AADE-19-NTCE-061

Fracture Pressure Prediction Using Radial Basis Function

Abdulmalek Ahmed S, Ahmed Abdulhamid Mahmoud and Salaheldin Elkatatny; King Fahd University of Petroleum & Minerals

Copyright 2019, AADE

This paper was prepared for presentation at the 2019 AADE National Technical Conference and Exhibition held at the Hilton Denver City Center, Denver, Colorado, April 9-10, 2019. This conference is sponsored by the American Association of Drilling Engineers. The information presented in this paper does not reflect any position, claim or endorsement made or implied by the American Association of Drilling Engineers, their officers or members. Questions concerning the content of this paper should be directed to the individual(s) listed as author(s) of this work.

Abstract

Formation fracture pressure is a critical parameter affecting the efficiency and economy of the drilling operations. The knowledge of the fracture pressure is significant to control the well since it will assist in avoiding problems associated with the drilling operations such as fluid loss, kicks, fracture the formation, differential pipe sticking, heaving shale, and blowouts . Thus, it is essential to predict fracture pressure accurately prior to start the drilling process to prevent these issues.

Many models are used to estimate the fracture pressure either from well logs or formation strengths. However, these models have some limitations such as some of the models can only be used in clean shales, applicable only for the pressure generated by under-compaction mechanism and some of them are not applicable in unloading formations. Few papers used artificial intelligence (AI) to estimate the fracture pressure. In this study, real field data contain only real-time surface drilling parameters were utilized to train the radial Basis function (RBF) to predict the fracture pressure. The predictability of the developed RBF model was compared with other fracture pressure models such as Pennebaker model

The results indicated that RBF predicted the fracture pressures with an excellent precision where the coefficient of determination (R^2) is greater than 0.99. RBF model outperformed the available fracture models by a its high accuracy and simple prediction of fracture pressure where it can predict the fracture pressure from only the real time surface drilling parameters, which are easily available.

Key Words: Fracture Pressure; Artificial Intelligence; Radial Basis function (RBF).

Introduction

In drilling, it is significant to predict the fracture pressure. It has a direct impact on the drilling effectiveness and the operations of the well such as wellbore planning, analyses of a stable wellbore, casing strategy, drilling fluid designs, drilling processes and structure optimizing (Hu et al., 2013). A knowledge of fracture pressure is significant in the selection of production and injection; knowing how hydrocarbons migrate; and avoiding problems associated with pressure and drilling operations (Keshavarzi & Jahanbakhshi, 2013).

Formation will be fractured when the mud hydrostatic pressure exceeds the critical fracture pressure. Thus, fracture pressure can affect the well plan in many areas such as mud weight design, cement preparation and casing design (Mitchell et al., 2011). The wrong prediction of fracture pressure may lead to dangerous problems such as failure and lost circulation that can cause kick and blowout (Adams, 1985). Fracture pressure is generally reported as the equivalent mud weight in ppg, pressure in psi, or pressure gradient in psi/ft.

There are two methods to measure the fracture pressure. One of them is the direct approach that relies on computing the needed pressure to crack the formations. This approach depends on the Leak off Teat (LOT) that is a regular step where the wellbore is pressurized by utilizing the drilling mud until it cracks the formation (Sadiq and Nashawi, 2000). The indirect method depends on utilizing empirical models to estimate the fracture pressure (Hossain & Al-Majed, 2015).

Many correlations and models were developed to predict fracture pressure from various parameters such as well logs, drilling parameters, or formation strength. Hubbert & Willis (1957) introduced a model to estimate the fracture pressure in zones of normal faults. They stated that fracture pressure is mainly affected by formation pressure and overburden stress. The lower limit of the fracture pressure was assumed to be 33% of the overburden stress while the upper limit of the fracture pressure was assumed to be 50% of the overburden stress.

$$\frac{F}{D_{min}} = \frac{1}{3}\left(\frac{S}{D} + 2\frac{P}{D}\right) \qquad \frac{F}{D_{max}} = \frac{1}{2}\left(\frac{S}{D} + \frac{P}{D}\right)$$

Matthews and Kelly (1967) developed an equation to predict the fracture pressure by proving that the matrix stress coefficient generally relies on the depth and formation pressure.

$$\frac{F}{D} = K\left(\frac{S}{D} - \frac{P}{D}\right) + \frac{P}{D}$$

Pennebaker (1968) modified the matrix stress coefficient of Matthews and Kelly (1967) by considering the depth and formation type instead of pore pressure.

