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Study of Pore Types Influence for Permeability Value in Carbonate Reservoir Using Differential Effective Medium (DEM) and Adaptive Neuro-Fuzzy Inference System Algorithm

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Abstract
The pore system in a carbonate reservoir is very complex compared to the pore system in clastic rocks. According to measurements of the velocity of propagation of sonic waves in rocks, there are three types classification of carbonate pore classifications: Interparticle, Vugs and Crack. The complexity of these pore types can lead to errors in the calculation or interpretation of the reservoir itself so that characterization of the carbonate reservoir tends to be more difficult.

In this research, elastic modulus modeling will be carried out by taking into account the pore complexity of the carbonate reservoir. Differential Effective Medium (DEM) is an elastic modulus modeling method that takes into account the heterogeneity of pores in the carbonate reservoir. This method adds pore type inclusions gradually into the host material to the desired proportion of the material. In addition, this study will also predict the permeability value of the reservoir using Adaptive Neuro-Fuzzy Inference System algorithm from well logging measurement data as the input and core data from laboratory measurements for training data and validating the predicted results of permeability values in well depths domain. So, the permeability value and pore type variations in well depth domain will be obtained for further interpretation.

Thus we can see which type of pore has a good permeability value in the carbonate reservoir. This kind of thing can also help the engineers to determine a good perforation zone in the well by considering the pores type in the carbonate reservoir and the permeability values that have been predicted before.

Introduction

Carbonate reservoirs consider as one of the main reservoir which produce oil and gas worldwide. Unfortunately, carbonate rocks are more complicated than siliciclastic rocks so that carbonate reservoirs are usually harder to understand compare to sand reservoirs. The difference between the carbonate reservoirs and the sand reservoirs is the distance of deposition. While local deposition happened in carbonate rocks, the grains that comprise siliciclastic rocks may travel hundreds of miles down river systems before deposition and lithification. This local deposition affected significantly carbonate rocks heterogeneity. One of the methods that usually use to characterize carbonate reservoirs is rock physics analysis. This method could determine and calculate pore types of carbonate rocks which are very complex through its elastic moduli. The porosity of carbonate rocks can be divided into three types: Interparticle or reference pores, existing between the carbonate grains and are considered as the dominant pore types in carbonate; stiff pores, represent moldic and vugs pores and are usually formed as a product of dissolved grains and fossils chamber; Cracks, represent micro-fractures and micro-cracks.

To do this research there are several methods to find quantity and distribution of pore type in carbonate reservoir that is Self-Consistent (SC), Kuster-Toksoz (KT), and Differential Effective Medium (DEM) method. In a previous research, *[Candikia et al., 2016]* Has conducted a research entitled comparative study of the Differential Effective Medium (DEM) method with the Kuster-Toksoz (KT) method. In the study it was explained that the Differential Effective Medium (DEM) method was better in determining the carbonate reservoir pore type. Therefore, the authors have a plan to use the Differential Effective Medium (DEM) method to generate pore type logs in the carbonate reservoir.

The next step is the author have to predict permeability value using Adaptive Neuro-Fuzzy Inference System. Fuzzy Logic (FL) that is capable to express the underlying characteristics of a system in human understandable rules is also used. A fuzzy set allows for the degree of membership of an item in a set to be any real number between 0 and 1. This allows human observations, expressions and expertise to be modeled more closely. Once the fuzzy sets have been defined, it is possible to use them in constructing rules for fuzzy expert systems and in performing fuzzy inference. This approach seems to be suitable to well log analysis as it allows the incorporation of intelligent and human knowledge to deal with each individual case. However, the extraction of fuzzy rules from the data can be difficult for analysts with little experience. This could be a major drawback for use in well log analysis. If a fuzzy rule extraction technique is made available, then fuzzy systems can still be used for well log analysis [*Wong et al., 1999 and Kuo et al., 1999*]. With the emergence of intelligent techniques that combine ANN and fuzzy together have been applied successfully in well log analysis [*Huang et al., 2001, Kadkhodaie Ilkhchi et al., 2008, Khaxar et al., 2007,* Johanyák *et al.2007]*. These techniques used in building the well log analysis model normally address the disadvantages encountered in ANN and fuzzy system.

