

Application of machine learning techniques in estimation of fracture porosity using fuzzy inference system for a FGB reservoir in Cuu Long basin, Vietnam

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Summary

Determination of porosity of a fractured granite basement (FGB) reservoir in the Cuu Long basin has always been a challenge for petrophysicists. In this study, an analysis of fracture porosity was successfully conducted, using a machine-learning technique, i.e., fuzzy inference system (FIS), the well log data including gamma ray (GR), deep resistivity (LLD), shallow resistivity (LLS), sonic (DT), bulk density (RHOB), neutron porosity (NPHI), photoelectric factor (PEF) and caliper (CAL) from two wells BHX01 and BHX02, were used as the input for FIS analyses. Fracture porosity calculated by conventional method was found between 0.01 and 2.24% for BHX01 and between 0.15 and 6.63% for BHX02, respectively. These values match very well with those predicted by various FIS techniques, i.e. Sugeno, Mamdani and Subtractive FIS models. It is expected that the approach of using FIS in petrophysical analysis as presented in this paper can be further applied for other fractured granite basement reservoirs in the Cuu Long and Nam Con Son basins, offshore southern Vietnam.

Key words: Machine learning, fuzzy interference system (FIS), well log analysis, fracture porosity, Cuu long basin.

1. Introduction

As shown in Figure 1 the study site is located in the northern Cuu Long basin, which was formed by the fragmentation, rifting, and subsidence of Pre-Tertiary basement and later filled with the end-of-Eocene to Pliocene-Quaternary continental, shallow marine and coastal plain deposits.

Common methods used to estimate primary porosity of a clastic reservoir are not always suitable to estimate the fracture porosity. As a result, petrophysicists keep trying to find new approaches to estimate fracture porosity. In this study, porosity of a fractured granite basement reservoir will be estimated by using a soft computing technique known as fuzzy inference system (FIS), whose results will be compared with those calculated based on a conventional method [1].

Concept of soft computing was first put forward by Zadeh [2], which is known to include the major methods such as fuzzy logic, evolutionary computation, neural computing, and probabilistic reasoning.

Fuzzy interference systems (FIS) are designed using fuzzy set, which is a kind of mathematical set, where each element of the set has a degree of membership. A fuzzy set does not require a crisp and a clearly defined boundary. It can contain elements with a partial degree of membership. A crisp set of reservoir porosity may include {fair, very good} where the degree of membership of an element (denoted as μ) is either 0 or 1; thus, there can only be one kind of reservoir porosity. For example, in Figure 2a, if porosity (ϕ_r) is greater than 0.5, reservoir porosity is very good ($\mu = 1.0$), but if porosity is lower than 0.5, it is poor ($\mu = 0$). A Fuzzy set, on the other hand, allows each



Figure 1. Study location.

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element to have partial membership; thus, one can write a fuzzy set as {poor, fair, good, very good}. As an example, in Figure 2b, if porosity is 0.4, it is classified as fair.

Fuzzy inference (reasoning) is the actual process of mapping from a given input to an output using fuzzy logic. Figure 3 shows the architecture of a fuzzy inference system.

As seen in Figure 3 the fuzzifier converts the raw input data into a linguistic variable using the membership function stored in the fuzzy knowledge base. The inference engine further converts the fuzzy input to the fuzzy output using if-then type fuzzy rules. The defuzzifier converts the fuzzy output of the inference engine to crisp using membership functions analogous to the ones used by the fuzzifier.

There are two main types of fuzzy interference methods based on clustering of numerical data, i.e. C-means and Subtractive. The former is a supervised algorithm that can only be used when there is a set of inputs and corresponding outputs to those inputs (training set). The final output of fuzzy C-means is not a FIS but rather a list of cluster centres and several membership grades for each data point. One can use the information returned by the fuzzy C-means routine to build a FIS. Two types of FIS can be modelled using C-means clustering,

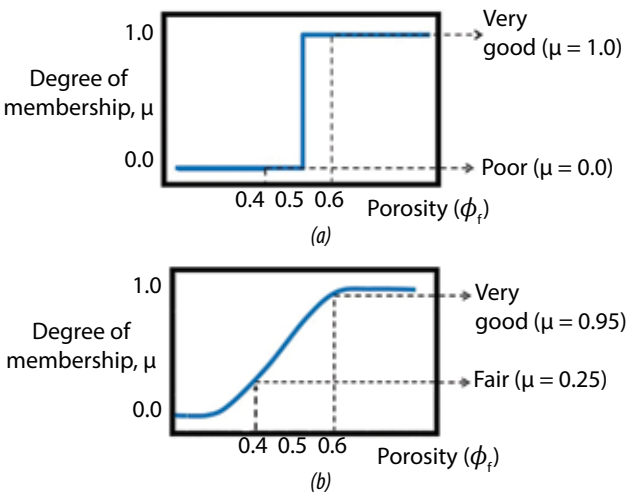


Figure 2. Membership function: (a) crisp set; (b) fuzzy set.