$$\frac{F}{D} = K_p \left(\frac{S}{D} - \frac{P}{D} \right) + \frac{P}{D}$$

Anderson et al. (1973) introduced an empirical equation to predict the fracture pressure as a function of the overburden stress, depth, Poisson's ratio, formation pressure, and the compressibility ratio of the porous to bulk rock matrix. Anderson model depends on Biot's strain and stress relations.

$$P_{fp} = \alpha P_f + \frac{2\gamma}{1-\gamma} \left(P_{ob} - \alpha\, P_f\right)$$

Where: P_{fp} is the fracture pressure (psi), P_f is the formation pressure (psi), P_{ob} is the overburdened stress (psi), α is the compressibility ratio of the porous to bulk rock matrix $\alpha = 1 - \frac{C_r}{C_b}$, C_r and C_b are the porous and bulk compressibility of the rock matrix (1/psi), respectively, and γ is the Poisson's ratio.

Radial Basis Function (RBF)

RBF is a part of the artificial neural network (ANN) and simply a function class. RBF can be linear, nonlinear model, a single layer, or multilayers (Orr, 1996). RBF has number of neurons less than the number of input data. It may require more neurons than normal feedforward networks. However, RBF could be formed in a fraction of the time that takes to train normal feedforward backpropagation networks. In case of a lot of training variable, RBF work best (Chen, 1991).

It is applicable for a huge amount of data. In RBF, the output parameter is most likely to the value of input parameter. RBF starts to set one neuron or more in the space of the input parameters. The neuron starts to compute the distances of the middle of the neuron and the middle of every neuron. The weight is approximated by Gaussian-based on the effect of every neuron. Multiplying the weight by the target value will predict the output (Alarfaj et al., 2012).

According to Sherrod (2008) the idea of RBF is that the output parameter is very close to the other parameters that have the same input parameters. RBF place a minimum neuron of one in the space that is defined by the input data. This space has dimensions similar to the number of input parameters. The evaluated neuron computes the distance between the neuron's center and every neuron's center in that space. Every distance has an applied function to predict the weights base on the effect of every neuron.

The closest neuron is the more effects it has on the output neuron. The estimated value is best predicted by multiplying the output value of the RBF function by the weight of the connection. The network of RBF has three layers: input, hidden and output. Hidden layer has the RBF function that is typically Gaussian function. A normalization of the input data is done by subtracting the median and dividing by the interquartile range.

From the previous discussion, many models have been developed to estimate fracture pressure from various parameters. However, every one of these models has its own limitations. Consequently, using the artificial intelligence (AI) in the drilling is becoming more and more applicable because it can consider all the unknown parameters in building the model.

Malallah & Nashawi (2005) used Feed-forward ANN to estimate the fracture gradient. 21,513 data points from 16 different wells were utilized with three input parameters, which are rock density, depth and pore pressure. 97.5% of the data were used to train the model and 2.5% for testing. The fracture pressure was predicted with an error of 6.5% using 25 neurons of one network layer and sigmoid function as the transform function.

Keshavarzi et al. (2011) used ANN to predict the fracture gradient. 130 data points of 3 input parameters, which are density of the rock, depth and formation pressure were utilized. The data was divided into three parts as follows 65% for training, the model was validated and tested using 20% and 15% of the data, respectively. The correlation coefficient (R) between the predicted and actual fracture pressures for traing data is 0.9962, R = 0.9928 for validation and R = 0.9827 for testing were achieved by using a feed-forward with a back propagation neural network.

Exact estimation of fracture pressure could save time, money and furthermore guarantee safe drilling operations. From the past studies, specialists utilized either well logs and/or formation strengths to estimate the fracture pressure. No previous model developed to estimate the fracture pressure utilizing the surface real-time drilling parameters that are easily available. The aim of this work is to apply RBF to estimate the fracture pressure by utilizing in excess of 3900 real field data based only on the surface real-time drilling parameters. Then, the RBF model will be compared with Pennebaker model, which is one of the mostly used models for prediction of the fracture pressure in the field.

Data Description

The data were collected from an onshore directional well. It has two bit sizes, which are 8.375 inches and 8.875 inches. Six lithologies were presented in the well with different formations, where five interbedded shales and sandstones at the bottom in addition to one carbonate layer at the top as shown in **Table 1**. A real time sensor was used to record the data every one foot.

