 | 15.57 | 0.02 | 36.59 | 14.35 | 0.003 | 45.12 | 17.77 | 0.02 | 34.15 |

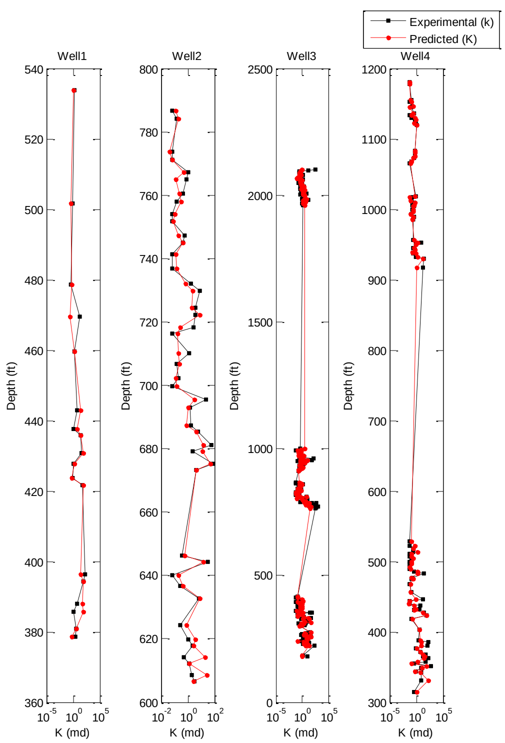


**Figure 2 – Comparison of core and predicted permeability for 4 wells using SVM algorithm**

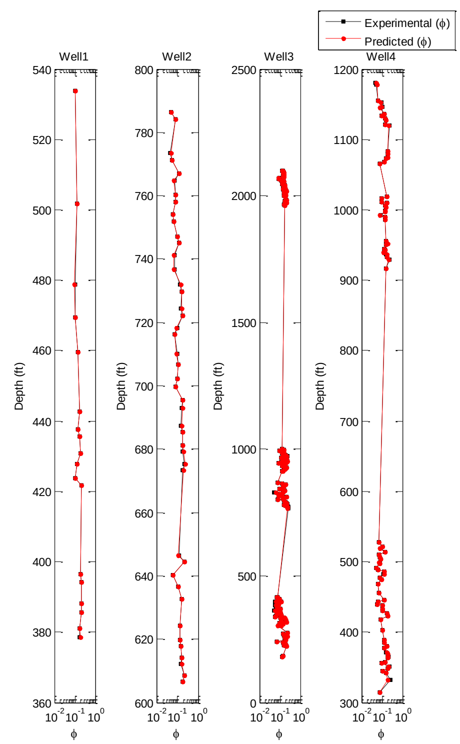


**Figure 3 – Comparison of core and predicted porosity for 4 wells using SVM algorithm**

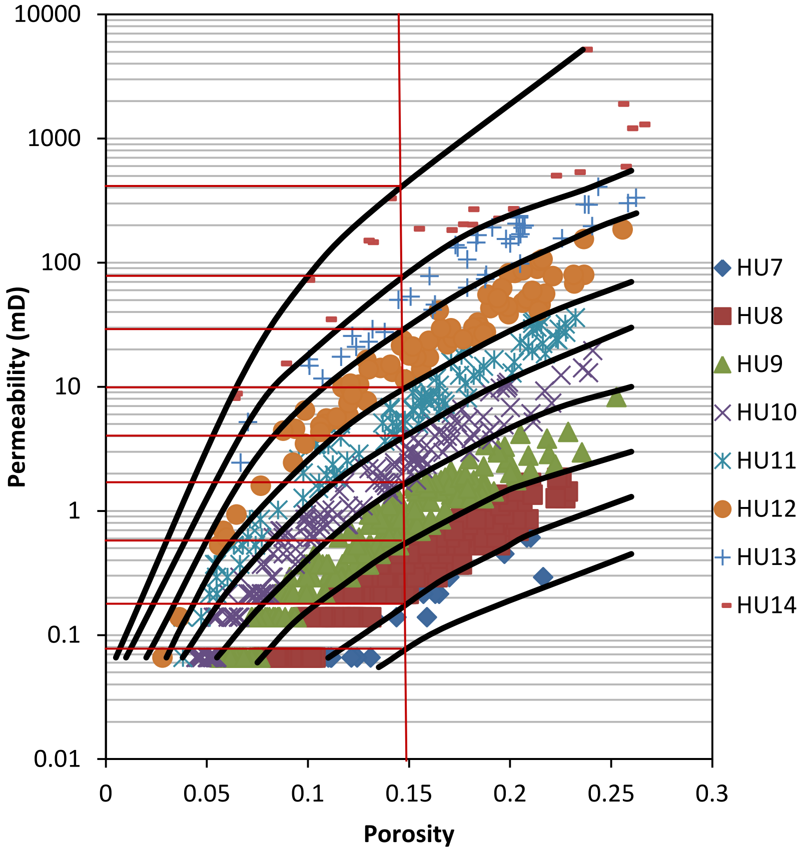


**Figure 4 – HUs estimated from core data**

### *Hydraulic Unit Predicted Directly from Well Logs*

In the present section HUs were first identified using core permeability and porosity data and the identified HUs were directly predicted by multiple classification technique using log data as input. Similar logs, as were used in the previous section to predict the permeability and porosity, were used to predict HUs. For each of the four wells, 70% (randomly selected) of thelog data along with the corresponding HUs was used as training data to train SVM. The validation check was performed on 15% of the remaining 30% data points and the testing of the model was carried out by feeding the log values for the rest 15% unseen data into the model. The performance of the model was evaluated by calculating the PCC.

