Petrophysical and capillary pressure properties of the upper Triassic Xujiahe Formation tight gas sandstones in western Sichuan, China

Ye Sujuan^{1*}, Lü Zhengxiang¹ and Li Rong²

¹ Exploration and Production Research Institute, Sinopec Southwest Company, Sichuan 610081, China

² Chengdu Institute of Geology and Mineral Resources, Sichuan 610081, China

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Abstract: The tight sandstones of the Upper Triassic Xujiahe Formation (T_3x) constitute important gas reservoirs in western Sichuan. The Xujiahe sandstones are characterized by low to very low porosity (av. 5.22% and 3.62% for the T_3x^4 and T_3x^2 sandstones, respectively), extremely low permeability (av. 0.060 mD and 0.058 mD for the T_3x^4 and T_3x^2 sandstones, respectively), strong heterogeneity, micro-nano pore throat, and poor pore throat sorting. As a result of complex pore structure and the occurrence of fractures, weak correlations exist between petrophysical properties and pore throat size, demonstrating that porosity or pore throat size alone does not serve as a good permeability predictor. Much improved correlations can be obtained between permeability and porosity when pore throat radii are incorporated. Correlations between porosity, permeability, and pore throat radii corresponding to different saturations of mercury were established, showing that the pore throat radius at 20% mercury saturation (R_{20}) is the best permeability predictor. Multivariate regression analysis and artificial neural network (ANN) methods were used to establish permeability prediction models and the unique characteristics of neural networks enable them to be more successful in predicting permeability than the multivariate regression model. In addition, four petrophysical rock types can be identified based on the distributions of R_{20} , each exhibiting distinct petrophysical properties and corresponding to different flow units.

Key words: Western Sichuan, upper Triassic Xujiahe Formation, tight sandstones, permeability, porosity, pore throat radius, regression analysis, artificial neural network

1 Introduction

The Western Sichuan Depression is located in the western part of the Sichuan Basin (Fig. 1) and contains upper Triassic to Quaternary terrestrial strata with thicknesses up to 8 km (Gu and Liu, 1997; Xu et al, 1997). The upper Triassic Xujiahe Formation hosts huge volumes of hydrocarbon especially natural gas in western Sichuan. With the discovery of Xujiahe gas reservoirs in the Xinchang and Dayi gas fields, its giant gas reserve potential has been confirmed.

The Xujiahe Formation comprises lacustrine, delta, and fluvial siliciclastics and can be divided into six lithologic units based on lithostratigraphic features, T_3x^1 (lowermost)– T_3x^6 (uppermost). The T_3x^1 , T_3x^3 , and T_3x^5 consist primarily of mudstones, whereas the T_3x^2 , T_3x^4 , and T_3x^6 are mainly composed of sandstones. Due to the great thickness of single sandstone body, the great cumulative thickness of sandstone beds, and the stable lateral continuity of sandstones, the T_3x^2 and T_3x^4 are the major gas-bearing sand units in the

Xujiahe Formation. The Xujiahe sandstones are deeply buried with depths greater than 3 km and have undergone complex diagenetic alterations (Lü, 2005; Lü and Liu, 2009; Xu et al, 2008), which thus make the sandstones tight to ultra-tight and highly heterogeneous. The sandstones are characterized by low–very low porosity and extremely low permeability (less than 5% and 0.1 mD, respectively) and are regarded as tight to ultra-tight sandstones with no gas storage and flow capacity. However, commercial gas flows have been obtained from the Xujiahe Formation with high-yield gas flows (more than 10×10^4 m³/day) produced from some wells, demonstrating its huge gas reserve potential. In order to analyze the exploration potential and risks of tight sandstones of the Xujiahe Formation, understanding reservoir petrophysical characteristics and pore systems is essential for characterization and modeling of gas reservoirs.