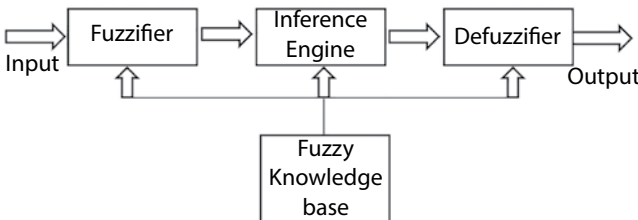


Figure 3. Architecture of a fuzzy inference system.

i.e. Mamdani and Sugeno that are similar in many aspects, and namely, the first two parts of the fuzzy inference process, fuzzifying the inputs and applying the fuzzy operator in the inference engine (Figure 3) are exactly the same. The most fundamental difference between Mamdani type FIS and Sugeno type FIS is the way the crisp output is generated from the fuzzy inputs. While Mamdani FIS uses the technique of defuzzification of a fuzzy output, Sugeno FIS uses weighted average to compute the crisp [3]. So basically, Sugeno model bi-passes the defuzzification. As a result, in Mamdani model there is an output membership function whereas in Sugeno model there is no output membership function. Subtractive is an unsupervised algorithm. It can be utilised when there are no corresponding outputs for a set of input data. This method is focusing on finding regions in the feature space with high densities of data points. The data points within a prespecified, fuzzy radius are then subtracted (removed), and the algorithm proceeds its search for a new point with the highest number of neighbours. The iteration continues until all points have been tested. The quality of the solution depends strongly on the choice of initial values [4].

Application of fuzzy interference systems in petrophysics has been used over the past two decades. Fang and Chen [5] predicted porosity and permeability from the compositional and textural characteristics of sandstones, using fuzzy modelling which is not only assumption-free but also tolerant of outliers. Fuzzy modelling is capable of making both linguistic and numeric predictions based on qualitative knowledge and/or quantitative data. Martinez et al. [6] presented a technique for the identification and characterisation of naturally fractured reservoirs. A fuzzy inference system was implemented in their study to obtain a fracture index using only data from conventional well logs. Additionally, model from O'Connell and Budiansky [7] for the prediction of elastic properties of fractured porous rocks is inverted using genetic algorithms to obtain crack density and crack aspect ratio. The results obtained are compared with core information available. Hambalek and Gonzalez [8] applied fuzzy logic theory in order to establish a narrow relation between well logs and the seven rock types (lithofacies) of the sedimentological model that describes a very complex reservoir in eastern Venezuela. Core analysis of five wells and the established fuzzy relations are used to get the lithofacies description and possible values of permeability in eighteen wells of the same area having only electrical logs. The efficiency

of the algorithm developed was verified against a control well with both log and core data. The results are very satisfactory and open the possibilities for future research and application. Abdulraheem [9] presented the use of fuzzy logic modelling to estimate permeability from wireline logs data for a carbonate reservoir in the Middle East. In this study, correlation coefficients are used as criteria for checking whether a given wireline log is suitable as an input for fuzzy modelling.

2. Methodology

Well log data gamma ray (GR), deep resistivity (LLD), shallow resistivity (LLS), sonic (DT), bulk density (RHOB), neutron porosity (NPHI), photoelectric factor (PEF), and caliper (CAL) were collected from 2 wells BHX01 and BHX02 at a study site in Cuu Long basin, Vietnam.

In this research, the depth interval from 2,515m to 3,015m of well BHX01 and that from 3,050m to 3,870m of well BHX02 were selected. Four reservoir zones of well BHX01 and five reservoir zones of well BHX02 [10] were used in the analyses as shown in Table 1.

The flowchart of the study is shown in Figure 4. First of all, fracture porosities were calculated using a conventional

method suggested by Elkewidy & Tiab [1] that is also described in detail in Giao and Sandunil [11] by Equations 1 - 3. Matrix density will be assumed to be 2.71g/cc, which is for limestone, and fluid density is 1.00g/cc, which is for water. This is because parameters of wireline logging tools used to acquire formation density and neutron porosity of formation are calibra

$$\phi_D = \frac{\rho_{ma} - \rho_b}{\rho_{ma} - \rho_f} \quad (1)$$

$$\phi_t = \frac{\phi_D + \phi_N}{2} \quad (2)$$

$$\phi_f = \frac{\phi_t^{m+1} - \phi_t^m}{\phi_t^m - 1} \quad (3)$$

Where:

ϕ_t : Total porosity, fraction;

ϕ_D : Porosity calculated from bulk density, fraction;

ϕ_N : Neutron porosity, fraction;

ϕ_f : Fracture porosity, fraction;

ρ_b : Bulk density, g/cc;

ρ_{ma} : Matrix density, g/cc;

ρ_f : Fluid density, g/cc;

m: Cementation factor, dimensionless.