A neural network (NN) is an intelligent tool for solving complex problems. A BPNN is a supervised training technique that sends the input values forward through the network then computes the difference between calculated output and corresponding desired output from the training dataset. The error is then propagated backward through the net and the weights are adjusted during a number of iterations, named epochs. The training ceases when the calculated output values best approximate the desired values [*Bhatt and Helle, 2002]*.

The basic theory of fuzzy sets was first introduced by *Zadeh, 1965*. In recent years, it has been shown that uncertainty may be due to fuzziness (possibility) rather than probability. FL is considered to be appropriate to deal with the nature of uncertainty in system and human errors, which were not considered in existing reliability theories. Generally, geological data are not clear-cut and habitually are associated with uncertainties. For example, prediction of core parameters from well log responses is difficult and is usually associated with error [*Nikravesh and Aminzadeh, 2003]*. FL derives useful information from this error and applies it as a powerful parameter for increasing the accuracy of the predictions. A fuzzy inference system (FIS) is a method to formulate inputs to an output using FL [*Kadkhodaie Ilkhchi et al., 2006]*.

Data and Method

In this study the author use wireline log data to create pore type models along the reservoir depth that is DTCO, RHOB, PHIE, and Petrophysical parameter such as mineral volume, mineral elastic parameter and fluid saturation in carbonate reservoir. Generally, there is three phase of pore type modelling in carbonate reservoir according [*Xu and Payne 2009]*. Fig 1. Bellow will give us the illustration how we create rock physics pore type log.

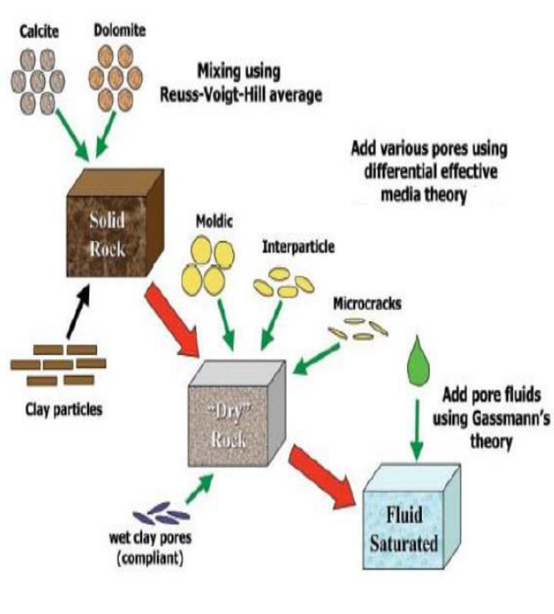

Figure 1: Detailed step of rock physics pore type modelling in carbonate reservoir (Xu and Payne, 2009).

The first step that we have to do to create rock physics pore type model is mixing the mineral and create frame rock model using Voigt-Reuss-Hill method. This is one of method that we use to mix the mineral that contained in carbonate reservoir in order to make background model or usually called solid rock phase. This method is averaging from two methods before that is Voigt method that arrange rock matrix in series and Reuss method that arrange rock matrix in parallel. Solid rock phase is the first step in carbonate reservoir modelling which assumes that the rock not has porosity at all (0% porosity) and all the content in this rock model is 100% mineral such as clay, dolomite and calcite. From this step we could calculate bulk and shear modulus of solid rock phase using Voigt-Reuss-Hill formula bellow *[Mavko et. al., 1998]*:

$$M_V = \sum_{i-n}^{N} f_i . M_i \tag{1}$$

$$\frac{1}{M_R} = \sum_{i-1}^{N} \frac{f_i}{M_i} \tag{2}$$

$$M_{VRH} = \frac{M_V + M_R}{2} \tag{3}$$

Where,

f_i : Mineral fraction

M_i : Elastic modulus of mineral

M_V : Voigt elastic modulus

M_R : Reuss elastic modulus

M_{VRH} : Voigt-Reuss-Hill elastic modulus

The next step method that has been used to input the pore type in the carbonate reservoir is DEM (Differential Effective Medium) method. The theory of DEM method models two-phase composites by incrementally adding a small amount of pores into a matrix. In DEM method, the effective moduli depend on the construction path taken in order to reach the final composite. The DEM method works by put inclusions into the background models. The models are continuously changed as the inclusion added *[Mavko et. al., 1998]*:

$$(1-y)\frac{d}{dy}\left[K^*(y)\right] = (K_2 - K^*)P^{(*2)}(y) \tag{4}$$

$$(1-y)\frac{d}{dy}[\mu^*(y)] = (\mu_2 - \mu^*)Q^{(*2)}(y) \tag{5}$$

Where,

y : Porosity

dy : Inclusion of 2nd pore type

$K^*(y)$: Effective Bulk Modulus of DEM (Phase 3)

K^* : Bulk Modulus of Solid Rock Model (Phase 1)

K_2 : Bulk Modulus of Dry Rock (Phase 2)

$P^{(*2)}$: Geometry factor for an inclusion of material

$\mu^*(y)$: Effective Shear Modulus of DEM (Phase 3)

μ^* : Shear Modulus of Solid Rock Model (Phase 1)

μ_2 : Shear Modulus of Dry Rock (Phase 2)

$Q^{(*2)}$: Geometry factor for an inclusion of material

Steps that needed in DEM method are not significantly different than KT method. DEM method also needs a background or matrix, the geometry factor, the elastic moduli of inclusion and fraction of inclusion as inputs. The difference lies on how to use this inputs. The first step is made a matrix or background by using Voight-Reuss-Hill method. Instead of looping aspect ratio, DEM method determined the aspect ratio value as an input to gain the factor geometry.

There are three aspect ratio values that need to be divined such as the aspect ratio of interparticle pores, stiff pores and crack pores. The determination of those three values are based on the Zhao classification who categorized the value of aspect ratio into three groups. The aspect ratio that represents crack pores is range from 0.01-0.02, the interparticle pores range from 0.12-0.15 and stiff pores vary between 0.7-0.8. The third step is to calculate the V_p reference with the assistance of DEM equation where consist the aspect ratio of interparticle pores, fraction of inclusion or porosity, the elastic moduli of matrix and also the elastic moduli of inclusions. This V_p reference is going to be the controller who decides whether the stiff pores are the one to be included into the process or the crack pores. If the V_p reference lower than V_p measurement or V_p from data, then stiff pores must add into the process. But if the V_p reference higher than V_p measurement, then crack pores need to be put into account. After the process has done, the effective elastic moduli are generated and will be compared with the real data to obtain the most representative model.

For the permeability prediction the author use wireline logging data for the input. Before using the log data, we have to normalize using minimum-maximum method so the range of data become 0-1 for every input and target. After we do data normalization, we have to do feature engineering and augmentation to select what kind of log data that have to use as the input. From the 11 feature the author will choose 6 feature which has quite strong correlation like the figure 2 bellow.