Permeability is one of the most significant properties in reservoir characterization because it determines the capacity of a reservoir to deliver hydrocarbons. It is a common practice to estimate permeability using porosity–permeability correlations generated from core analysis. However, it has been demonstrated that the relationships are generally poor

*Corresponding author. email: sujuan_ye@hotmail.com

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Fig. 1 Location map and tectonic elements of the Sichuan Basin (simplified from Meng et al, 2005)

when rocks are highly heterogeneous. Many efforts have been made to understand the factors controlling permeability and establish a relationship between these factors and permeability. Several studies have recognized the dependence of permeability on various rock properties such as grain size, sorting, compaction, cementation, and authigenic clay composition (Beard and Weyl, 1973; Bloch, 1991; Coskun et al, 1993). Other investigators have reported empirical relationships between capillary pressure parameters and permeability/porosity (Pittman, 1992; Swanson, 1981; Kolodzie, 1980; Katz and Thompson, 1986; 1987; Xiao et al, 2008; Zhang et al, 2006). Many studies have aimed to predict pore structure parameters and permeability from nuclear magnetic resonance (NMR) well-log data (Xiao and Zhang, 2008; Christopher et al, 2010; Zhao et al, 2006). So far, no studies have been conducted to establish a permeability prediction model for the Xujiahe sandstones in western Sichuan, which creates difficulties in performing permeability-based reservoir classification and evaluation.

The aims of this study are to report on the reservoir petrophysical and pore structure characteristics, investigate the dependence of permeability on the distribution of pore throat size derived from mercury injection analysis, find the pore throat radius that is the best permeability predictor, present empirical relationships between porosity, permeability, and pore throat radius, and establish permeability prediction models. This paper concentrates mainly on the estimation of

permeability using regression analysis and artificial neural network (ANN) techniques.

2 Petrophysical and pore structure properties

2.1 Distribution of petrophysical properties

Core porosity and permeability data ($n=4,939$ and $4,124$, respectively) together with a total of 772 core capillary pressure data from 37 wells were used in this study.

The overall porosity and permeability distributions of Xujiahe sandstones are shown in Fig. 2. Compared with the T_3x^4 sandstones, the T_3x^2 sandstones typically display lower porosity and permeability with significant difference in porosity (t-test, $p\text{-value}<2.2\times10^{-26}$) and minor difference in permeability (t-test, $p\text{-value}=0.27$). The T_3x^2 sandstones have a fairly narrow range of porosity values (0.31%-12.41%, average: 3.62%) with 75% of samples having porosity less than 4.4%; permeability values range from 0.001 mD to 302 mD (average: 0.058 mD) with 75% of samples having permeability less than 0.1 mD. The T_3x^4 sandstones have a relatively wide range of porosity values (0.25%-16.27%, average: 5.22%) with 75% of samples having porosity lower than 7.3%; permeability values vary between 0.001 mD and 1,070 mD (average: 0.06 mD) with 75% of samples having permeability lower than 0.16 mD. Besides, the reservoirs show highly heterogeneous permeability with extremely high

Fig. 2 Distributions of porosity and permeability for samples from the T_3x^4 and T_3x^2 sandstones

range, variation coefficient, and heterogeneity coefficient values in permeability. In summary, the Xujiache sandstones are characterized by low to very low porosity, extremely low permeability, and strong heterogeneity and are thus classified as tight to ultra-tight sand reservoirs according to the U.S. Federal Energy Regulatory Commission (FERC) definition.

2.2 Permeability vs. porosity

The porosity–permeability data reveal a trend of increasing permeability with increasing porosity (Fig. 3). However, even with apparently fractured samples excluded, the cross-plots between porosity and the $\log_{10}$ of permeability of the T_3x^2 and T_3x^4 samples result in R (correlation coefficient) of 0.31 and 0.4, respectively, indicating that at any given porosity, more than one order of magnitude permeability variation can be observed. This large variation is caused by complex pore structures and the occurrence of micro-fractures. In comparison with the T_3x^2 reservoirs, the T_3x^4 reservoirs show a better porosity–permeability relationship, demonstrating that the T_3x^2 reservoirs have more complex pore structure and are more seriously affected by fractures.