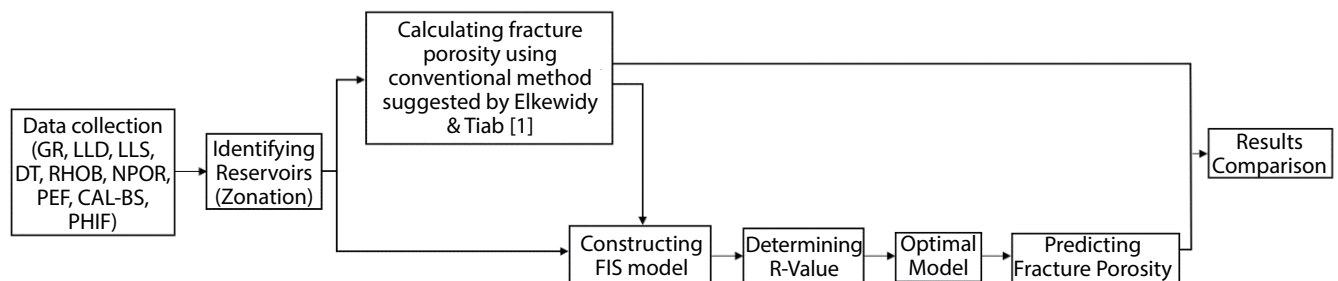


Figure 4. Flow chart of the methodology.

Table 1. Measured depth and true vertical depth of the analysed reservoir zones

Zone	BHX01		BHX02	
	MD (m)	TVD (m)	MD (m)	TVD (m)
Zone 1	2,515 - 2,540	2,514 - 2,540	3,050 - 3,190	2,655 - 2,790
Zone 2	2,540 - 2,655	2,540 - 2,655	3,190 - 3,415	2,790 - 3,015
Zone 3	2,655 - 2,790	2,655 - 2,790	3,415 - 3,525	3,015 - 3,114
Zone 4	2,790 - 3,015	2,790 - 3,015	3,525 - 3,700	3,114 - 3,314
Zone 5	N/A	N/A	3,700 - 3,868	3,314 - 3,466

Table 2. Fracture porosity calculated by conventional approach [1]

BHX01					BHX02				
Zone	MD (m)	TVD (m)	Average ϕ_f (%)	m	Zone	MD (m)	TVD (m)	Average ϕ_f (%)	m
1	2,515 - 2,540	2,514 - 2,540	2.24	1.75	1	3,050 - 3,190	2,655 - 2,790	0.69	2.38
2	2,540 - 2,655	2,540 - 2,655	0.13	2.32	2	3,190 - 3,415	2,790 - 3,015	0.18	2.38
3	2,655 - 2,790	2,655 - 2,790	0.03	2.60	3	3,415 - 3,525	3,015 - 3,114	2.25	1.52
4	2,790 - 3,015	2,790 - 3,015	0.14	2.60	4	3,525 - 3,700	3,114 - 3,314	5.43	1.21
					5	3,700 - 3,868	3,314 - 3,466	3.59	1.28

In the next step, two analyses were conducted to predict porosity using three different FIS models, i.e., Sugeno, Mamdani and Subtractive. In the first analysis

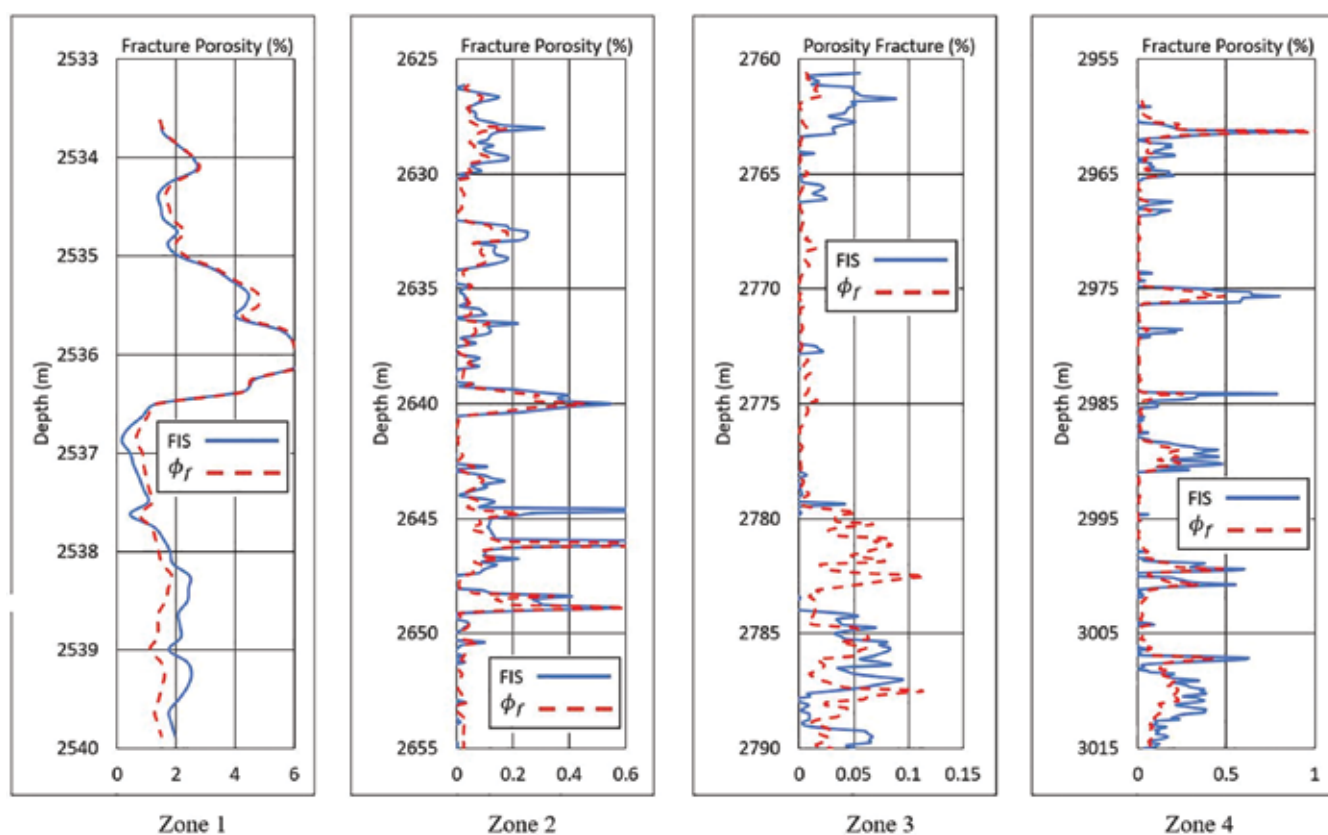
(Analysis I), FIS-based prediction was done for every reservoir zone of wells BHX01 and BHX02, separately, i.e., for each zone 75% of well log data are used for training