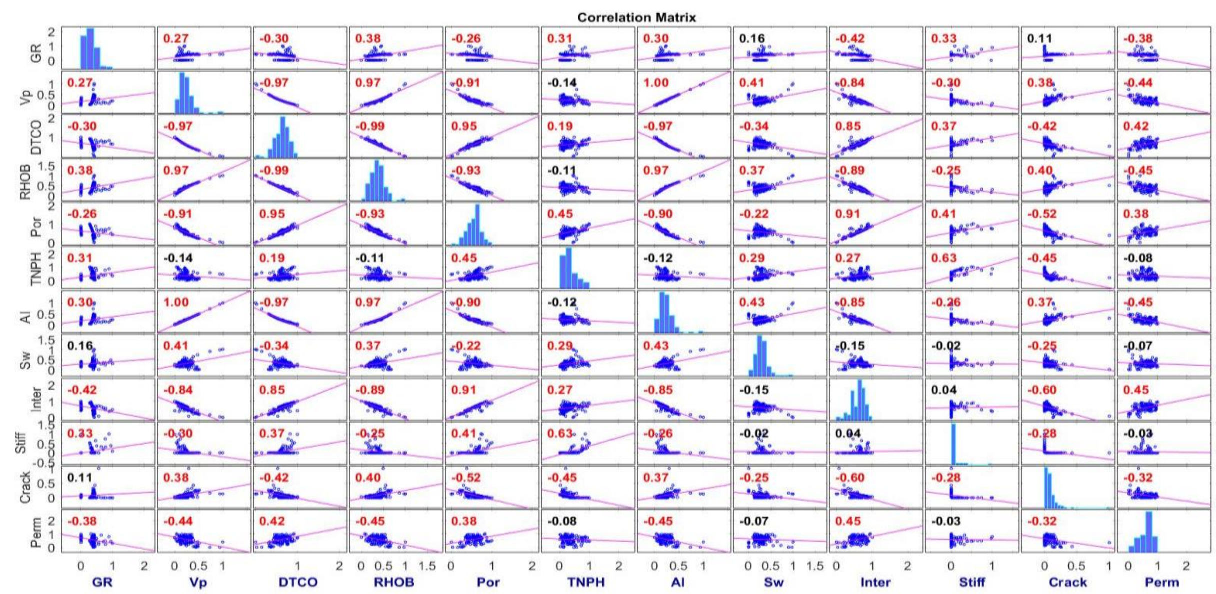

Figure 2: Feature Engineering and Augmentation using matrix Pearson correlation for select the best input for permeability prediction.

From the figure 2 we can see that 6 feature that is (Primary Velocity, DTCO, RHOB, Porosity, Acoustic Impedance and Interparticle Porosity) has a good correlation with the target. After feature selection is finish we have to design Neuro-Fuzzy model in the present research proceeds as following:

1. Removing erroneous and outliers from the raw well log data
2. Organizing data into input data sets including 6 features and 1 output (Permeability)
3. Normalization of input and output data sets (between the ranges 0-1) to renders the data dimensionless and removes the effect of scaling.
4. Dividing the data into: Training and Testing data sets.
5. Clustering the input and output data sets using Fuzzy Subtractive Clustering methods.
6. Fuzzyfication, which involves the conversion of numeric data in real world domain to fuzzy numbers in fuzzy domain, this takes place by building the fuzzy inference system (FIS), which involves setting the membership functions and establishment of fuzzy rules.
7. Defuzzyfication, which is optional, involves the conversion of the derived fuzzy number to the numeric data in real world domain.

Generally, Neuro-Fuzzy Inference System consist of 5 layers that we can see in the figure 3 bellow.

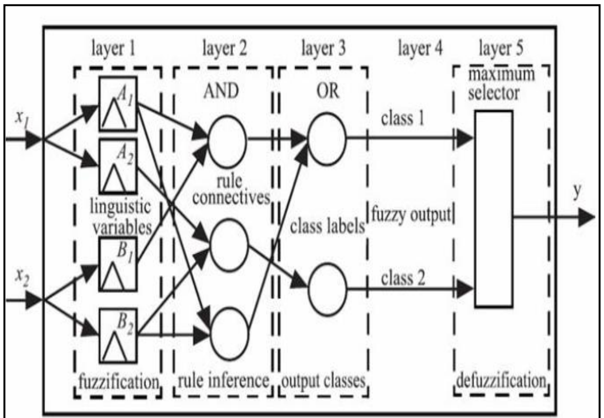

Figure 3: Neuro-Fuzzy Inference System Architecture

Fuzzy modeling technique can be classified into three categories, namely the linguistic (Mamdani-type), the relational equation, and the Takagi, Sugeno and Kang (TSK). Takagi and Sugeno, 1985, is a FIS in which output membership functions are constant or linear and are extracted by a clustering process. Each of these clusters refers to a membership function. Each membership function generates a set of fuzzy if–then rules for formulating inputs to outputs.

Hybrid NF systems combine the advantages of fuzzy systems (which deal with explicit knowledge) with those of NN (which deal with implicit knowledge). On the other hand, Fuzzy Logic (FL) enhances generalization capability of a Neural Network (NN) system by providing more reliable output when extrapolation is needed beyond the limits of the training data.