2.3 Pore structure characteristics

Many studies have recognized that geometry, aperture,

distribution, and connectivity of pore throats can be described by pore structure parameters derived from mercury injection analysis (Van Brakel et al, 1981; Purcell, 1949). According to the pore structure data (Table 1), the pore throat sizes of the Xujiache sandstones are generally less than $0.5 \mu\text{m}$, corresponding to micro-nano pore throats (Nelson, 2009). The T_3x^2 and T_3x^4 sandstones exhibit similar pore structures, with 50% of samples having R_{50} (pore throat radius corresponding to a mercury saturation of 50%) less than $0.04 \mu\text{m}$ and 75% of samples having R_{50} less than $0.06 \mu\text{m}$. The pore throat sorting coefficients are often high, showing a poorly-sorted pore throat size distribution. In general, the Xujiache sandstones are characterized by micro-nano pore throats, poor pore throat sorting, and low flow capacity.

2.4 Relationship of pore throat size and porosity/permeability

Fig. 4 shows no significant correlation between porosity and R_{50} , indicating big differences in rock texture and pore structure. Some samples with low porosity have low P_{50} (capillary pressure corresponding to 50% mercury saturation) and large R_{50} and can thus form gas reservoirs, whereas some samples with high porosity have high P_{50} and small R_{50} and display poor pore connectivity.

Fig. 3 Permeability–porosity crossplots with $\text{Ln}(R_{50})$ superimposed for samples from the T_3x^4 and T_3x^2 sandstones. At a given porosity, samples with high R_{50} have high values of permeability.

Table 1 Statistical summary of pore structure parameter values

	<i>N</i>	Minimum	Maximum	Mean	Median
T_3x^4					
Porosity, %	394	0.66	12.33	5.12	5.32
Permeability, mD	377	0.001	352.78	0.14	0.12
P_{50} , MPa	309	1.41	150	19.14	21.03
R_{50} , μm	309	0.005	0.53	0.039	0.038
Sorting coefficient	398	0.46	5.66	2.31	2.07
Skew	398	-2.47	3.02	0.24	0.024
Variation coefficient	398	0.03	2.67	0.25	0.17
T_3x^2					
Porosity, %	378	0.31	6.82	3.02	2.88
Permeability, mD	323	0.002	509.8	0.057	0.045
P_{50} , MPa	223	3.94	150.6	21.39	19.6
R_{50} , μm	223	0.005	0.19	0.035	0.04
Sorting coefficient	378	0.5	5.29	2.14	1.78
Skew	378	-2.67	3.94	0.089	0.025
Variation coefficient	378	0.03	3.66	0.26	0.14

Permeability correlates in general with pore structure parameters. Samples with high permeability exhibit low P_{50} , high R_{50} , and low sorting coefficient. However, due to the effects of fractures and porosity, at any given R_{50} , a spread

of permeability in excess of one order of magnitude can be observed (Fig. 4). Fig. 3 illustrates the effect of pore throat size distribution on permeability–porosity correlations. Samples with low permeability for a given porosity have low R_{50} . In turn, samples with high permeability for a given porosity show high R_{50} .

3 Relationships among permeability, porosity, and pore throat size

Many studies have recognized that permeability is dependent upon pore structure. Swanson (1981) developed the following relationship to estimate permeability:

$$K_{\text{air}} = 339(S_{\text{Hg}} / P_{\text{c}})_{\text{apex}}^{1.691} \quad (1)$$

where, K_{air} is air permeability (mD), S_{Hg} is the bulk volume mercury saturation (%), and P_{c} is capillary pressure (psi) corresponding to the apex of a hyperbolic log-log mercury injection plot. This equation does not include porosity as a parameter.