Table 3. Results of fracture porosity predicted by FIS in Analyses I and II

Analysis I										Analysis II (data from zones 3 & 4 of BHX01 were trained to predict porosity of zones 1 & 2 of BHX02)				
BHX01					BHX02									
Zone	Conven-tional	FIS Model			Zone	Conven-tional	FIS Model			Zone	Conven-tional	FIS Model		
		C-mean		Subtrac-tive			C-mean		Subtrac-tive			C-mean		Subtrac-tive
		Sugeno	Mamdani				Sugeno	Mamdani				Sugeno	Mamdani	
1	2.24	2.31	3.02	2.27	1	0.47	0.51	0.63	0.44	1	0.69	0.33	0.26	0.39
2	0.06	0.06	0.09	0.06	2	0.15	0.10	0.18	0.16	2	0.17	0.24	0.21	0.15
3	0.01	0.00	0.02	0.01	3	1.37	1.21	1.70	1.34	3	N/A	N/A	N/A	N/A
4	0.07	0.03	0.08	0.07	4	6.63	6.52	5.92	6.58	4	N/A	N/A	N/A	N/A
N/A	N/A	N/A	N/A	N/A	5	3.03	3.02	3.41	3.02	5	N/A	N/A	N/A	N/A

Table 4. Correlation coefficients in two Analyses I & II, using Sugeno, Mamdani and Subtractive models

Analysis I								Analysis II			
BHX01				BHX02				(data from zones 3 & 4 of BHX01 were trained to predict porosity of zones 1 & 2 of BHX02)			
Zone	C-mean		Subtractive	Zone	C-mean		Subtractive	Zone	C-mean		Subtractive
	Sugeno	Mamdani			Sugeno	Mamdani			Sugeno	Mamdani	
1	0.962	0.802	1.000	1	0.952	0.838	0.994	1	0.954	0.374	0.591
2	0.809	0.720	0.834	2	0.910	0.848	0.977	2	0.833	0.630	0.901
3	0.924	0.905	0.985	3	0.992	0.552	0.993	3	N/A	N/A	N/A
4	0.831	0.820	0.954	4	0.999	0.804	1.000	4	N/A	N/A	N/A
N/A	N/A	N/A	N/A	5	0.997	0.882	1.000	5	N/A	N/A	N/A