It is notable that there is a high vulnerability in the field data, especially in real-time surface drilling parameters. Therefore, the data is filtered out. Dangerous issues can be happened by outlier's in the estimation of fracture pressure, for example, the data which is irrational because of devices and human mistakes. Several trials were inspected to examine the impact of the collected parameters on the fracture pressure. These trials will help us in removing the unnecessary parameters to achieve efficient prediction of fracture pressure. In every trial, the influence of a solitary parameter on the fracture pressure estimation was detected while the alternate parameters were kept consistent.

Table 1: Well Description

<table>
<tr><th>Thickness (ft)</th><th>Description</th><th>Formation</th></tr>
<tr><td>923</td><td>Limestone, Dolomite and Anhydrite</td><td rowspan="2">A</td></tr>
<tr><td>119</td><td>Shale</td></tr>
<tr><td>299</td><td>Sandy Shale</td><td rowspan="2">B</td></tr>
<tr><td rowspan="2">645</td><td rowspan="2">Sandstone</td></tr>
<tr><td>C</td></tr>
<tr><td rowspan="2">2494</td><td rowspan="2">Shale</td><td>D</td></tr>
<tr><td rowspan="2">E</td></tr>
<tr><td rowspan="2">243</td><td rowspan="2">Sandstone</td></tr>
<tr><td>F</td></tr>
</table>

In the prediction of fracture pressure, data set of 3925 points covering all the different formations under study were used. In view of the literature, statistical analyses and trials, seven parameters were chosen as inputs to train the RBF model to estimate the output that is fracture pressure. These parameters are described in the methodology section. **Table 2** presents the statistical analyses for the input data. The weigh on bit (WOB) is varying from 21.9 klb to 27.8 klb. The range of rotation per minutes (RPM) is in between 62 rpm and 90 rpm. The drilling torque (T) has a minimum reading of 9.240 klb_f and a maximum reading of 10.240 klb_f. The rate of penetration (ROP) is varying from 2.620 (ft/hr) to 8.070 (ft/hr). The density of the mud (mud weight) has a minimum MW = 102.920 (lb/ft^3) and a maximum MW =110.680 (lb/ft^3). The pore pressure (P_p) is in between 64.290 (lb/ft^3) and 79.930 (lb/ft^3).

Table 2: Statistical Analysis of the Input Data in Fracture Pressure Prediction.

Parameter	WOB(klbs)	RPM(rpm)	TORQUE(klb*f)	ROPft/hr(ft/hr)	MWIN(lb/ft3)	Pore Pressure (lb/ft3)
Maximum	27.800	90.000	10.240	8.070	110.680	79.930
Minimum	21.900	62.000	9.240	2.620	102.920	64.290
Arithmetic Mean	25.776	81.622	9.686	4.304	109.060	71.030
Harmonic Mean	25.686	80.549	9.683	4.015	109.031	70.884
Mode	26.800	90.000	9.800	4.460	109.370	64.290
Range	5.900	28.000	1.000	5.450	7.760	15.640
Variation	2.218	83.183	0.035	1.503	3.114	10.387
Standard deviation	1.489	9.120	0.187	1.226	1.765	3.223
Skewness	-0.707	-0.475	0.217	1.101	-2.509	0.120
Kurtosis	2.085	1.312	2.834	3.781	8.351	2.921
Coefficient of variation	0.058	0.112	0.019	0.285	0.016	0.045
Correlation Coefficient	0.159	0.185	0.214	0.832	0.132	0.832

Methodology

In fracture pressure prediction, dataset of 3925 points collected from all the formations under study is utilized to estimate the fracture pressure using the RBF. Different trials have been done to choose the preferable data distribution for the training and testing data sets. It was found that the distribution of 80% for training and 20% for testing is the best distribution. Eighty percent of the data (3140 data points) were used to train the radial basis function (RBF) model and then the remaining twenty percent of the data (785 data points) were used to test the RBF model. The selected input parameters are rotation per minute (RPM), weight on bit (WOB), rate of penetration (ROP), mud weight (MW), drilling torque (T), and pore pressure (P_p).

Several radial basis function (RBF) trials were run to achieve the optimal selection of network function, spread and number of neurons. Three network functions were studied such as *newrbe*, *newgrnn*, and *newrb*. However, *newrbe* and *newgrnn* were not applicable in the prediction of fracture pressure and the processing speed was very slow. In *newrb* function, firstly the effect of neurons number on fracture pressure prediction has been studied at constant spread of 1 as shown in **Table 3**. It is clear that, 17 neurons have the highest R and lowest absolute average percentage error (AAPE). Then, the effect of the spread is studied at constant neuron's number of 17 neurons as shown in **Table 4**. Based on the best accuracy in the prediction of the fracture pressure, spread of 0.5 gave the best results. So, the RBF model with *newrb* function, 17 neurons, and spread of 0.5 was found to be the optimum model for fracture pressure prediction.