Kolodzie (1980) refined and published the Winland

Fig. 4 Scatter plots showing that porosity has no correlation with R_{50} and permeability has a positive correlation with R_{50}

equation to express permeability as a function of porosity, permeability, and r_{35} :

$$\text{Log} r_{35} = 0.732 + 0.588 \text{Log} K_{\text{air}} - 0.864 \text{Log} \phi \quad (2)$$

where, r_{35} is the pore aperture corresponding to a mercury saturation of 35% (μm), K_{air} is uncorrected air permeability (mD), and ϕ is porosity (%).

Pittman (1992; 2001) extended the Winland approach and developed a series of equations in which pore aperture radii correspond to mercury saturation ranging from 10% to 75% and suggested pore throat size at 25% mercury saturation (r_{25}) as the best permeability predictor:

$$\text{Log} K = -1.221 + 1.415 \text{Log} \phi + 1.512 \text{Log} r_{25} \quad (3)$$

where, K is uncorrected air permeability (mD), ϕ is porosity (%), and r_{25} is the pore throat radius corresponding to 25% of saturation (μm).

According to the petrophysical and pore structure analysis of the Xujiahe sandstones, both porosity and pore throat size are related to permeability. Thus, porosity and pore throat radius were selected as the dependent variables in the estimation of permeability. In order to eliminate the effect of fractures and thus enable the understanding of reservoir matrix properties, samples with apparent fractures were excluded. In this study two data sets (192 and 173 samples, respectively) were used for the T_3x^4 and T_3x^2 sandstones.

3.1 Multivariate regression analysis

In order to find the pore throat radius that is the best permeability predictor, pore throat radii corresponding to 10% to 50% mercury saturation were used to establish the relationship between permeability, porosity, and pore throat size.

The results are shown in Table 2. The statistical significance of the pore throat radius decreases with increasing mercury saturation, indicating that the large pore throats contribute much to the total permeability. The correlation coefficients and root mean squared error (RMSE) in the permeability calculation from known porosity and pore throat radius are showed in Table 2. The multi-parameter correlations that relate permeability to porosity and pore throat radius are much better than the porosity–permeability correlations. The decrease of correlation coefficients and increase of RMSE with increasing mercury saturation were observed for both T_3x^2 and T_3x^4 sandstones, showing the dominant contribution of large pore throats to the total permeability. For both T_3x^2 and T_3x^4 samples, equations derived from R_{20} yield the best correlation coefficients of 0.80 and 0.81, respectively. Accordingly, the pore throat radius corresponding to 20% mercury saturation (R_{20}) is regarded as the best permeability predictor. According to R_{20} equations of Table 2, permeability is dependent on pore geometry and porosity, with R_{20} being the dominant control on the flow characteristics of reservoirs. The comparisons between measured and estimated permeability using the R_{20} equations are presented in Fig. 5.