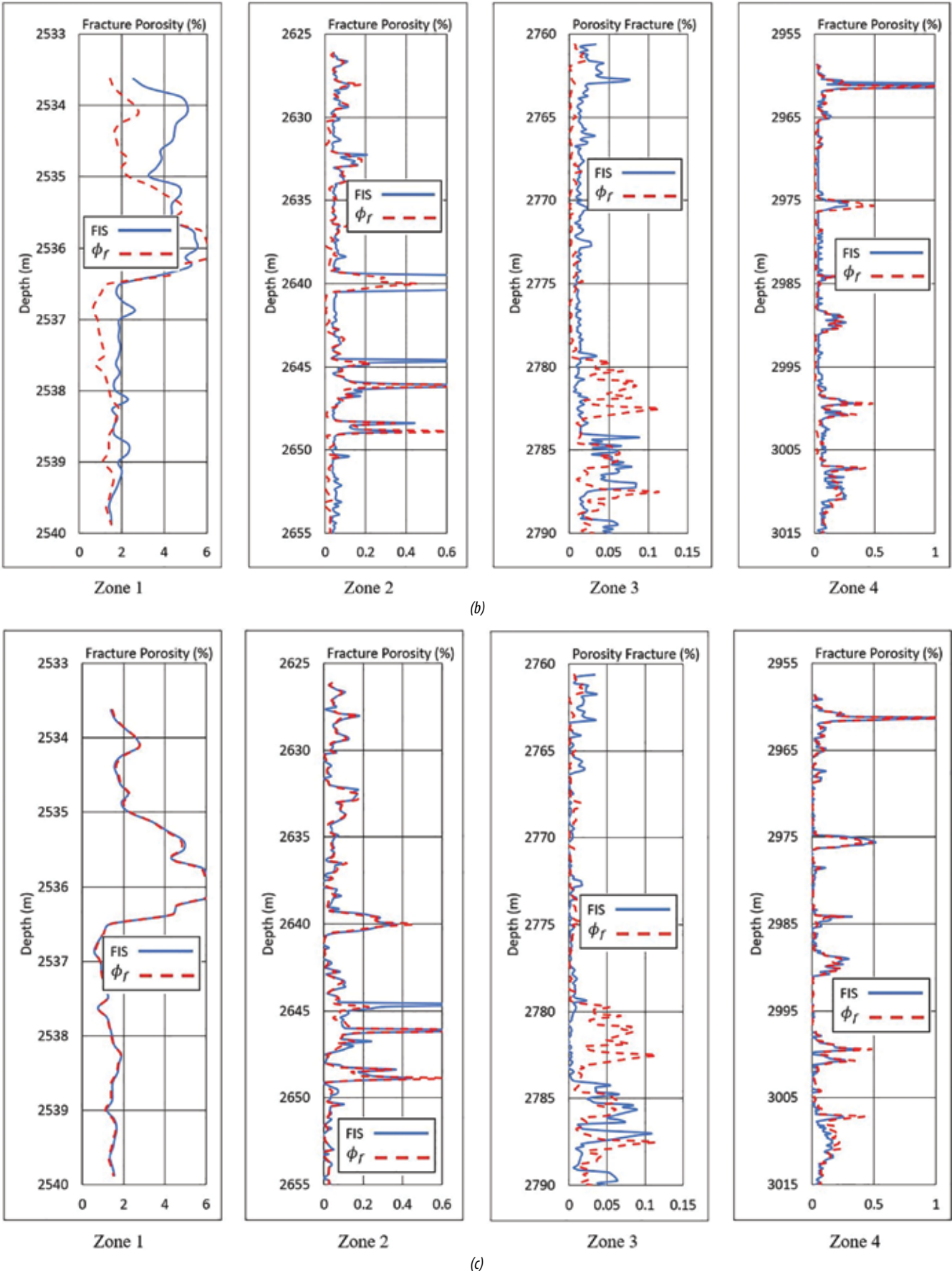
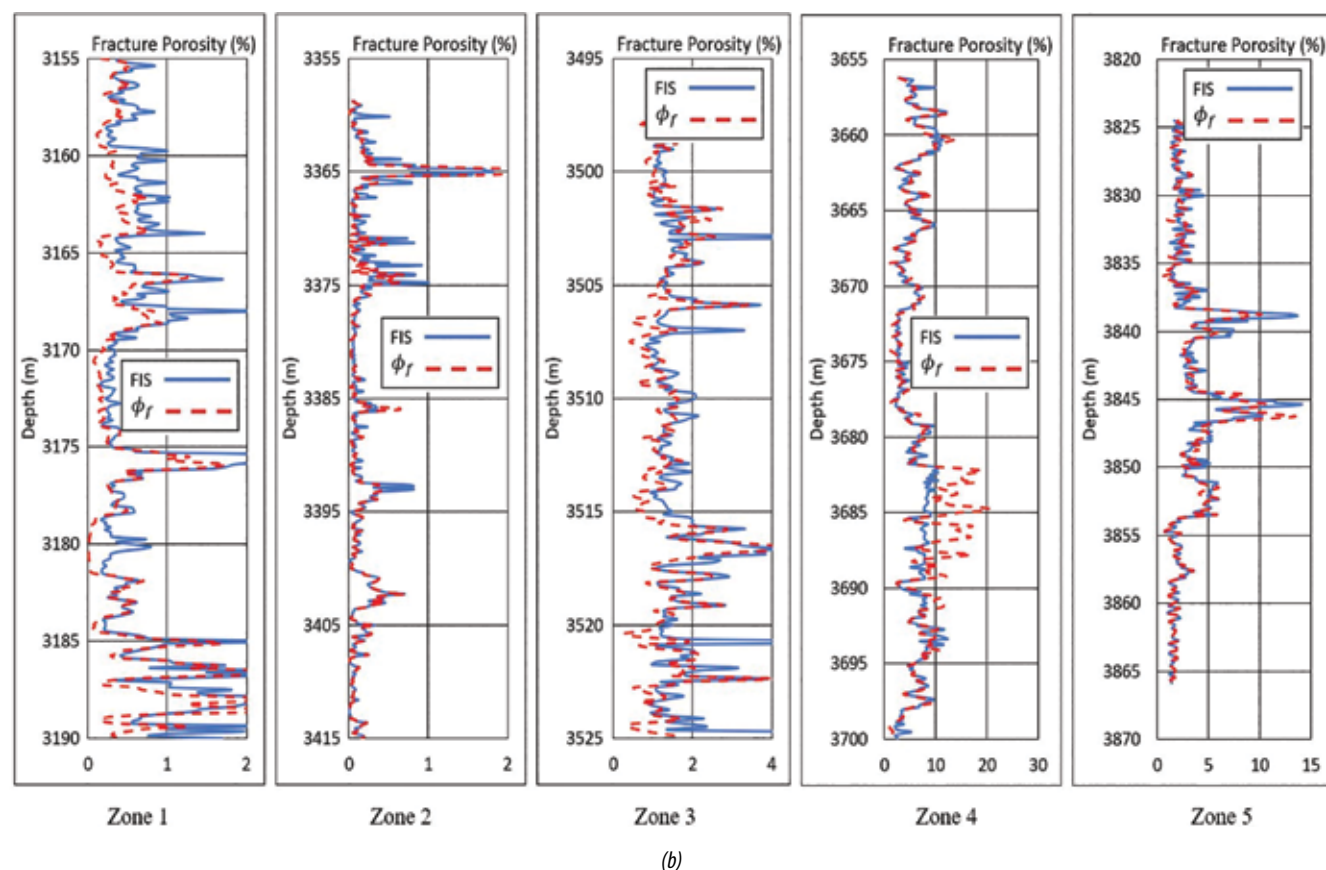