Table 3: The Effect of Neurons Number in *Newrb* Network Function.

# of Neurons	R_Train	AAPE_Train	R_Test	AAPE_Test
1	0.947	0.392	0.944	0.399
2	0.948	0.391	0.944	0.398
3	0.948	0.390	0.944	0.398
4	0.948	0.390	0.944	0.398
5	0.948	0.390	0.944	0.397
6	0.746	1.205	0.732	1.190
7	0.000	1.320	0.000	1.304
8	0.961	0.323	0.959	0.334
9	0.960	0.320	0.961	0.324
10	0.969	0.276	0.969	0.281
11	0.960	0.320	0.961	0.324
12	0.966	0.293	0.967	0.294
13	0.969	0.277	0.969	0.281
14	0.966	0.293	0.967	0.294
15	0.960	0.320	0.961	0.324
16	0.969	0.277	0.969	0.281
17	0.978	0.238	0.976	0.250
18	0.961	0.324	0.959	0.335
19	0.960	0.320	0.961	0.324
20	0.960	0.320	0.961	0.324
21	0.960	0.320	0.961	0.324
22	0.983	0.207	0.982	0.213
23	0.986	0.186	0.986	0.192
24	0.985	0.196	0.984	0.206
25	0.988	0.173	0.987	0.183

Results and Discussion

For the fracture pressure prediction, 80% of the data were used to train the RBF model which predicted the fracture pressure with very high R and low AAPE of 0.987 0.184%, respectively, as shown in **Fig. 1a**. **Fig. 2a** shows the correlation in term of correlation of determination (R^2) between the estimated and the real fracture pressure points where R^2 is 0.974.

20% of the data was used to testing the RBF model. RBF model predicted the unseen fracture pressure values at high accuracy (R = 0.989 and AAPE = 0.175%) as shown in **Fig. 1b**. **Fig. 2b** shows the correlation in term of (R^2) between the estimated and the real fracture pressure points where R^2 is 0.978.

Table 4: The Influence of Spread in *Newrb* Network Function.

Spread	R_Train	AAPE_Train	R_Test	AAPE_Test
0.1	0.0000	1.3203	0.0000	1.3040
0.4	0.9361	0.4088	0.9289	0.4326
0.5	0.9833	0.2068	0.9821	0.2193
0.6	0.9820	0.2130	0.9806	0.2250
0.75	0.9692	0.2772	0.9688	0.2813
1	0.9779	0.2381	0.9760	0.2503
1.5	0.9819	0.2154	0.9809	0.2237
5	0.7051	0.9053	0.6890	0.9151
9	0.4164	1.1902	0.3737	1.2052
10	0.7802	0.9409	0.7528	0.9679

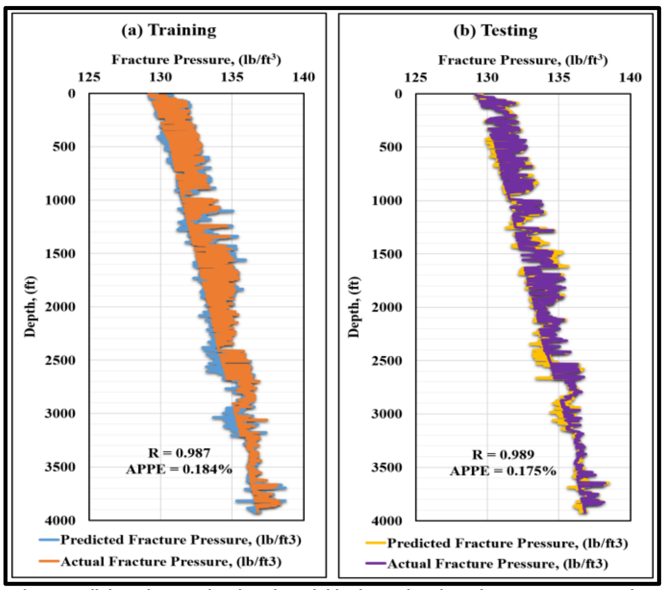

Fig. 1: Radial Basis Function (RBF) Model in the Estimation of Fracture Pressure for Training (a) and Testing (b) Data.