SVM with polynomial kernels was used to build the model. For each well the SVMs complexity constant C and polynomial exponent E was varied in order to tune the SVM to obtain the best possible performance. Table 2 lists the PCC of HUs obtained for the four wells using SVM algorithm predicted directly from well logs. For comparison, Table 2 also lists the PCC of estimated HUs obtained with the previous approach. It is clear from Table 2 that although similar algorithm was used, the approach of predicting HUs directly from well logs yielded better accuracy when compared to the other approach. The inferior accuracy of the former approach might be due to the accumulation of errors while predicting permeability and porosity and these combined errors of two parameters is contributing to low classification accuracy.

**Table 2 – Comparison of the two approaches in predicting HUs**

| Well # | HUs predicted directly from well logs | HUs estimated using predicted permeability and porosity |
|---|---|---|
| | SVM (PCC) | SVM (PCC) |
| Well 1 | 55.6 | 50.00 |
| Well 2 | 57.9 | 45.45 |
| Well 3 | 56.5 | 39.74 |
| Well 4 | 74.3 | 45.12 |

## Conclusions

1. Capabilities of three latest computational intelligence techniques such as ANFIS, SVM and FN in predicting permeability and porosity are presented.
2. SVM algorithm outperformed the other two techniques in predicting permeability and porosity for all the four wells considered.
3. Calculation of HUs from predicted permeability and porosity yielded inferior accuracy due to the accumulation of errors during the estimation of permeability and porosity.
4. HUs predicted from well logs yielded better accuracy indicating that it is a better to estimate HUs by directly relating them to well logs.

## Nomenclature

| | |
|---|---|
| $x_1$, $x_2$, $x_3$, $x_4$, $x_5$, $x_6$ | the input to nodes |
| $\mu_i$ | the membership function for ith node |
| $a_i$ ,$c_i$ | the parameter set for membership function of ith node |
| $O_{J,I}$ | the output of the *ith* node in layer-jth |
| $w_i$ | the ith rule firing strength |
| $p_i$, $pp_i$, $q_i$, $qq_i$, $s_i$, $ss_i$, $u_i$ | the node's parameter set |
| $\phi_e$ | effective porosity |
| $F_s$ | shape factor |
| $\tau$ | tortuosity |
| $S_{gv}$ | surface area per unit grain volume |
| FZI | flow zone index |
| $I_{rq}$ | reservoir quality index |
| $\varphi_z$ | normalized effective porosity |
| HU | hydraulic unit |
| AAE | average absolute error |
| PCC | percentage correct classification |

## References

Abbaszadeh, M., Fujii, H. and Fujimoto, F., (1996). Permeability prediction by hydraulic flow units - theory and applications. SPE Formation Evaluation, 11, 263-271.

Al-Ajmi, F.A., and Holditch, S.A. (2000). Permeability estimation using hydraulic flow units in a central Arabia reservoir, SPE Annual Technical Conference and Exhibition,Dallas, Texas, 1–4 October 2000, SPE 63254.

Al-Anazi, I., Gates, D. (2010). A support vector machine algorithm to classify lithofacies and model permeability in heterogeneous reservoirs, Engineering Geology 114 (2010) 267–277.

Altunbay, M., Georgi, D. and Takezi, H.M. (1997). Permeability prediction for carbonates: Still a challenge?, SPE Middle East Oil Show, Manama Bahrain, 15-18 March, 1997, SPE 37753.

Amaefule, J.O., Altunbay, M., Tiab, D., Kersey, D.G., Keelan, D.K., (1993). Enhanced reservoir description: using core and log data to identify hydraulic (flow) units and predict permeability in uncored intervals/wells, 68th Annual Technical Conference and Exhibition, Houston, Tex., 3-6 OCtober 1993, SPE 26436

Aminian, A.K.S. Ouerokun, A. and Thomas, B. (2003). Prediction of flow units and permeability using Artificial Neural Networks, SPE Western Regional/AAPG Pacific Section Joint Meeting, Long Beach, California, USA, 19-24 May, 2003, SPE 83586.

Baldwin, J.L., Bateman, R.M. and Wheatley, C.L. (1990). Application of a Neural Network to the problem of Mineral Identification from Well logs, The log Analyst, Sept-Oct, 1990, 279-293.

Chakrabarty, T. (1996). A new Robust Algorithm for Rapid Determination of porosity and Lithology from Well Logs. 47th Annual Technical Meeting of the Petroleum Society in Calgary, Alberta, Canada. paper 96-17. A.

Cortes, C. and Vapnik, V. (1995). Support-Vector Networks. Mach. Learn, 20, 273-297.