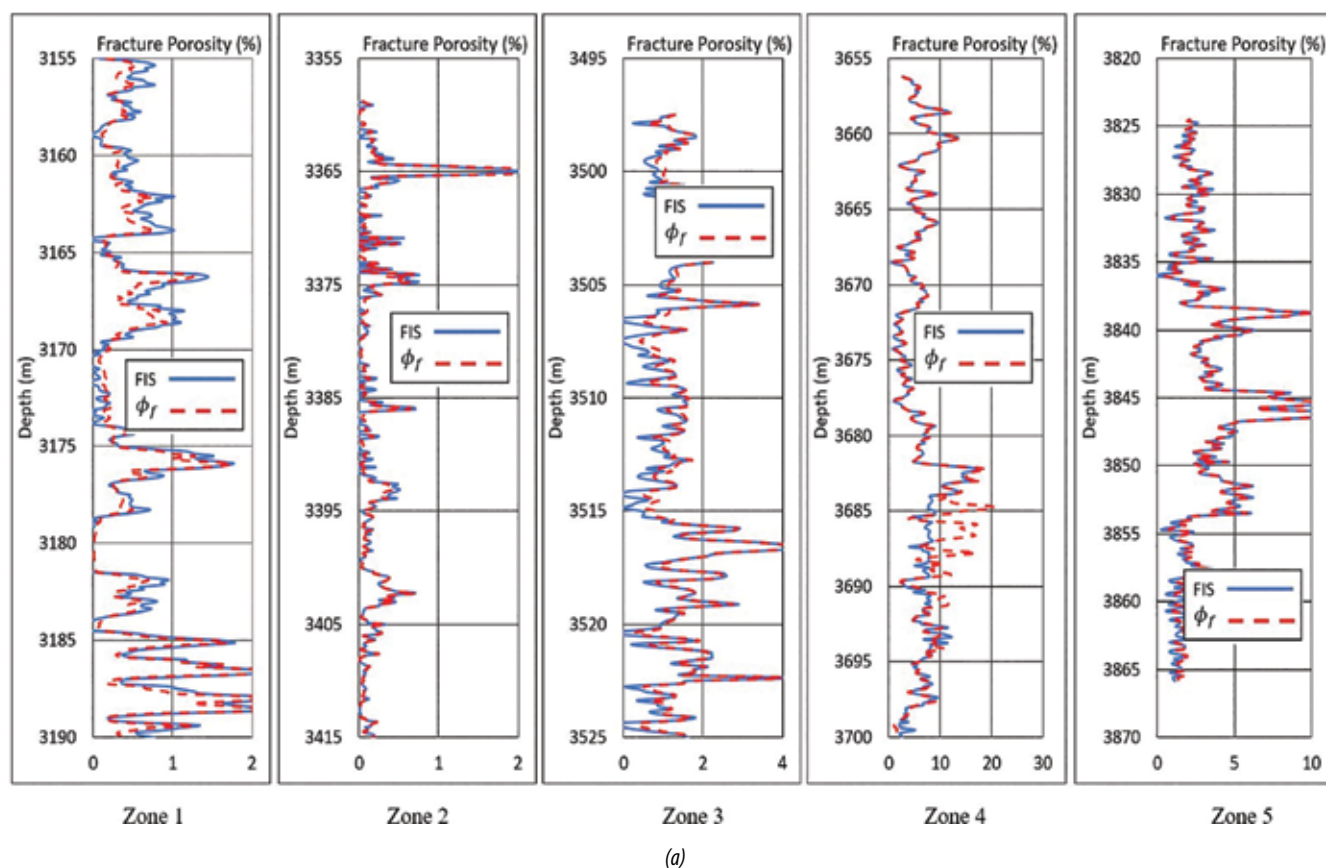