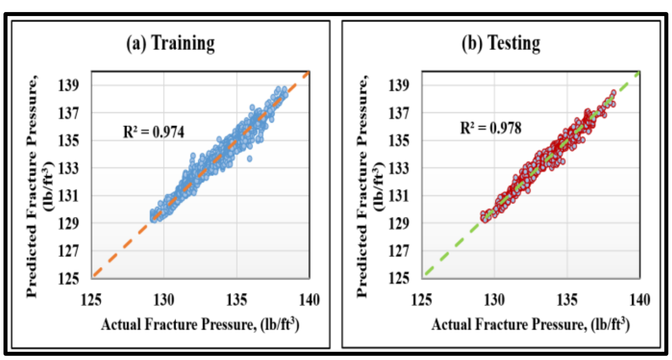

Fig. 2: Radial Basis Function (RBF) Fracture Pressure VS. Real Fracture Pressure for Training (a) and Testing (b) Data.

For more confirmation of the power of the new RBF model, it was applied to estimate the fracture pressure and compared it with Pennebaker model that is one of the mostly used models for prediction of the fracture pressure in the oil field. By applying the RBF model for the fracture pressure prediction, a high accuracy (R = 0.987, AAPE = 0.182% and R^2 = 0.975) were achieved as shown in **Fig. 3a** and **Fig. 4a**.

For Penebaker model, matrix stress coefficient was computed from the chart of Penebaker for all the depths. Also, the overburden stress was calculated at every depth. Then, matrix stress coefficient and overburden stress were substituted in Penebaker equation to predict the fracture pressure. Penebaker model predicted the fracture pressure with low accuracy as indicated by R and the high AAPE of 0.921 and 9.483%, respectively as shown in **Fig. 3b**. Comparing the predicted values of fracture pressure vs. the actual ones, R^2 was 0.849 as shown in **Fig. 4b**.

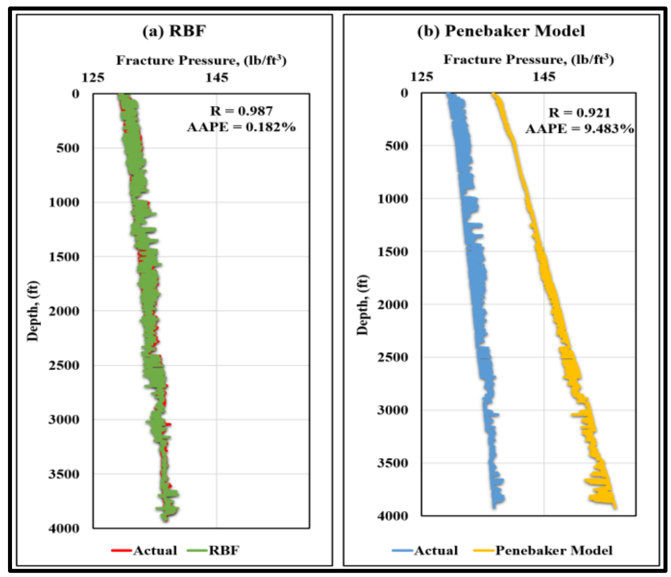

Fig. 3: The New Radial Basis Function (RBF) Model (a) in Comparison with Penebaker Model (b) for Fracture Pressure Prediction.

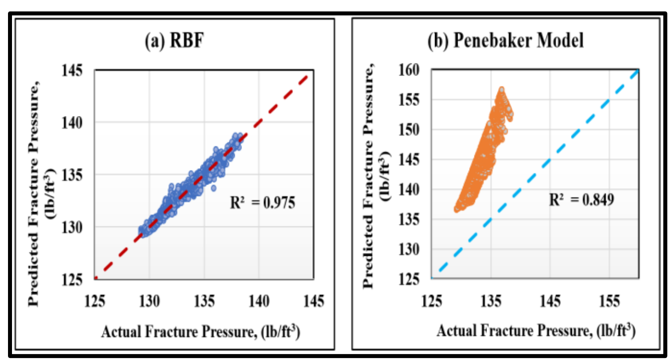

Fig. 4: Comparing the Predicted Fracture Pressure Values and the Actual Values for the New Radial Basis Function (RBF) Model (a) and the Penebaker Model (b).