Table 2 Empirical equations developed from regression analysis

Equations	Correlation coefficient	RMSE
T_3x^4		
Number of samples	192	
$\text{Log} K = -2.17 + 0.2806 \text{Log} \phi + 0.8478 \text{Log} R_{\text{Pd}}$	0.61	0.93
$\text{Log} K = -0.73 + 0.4794 \text{Log} \phi + 1.3771 \text{Log} R_{10}$	0.72	0.78
$\text{Log} K = -1.25 + 0.4638 \text{Log} \phi + 0.7897 \text{Log} R_{15}$	0.79	0.73
$\text{Log} K = -1.68 + 0.4699 \text{Log} \phi + 0.9345 \text{Log} R_{20}$	0.81	0.71
$\text{Log} K = -1.50 + 0.4457 \text{Log} \phi + 0.8843 \text{Log} R_{25}$	0.77	0.72
$\text{Log} K = -1.59 + 0.5064 \text{Log} \phi + 0.7813 \text{Log} R_{30}$	0.73	0.76
$\text{Log} K = -1.55 + 0.5414 \text{Log} \phi + 0.7440 \text{Log} R_{35}$	0.70	0.80
$\text{Log} K = -1.41 + 0.6105 \text{Log} \phi + 0.7589 \text{Log} R_{40}$	0.70	0.80
$\text{Log} K = -1.23 + 0.6241 \text{Log} \phi + 0.6879 \text{Log} R_{50}$	0.70	0.76
$\text{Log} K = -4.28 + 0.9661 \text{Log} \phi$	0.45	1.08
T_3x^2		
Number of samples	173	
$\text{Log} K = -2.74 + 0.8681 \text{Log} \phi + 0.7738 \text{Log} R_{\text{Pd}}$	0.68	0.65
$\text{Log} K = 0.49 + 0.7318 \text{Log} \phi + 2.4535 \text{Log} R_{10}$	0.74	0.64
$\text{Log} K = -0.88 + 0.5866 \text{Log} \phi + 1.4333 \text{Log} R_{15}$	0.78	0.60
$\text{Log} K = -2.13 + 0.9377 \text{Log} \phi + 0.9326 \text{Log} R_{20}$	0.80	0.58
$\text{Log} K = -2.33 + 0.9902 \text{Log} \phi + 0.7687 \text{Log} R_{25}$	0.77	0.61
$\text{Log} K = -2.30 + 1.0166 \text{Log} \phi + 0.7129 \text{Log} R_{30}$	0.76	0.62
$\text{Log} K = -2.22 + 1.0221 \text{Log} \phi + 0.6823 \text{Log} R_{35}$	0.76	0.63
$\text{Log} K = -2.21 + 1.0410 \text{Log} \phi + 0.6225 \text{Log} R_{40}$	0.75	0.64
$\text{Log} K = -2.25 + 1.0699 \text{Log} \phi + 0.5152 \text{Log} R_{50}$	0.72	0.67
$\text{Log} K = -4.12 + 1.2088 \text{Log} \phi$	0.61	0.77

3.2 Artificial neural network (ANN)

An artificial neural network is a mathematical model that mimics the way the human brain works and is a parallel distributed processing model. Unlike multivariate regression analysis, neural networks are general purpose systems that are usually used to model non-linear complex relationships between inputs and outputs. The major advantage of a neural network solution is that it does not need to explicitly specify the relationship among these parameters. Since neural networks “learn” to solve problems through examples, they are especially suitable for problems that can not be described in terms of an algorithm or set of equations.

In this study, we created a three-layer feed-forward network with a sigmoid transfer function in the hidden layer and a linear function in the output layer. In order to test the reliability of the results, each data set was divided into two parts, including training and testing. The training algorithm used in the model is momentum back propagation. During the training process, the logarithm of porosity and pore aperture radii corresponding to 20% to 50% mercury saturation were fed as inputs and the logarithm of permeability as output. The prediction results (Table 3) show similar trends of decreasing correlation coefficients and increasing RMSE with increasing mercury saturation. Pore throat radius at 20% mercury saturation (R_{20}) yields the best correlation coefficient and RMSE. Fig. 6 compares measured permeability with ANN estimated permeability using R_{20} . The correlation coefficients between measured and estimated permeability are 0.87 and 0.85 respectively, which are better than those yielded by multivariate regression analysis.