Figure 5. Fracture porosity calculated for zones 1 - 4, well BHX01, Analysis I by (a) Sugeno model, (b) Mamdani model, (c) Subtractive model.



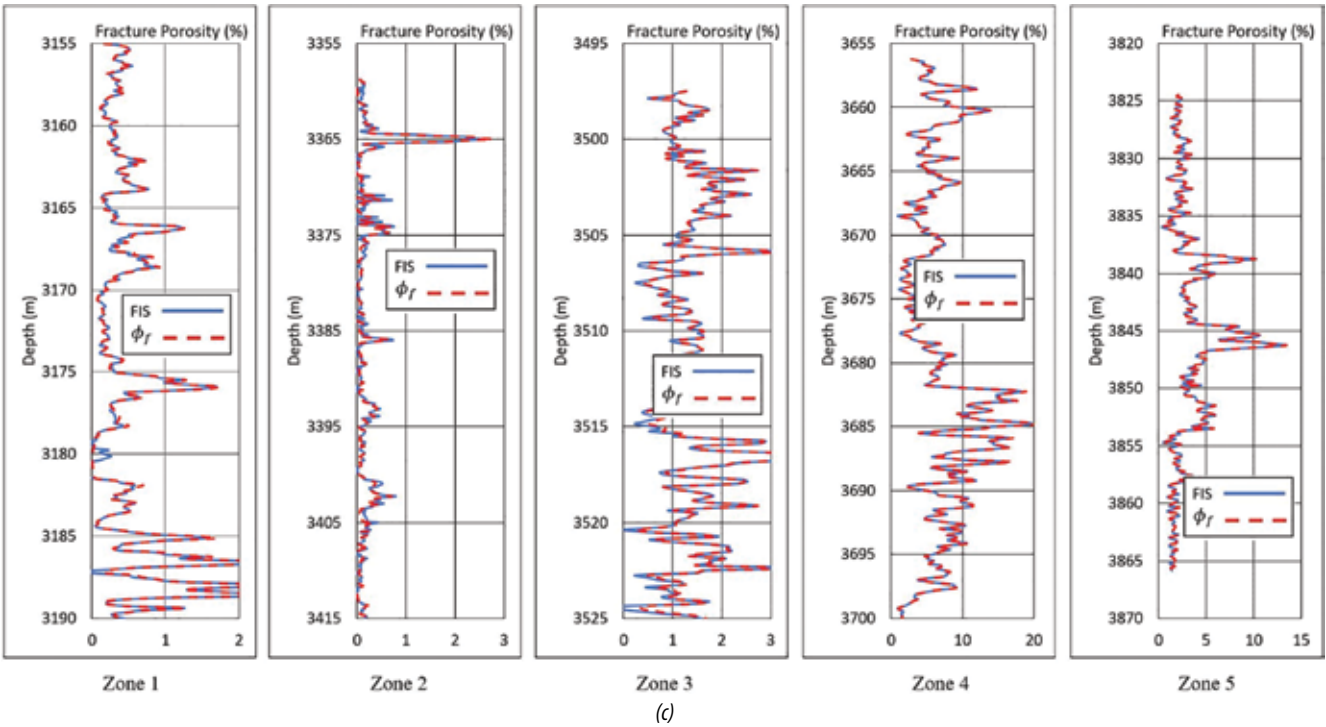


Figure 6. Fracture porosity calculated for zones 1 - 5, well BHX02, Analysis I by (a) Sugeno model, (b) Mamdani model, (c) Subtractive model.