Delfiner, P., Peyret, O. and Serra, O. (1987). Automatic Determination of Lithology from Well Logs, SPE Formation Evaluation, Sept 1987, 303-310.

Elkewidy, T.I., (1996). Characterization of hydraulic (flow) units in Heterogeneous clastic and carbonate reservoirs. Ph.D Dissertation, University of Oklahoma, Norman, USA.

Gardner, R. I. and Albrechtsons, E.A. (1995). Hydraulic zonation and permeability modelling of the Hibernia formation using an integrated mathematical, petrophysical and geological approach, The petroleum Society of CIM, 46th Annual Technical Meeting of the Petroleum Society of CIM, Alberta, Canada, May 14-17, 1995.

Guo, G., Diaz, M.A., Paz, F. Smalley, J. and Waninger, E.A. (2007). Rock typing as an effective tool for permeability and water-saturation modeling: A case study in a classic reservoir in the Oriente basin, SPE Annual Technical Conference and Exhibition, Dallas, 9-12 Oct., 2007, SPE 97033

Jang, J.S.R., (1993). ANFIS: adaptive-network-based fuzzy inference system. IEEE Transactions on Systems, Man and Cybernetics 23, 665–685.

Kapur, L., Lake, L.W., Sepehmoori, K. (1998). Facies Prediction from Core and Log Data Using Artificial Neural Network Technology, SPWLA 39th Annual Logging Symposium, May 26-29, 1998.

Nooruddin, H.A. and Hossain, M.E., “Modified Kozeny-Carmen Correlation for Enhanced Hydraulic Flow Unit Characterization”, Journal of Petroleum Science and Engineering. Vol. 80, (2011), pp. 107 – 115.

Orodu, O.D. Tang, Z. and Fei, Q. (2009). Hydraulic (Flow) Unit Determination and Permeability Prediction: A Case Study of Block Shen-95, Liaohe Oilfield, North-East China, Journal of Applied Science 9 (10): 1801-1816.

Qi, L. and Carr, T.R. (2006). Neural Network Prediction of Carbonate Lithofacies from Well Logs, Big Bow and Sand Arroyo Creek Fields, Southwest Kansas, Computers & Geosciences 32 (2006) 947-964.

Rezaei, M. and Movahed, B. (2008). Lithofacies Prediction and Permeability Values Estimation from Conventional Well-Logs Applying Fuzzy Logic - Case Study: Alwyn North Field, 19th World Petroleum Congress, Spain 2008.

Rogers, S.J, Fang, J.H, Karr, C.L, Stanley, D.A. (1992). Determination of Lithology from Well Logs Using a Neural Network, Bull Am Assoc Petrol Geol V76, N5, May 1992, P731-739.

Saggaf, M.M. and Nebrija, E.L, (1999). Estimation of Lithologies and Depositional Facies from Wireline Logs, Earth Resources Laboratory Industry Consortia Annual Report; 1999.

Scholkopf, B., Sung, K.K., Burges, C.J.C., Girosi, F., Niyogi, P., Poggio, T., Vapnik, V. (1997). Comparing support vector machines with Gaussian kernels to radial basis function classifiers. IEEE Trans. Signal Process, 45, 2758-2765.

Shahvar, M.B., Kharrat, R. Matin, M. (2010). Applying flow zone index approach and artificial neural netowrks modelling technique for characterizing a heterogeneous carbonate reservoir using dynamic data: Case study of an Iranian reservoir. Trinidad and Tobago Energy Resources Conference, Port of Spain, Trinidad, 27-30 June, 20120, SPE 132898

Shenawi, S., Al-Mohammadi, H., Faqehy, M. (2009). Development of generalized porosity-permeability transforms by hydraulic units for carbonate oil reservoirs in Saudi Arabia. SPE/EAGE Reservoir Characterization and Simulation Conference, Abu Dhabi, UAE, 19-21 October 2009, SPE 125380.

Singh, U.K., (2011) Fuzzy Inference System for Identification of geological stratigraphy off Prydz Bay, East Antarctica, Journal of Applied Geophysics, 75 (2011), 687-698.

Soto, R. and Garcia, J.C. (2001). Permeability prediction using hydraulic flow units and hybrid soft computing systems, SPE Annual Technical Conference and Exhibition, New Orleans, Lousiana, 30 Sept. - 3 Oct. 2001, SPE 71455.

Soto, R.B., Torres, F., Arango, S. and Cobaleda, G. (2001). Improved reservoir permeability models from flow units and soft computing techniques: A case study, Suria and Reforma-Libertad fields, Columbia, SPE Latin American and Caribean Petroleum Engineering Conference, Buenos Aires, 25-28 March 2001, SPE 69625

Svirsky, D., Ryazanov, A. and Pankov, M. (2004). Hydraulic Flow Units resolve reservoir description challenges in a Siberial oil field, SPE Asia Pacific Conference on Integrated Modeling for Asset Management, Kuala Lumpur, Malaysia, 29-30 March 2004, SPE 87056

Wyllie, M.R.J. and G.H.F. Gardner (1958). The generalized Kozeny-Carmen equation, World Oil, March and April, 1958.