Fig. 5 Comparisons between measured and predicted permeability using R_{20} equations from Table 2

Table 3 Correlations between measured and ANN estimated permeability

Inputs	Correlation coefficient	RMSE
T_3x^4		
Log Φ and Log R_{pd}	0.63	0.93
Log Φ and Log R_{10}	0.84	0.68
Log Φ and Log R_{15}	0.86	0.63
Log Φ and Log R_{20}	0.87	0.61
Log Φ and Log R_{25}	0.86	0.64
Log Φ and Log R_{30}	0.83	0.69
Log Φ and Log R_{35}	0.80	0.75
Log Φ and Log R_{40}	0.78	0.79
Log Φ and Log R_{50}	0.66	0.76
Log Φ	0.48	1.05
T_3x^2		
Log Φ and Log R_{pd}	0.68	0.69
Log Φ and Log R_{10}	0.81	0.55
Log Φ and Log R_{15}	0.84	0.49
Log Φ and Log R_{20}	0.85	0.47
Log Φ and Log R_{25}	0.84	0.48
Log Φ and Log R_{30}	0.82	0.51
Log Φ and Log R_{35}	0.81	0.53
Log Φ and Log R_{40}	0.79	0.55
Log Φ and Log R_{50}	0.79	0.67
Log Φ	0.63	0.85

3.3 Petrophysical rock types

Since R_{20} is the dominant control on the flow characteristics of reservoirs, the Xujiache sandstones can be subdivided into different rock types on the basis of R_{20} distributions. By using k -means cluster analysis, samples were grouped into four clusters and the distributions of R_{20} in each cluster are shown in Fig. 7, and representative capillary pressure curves are presented in Fig. 8:

Type 1 (nano porous): $R_{20} < 0.1 \mu\text{m}$

Type 2 (nano-micro porous): $0.1 < R_{20} < 0.2 \mu\text{m}$

Type 3 (micro porous): $0.2 < R_{20} < 0.3 \mu\text{m}$

Type 4 (micro porous): $R_{20} > 0.3 \mu\text{m}$

The petrophysical characteristics of four types of rocks are shown in Table 4. The distributions of permeability, R_{20} , R_{50} , and irreducible water saturation (S_{wi}) for Type 1 to Type 4 rocks are significantly different, indicating that different types of rocks have different flow capacity. Type 3 and Type 4 sandstones exhibit better flow capacity than Type 1 and Type 2 rocks and determine the production behavior of wells.

According to the study of influential factors on reservoir quality, R_{20} values of the Xujiache sandstones are closely related to grain-size, sorting, detrital composition, and the amount of authigenic minerals. Coarse-grained and medium-grained sandstones have large R_{20} and tend to show good flow capacity. Siltstones, argillaceous siltstones, conglomerates, fine-grained sandstones, and calcareous sandstones are generally characterized by poor pore structure and are usually classified as Type 1 or Type 2.

After identifying rock types based on relevant data obtained from the cores, cuttings, and well logs, permeability can be determined from the mean R_{20} value for the corresponding rock type and known porosity using R_{20} equations from Table 2 or neural networks.

Table 4 Statistical summary of petrophysical properties of four types of rocks*

	Porosity, %	Permeability, mD	R_{20} , μm	R_{50} , μm	S_{wi} , %
T_3x^4					
Type 1	4.74 (2.29)	0.039 (0.091)	0.046 (0.025)	0.016 (0.011)	50 (14)
Type 2	6.29 (2.38)	0.063 (0.089)	0.144 (0.028)	0.023 (0.021)	34 (11)
Type 3	5.68 (1.80)	0.129 (0.09)	0.244 (0.027)	0.032 (0.022)	27 (9)
Type 4	6.18 (2.12)	0.199 (1.22)	0.459 (0.24)	0.08 (0.087)	17 (9)
T_3x^2					
Type 1	2.69 (1.13)	0.024 (0.018)	0.067 (0.015)	0.017 (0.012)	33 (13)
Type 2	3.02 (1.0)	0.048 (0.077)	0.147 (0.028)	0.033 (0.017)	28 (11)
Type 3	2.96 (1.06)	0.07 (0.319)	0.237 (0.025)	0.051 (0.018)	25 (9)
Type 4	2.95 (0.94)	0.108 (0.306)	0.341 (0.052)	0.067 (0.028)	19 (8)

* Data in table: mean (standard deviation)

Fig. 6 Cross-plots of measured and ANN predicted permeability using R_{20}

Fig. 7 Distributions of R_{20} in four different types of sandstones

Fig. 8 Typical capillary pressure curves for different types of sandstones

4 Discussion and conclusions

Examination of porosity, permeability, and capillary pressure data shows that the Xujiahe sandstones are characterized by low to very low porosity, extremely low permeability, strong heterogeneity, nano-micro pore throats, and poor pore throat sorting and are thus classified as tight to ultra-tight sand reservoirs.