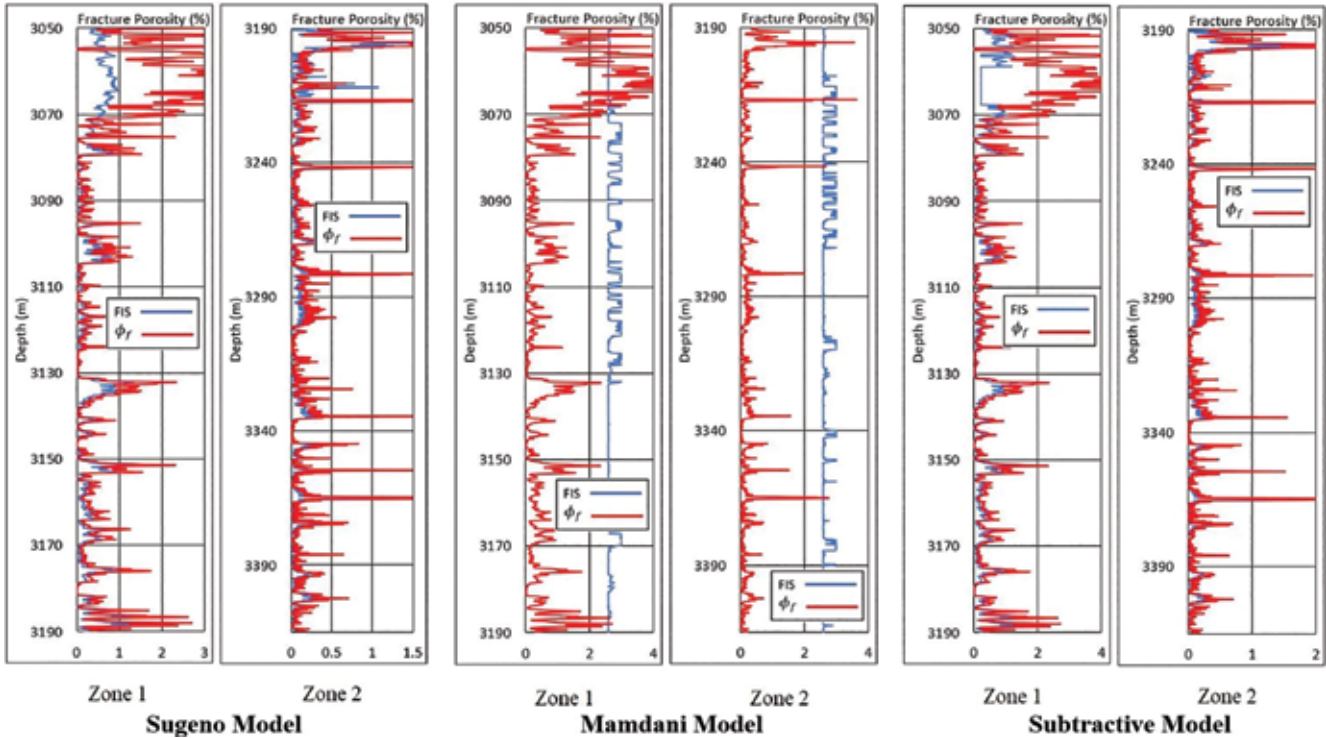


Figure 7. Fracture porosity calculated by Sugeno, Mamdani and Subtractive models for zones 1 and 2, well BHX02, Analysis II.

and the remaining 25% of the well log data are used for prediction. In the second analysis (Analysis II), the well log data of zones 3 and 4 of BHX01 were used to train the FIS models to predict the fracture porosity of zones 1 and 2 of BHX02 as indicated in Table 1.

3. Results and discussion

The average fracture porosities for each reservoir zone as calculated using Elkewidy & Tiab's method [1] shown in Table 2 are found to be between 0.03 and 2.24 for BHX01, and 0.18 and 5.43 for BHX02, respectively. These

conventionally-calculated values were further used to train the FIS models. Table 3 shows the results of Analysis I, indicating the average fracture porosities predicted by Sugeno, Mamdani and Subtractive in comparison with those calculated by the conventional method.

The results of fracture porosity predicted by FIS models are plotted in Figure 5 and Figure 6 as well as shown in Table 3, which are quite close to those calculated by the conventional method shown in Table 2. Among three FIS models, the values predicted by two models of Sugeno and Subtractive are better than those obtained by Mamdani model. This remark is further supported by the calculated correlation coefficient of each FIS analysis as shown in Table 4, which are lower in case of Mamdani model. Out of the three models, Subtractive model gave the best results.

As seen in Figures 5 - 7, the fracture porosity curves predicted by Sugeno and Subtractive models follow well the shape of the conventionally-calculated curve of ϕ_r .

4. Conclusions

The FIS Sugeno and Subtractive models proved to be good methods to predict fracture porosity, which is between 0.00 - 2.31 and 0.01 - 2.27 for well BHX01, 0.10 - 6.52 and 0.16 - 6.58 for well BHX02, respectively.

Fracture porosity predicted by FIS Mamdani are more deviated from the values calculated by Elkewidy & Tiab's method [1] comparing to those predicted by Sugeno and Subtractive models, the fact which is additionally supported by lower values of correlation coefficient.

Out of the three models employed, FIS Subtractive was the best to predict fracture porosity with the highest correlation coefficients.

Although Analysis I that used the well log data in one well to predict fracture porosity prediction for the same well gave better results than Analysis II that used the well data from one well to predict fracture porosity in another well, the results obtained by the latter are also very satisfactory and encouraging for a wider application in practice to predict the porosity of a fractured granite basement reservoirs in the Cuu Long and Nam Con Son basins.

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