Conclusions

Radial basis function (RBF) was utilized to estimate the fracture pressure using more than 3900 real field data points of five real drilling surface parameters (WOB, RPM, ROP, T and MW). The following points can be concluded from the obtained results:

- The RBF-based model outperformed an available empirical model (Penebaker model) in predicting the formation fracture pressure. RBF model has the ability to predict fracture pressure with an excellent precision (R = 0.987, AAPE = 0.182% and R^2 = 0.975) whereas Penebaker model predicts the fracture pressure with accuracy of (R = 0.921, AAPE = 9.483% and R^2 = 0.849).
- RBF-based model has also the advantage of the simple prediction of fracture pressure that is shown from its ability to predict fracture pressure from only the real-time surface drilling parameters, which are easily available.
- Formation properties are also major parameters that need to be considered to predict fracture pressure. However, the effect of formation properties was included indirectly by incorporating the real-time drilling surface parameters such as ROP and torque.

Nomenclature

ROP = *Rate of penetration*
WOB = *Weight on bit*
RPM = *Rotary speed*
T = *Drilling torque*
MW = *Mud weigh*
R = *Correlation coefficient*
AAPE = *Absolute average percentage error*
R^2 = *Coefficient of determination*
AI = *Artificial intelligence*
RBF = *Radial basis function*
$\frac{F}{D}$ = *Fracture pressure gradient*
$\frac{P}{D}$ = *Pore pressure gradient*
$\frac{S}{D}$ = *Overburden pressure gradient*
K_p = *Pennebaker matrix stress coefficient*
P_p = *Pore pressure*

References

1. Adams, N. J. Drilling engineering: A complete well planning approach. Tulsa, OK: Pennwell, (1985).
2. Anderson, R. A., Ingram, D. S., & Zanier, A. M. Determining Fracture Pressure Gradients From Well Logs. Society of Petroleum Engineers. doi:10.2118/4135-PA. (1973, November 1).
3. Hossain, M.E., and Al-Majed, A.A.: Fundamentals of Sustainable Drilling Engineering. Scrivener Publishing LLC., 27 Feb (2015).
4. Hu, L., Deng, J., Zhu, H., Lin, H., Chen, Z., Deng, F., & Yan, C.: A new pore pressure prediction method-back propagation artificial neural network. In: Research Gate, 18, 18:4093-4107. (2013).
5. Hubbert, M. K., & Willis, D. G.. Mechanics Of Hydraulic Fracturing. Society of Petroleum Engineers. (1957, January 1).
6. Keshavarzi & Jahanbakhshi: Real-time prediction of pore pressure gradient through an artificial intelligence approach: a case study from one of middle east oil fields, European Journal of Environmental and Civil Engineering, 17:8, 675-686. (2013).
7. Keshavarzi, R., Jahanbakhshi, R., & Rashidi, M. Predicting Formation Fracture Gradient In Oil And Gas Wells: A Neural Network Approach. American Rock Mechanics Association (2011, January 1).
8. Malallah, A., & Nashawi, I. S. Estimating the fracture gradient coefficient using neural networks for a field in the Middle East. Journal of Petroleum Science and Engineering, 49 (3-4), 193-211. doi:10.1016/j.petrol.2005.05.006. (2005).
9. Matthews, W.R.; Kelly, J.: How to predict formation pressure and fracture gradient. Oil Gas J. 65, 92–1066 (1967).
10. Mitchell, R. L., Miska, S. Z., & Aadnoy, B. S.: Fundamentals of drilling engineering. Richardson, TX: Society of Petroleum Engineers. (2011).
11. Pennebaker, E.S.: Detection of Abnormal-Pressure Formation from Seismic Field Data. American Petroleum Institute, Washington (1968).
12. Sadiq, T., & Nashawi, I. S.. Using Neural Networks for Prediction of Formation Fracture Gradient. Society of Petroleum Engineers. doi:10.2118/65463-MS. (2000).
13. Orr, M. J,. Introduction to Radial Basis Function Networks. Retrieved November 22, 2017, from https://www.cc.gatech.edu/~isbell/tutorials/rbf-intro.pdf, (1996, April).
14. Chen, S., C.F.N. Cowan, and P.M. Grant. "Orthogonal Least Squares Learning Algorithm for Radial Basis Function Networks," IEEE Transactions on Neural Networks, Vol. 2, No. 2, pp. 302–309. (1991).
15. Alarfaj, M. K., Abdulraheem, A., & Busaleh, Y. R. Estimating Dewpoint Pressure Using Artificial Intelligence. Society of Petroleum Engineers. doi:10.2118/160919-MS. (2012, January 1).
16. Sherrod, P. H.. DTREG Predictive Modeling Software User Manual. s.l.:www.dtreg.com. (2008).