As a result of complex pore structure and the occurrence of fractures, poor correlations exist between (1) porosity and permeability, (2) porosity and pore throat size, and (3) permeability and pore throat size. Therefore, porosity or pore throat size alone does not serve as a good permeability predictor.

Much improved correlations can be obtained between permeability and porosity when pore throat radii are incorporated, demonstrating the dependence of permeability on porosity and pore throat size. By correlating porosity, permeability, and pore throat radii corresponding to different saturations of mercury, equations derived from pore throat radii at 20% mercury saturation (R_{20}) yield the best correlation coefficients and RMSEs for both T_3x^4 and T_3x^2 sandstones and hence R_{20} is the best permeability estimator for the Xujiahe sandstones. These results are different from those of Kolodzie (1980) and Pittman (1992; 2001), who proposed R_{35} and R_{25} respectively as the best pore throat representative for estimating permeability. A possible explanation for this difference is that the Xujiahe sandstones have undergone complex diagenetic alteration and the proportion of micro- or nano-pores in the Xujiahe sandstones is higher than that in samples used by Kolodzie and Pittman. The pore throat distribution and contribution to permeability by pore throats with different sizes can be derived from mercury injection capillary pressure curves using the Washburn equation (1921) and Purcell model (1949) respectively. The mercury saturation corresponding to the pore throat that contributes most to permeability shows a positive correlation with porosity (Fig. 9, $R=0.80$). For samples with higher porosity, pore throats at higher mercury saturation appear to contribute more to permeability. The average mercury saturation

Fig. 9 Cross-plot of mercury saturation corresponding to the pore throat size that contributes most to permeability and porosity

corresponding to the pore throat that contributes most to permeability is 20.3%, demonstrating the rationality of using R_{20} as the permeability predictor.

Generally, the larger pore throats are much more important than the smaller ones in determining permeability and permeability should thus be the most sensitive to the maximum pore throat radius (R_{pd}). However, because of the sensitivity of displacement pressure (or R_{pd}) to fractures, the correlation among permeability, porosity, and R_{pd} is relatively poor (Table 2). In addition, as the pore throat size distribution widens, the correlation between permeability and porosity/ R_{pd} degrades because the contribution to permeability by the pore throats with different sizes increases. The pore throat sorting of T_3x^4 sandstones is poorer than that of T_3x^2 sandstones (Table 1) and consequently the correlations are poor for T_3x^4 sandstones (Table 2 and Table 3). This study demonstrates that the R_{20} is the dominant control on the flow characteristics of these reservoirs in comparison with porosity.

Two different methods, including multivariate regression analysis and an artificial neural network, were used to establish a permeability prediction model. The neural network technique performs better than the multivariate regression model. Using proposed models, permeability can be estimated more accurately when relevant data can be obtained from cores, cuttings, and well logs. Additionally, a series of empirical equations of Table 2 make it possible to calculate pore throat radii corresponding to mercury saturation from 0 to 50% and construct a pore throat radius distribution curve from porosity and permeability.

Furthermore, four petrophysical rock types were defined according to the distributions of R_{20} , each exhibiting different petrophysical properties and corresponding to different flow units. By investigating well-log responses and nuclear magnetic resonance (NMR) well-log responses for each type of rocks, the petrophysical rock types can be identified and consequently the petrophysical and reservoir flow properties can be predicted.

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