Fuzzy clustering is necessary to classify the input and output datasets into groups using clustering methods. In this study, a subtractive clustering method, which is a useful and effective way to FL modeling, is used for extraction of clusters and fuzzy if–then rules. The details of subtractive clustering could be found in [*Chiu, 1994*], [*Chen and Wang ,1999*], [*Jarrah and Halawani, 2001*].The important parameter in subtractive clustering which controls number of clusters and fuzzy if–then rules is clustering radius. This parameter could take values between the range of [0, 1]. Specifying a smaller cluster (say 0.1) radius will usually yield more and smaller clusters in the data resulting in more rules. In contrast, a large cluster radius (say 0.9) yields a few large clusters in the data resulting in few rules.

The effectiveness of a fuzzy model is relying on the search for an optimal clustering radius, which is a controlling parameter for determining the number of fuzzy if–then rules. Few rules could not cover the entire domains, and more rules will complicate the system behavior and may lead to low performance of the model. Regarding the permeability model, four centers result from clustering, thus the fuzzy model was established by four fuzzy if-then rules and four membership functions for input and output data. Porosity model, on the other hand, contains five centers (clusters), five rules and five membership functions. Figures 6 and 7 shows the subtractive clusters of permeability and porosity data.

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves setting the membership functions and establishment of fuzzy rules, [*Matlab fuzzy logic user's guide, 2009*].

Setting the Membership Functions (MF). A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse, a fancy name for a simple concept. The only condition a membership function must really satisfy is that it must vary between 0 and 1. The function itself can be an arbitrary curve whose shape we can define as a function that suits us from the point of view of simplicity, convenience, speed, and efficiency. In this research we have calculate and make the variation of Range of Influence in Fuzzy Subtractive Clustering in MATLAB from 0.01-1 to get the best parameter in ANFIS like we can see on the table below.

R	Training MAPE	Testing MAPE	MF for each Input Data
1	0.09	0.24	2
0.9	0.09	0.24	2
0.8	0.09	0.24	2
0.7	0.09	0.27	3
0.6	0.09	0.26	3
0.5	0.08	0.26	4
0.4	0.09	0.31	4
0.3	0.08	0.31	6
0.2	0.05	0.39	11
0.1	0	0.3	51
0.09	0	0.26	59
0.08	0	0.2	68
0.07	**0**	**0.18**	**70**
0.06	0	0.25	82
0.05	0	0.25	90
0.04	0	0.25	96
0.03	0	0.25	99
0.02	0	0.25	101
0.01	0	0.26	101

Table 1: Variation Range of Influence value in Fuzzy Inference System for getting minimum Mean Absolute Percentage Error.

From the table 1 we can see that range of influence value for 0.07 give the best result for training and testing data and give us 70 membership function for each input in ANFIS algorithm.

For 70 membership function for each input in this research we use Gaussian membership function in the FIS structure, output membership functions are linear equations constructed from inputs. ANFIS is a class of adaptive networks which are functionally equivalent to fuzzy inference systems, where the parameters are chosen so as to tailor the membership functions to the input/output data in order to account for all the variations in the data values. This technique is known as neuro-adaptive learning and is similar to that of neural networks. ANFIS is based on a neuro-adaptive learning technique. Using a given input/output data set, ANFIS constructs a fuzzy inference system whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type method. This allows fuzzy systems to learn from the data they are modeling.

To describe the ANFIS methodology, the fuzzy inference systems is represented as an adaptive network in the following way. Suppose a fuzzy inference system with two inputs x and y and one output; its rule base contains two fuzzy if-then rules of Takagi and Sugeno's type:

Rule 1: If x is $A1$ and y is $B1$, then $f1 = p1\,x + q1\,y + r1$
Rule 2: If x is $A2$ and y is $B2$, then $f2 = p2\,x + q2\,y + r2$

For the complete ANFIS parameter in this research we can see in the figure 4 for the membership function and figure 5 for ANFIS input-output and structure below.

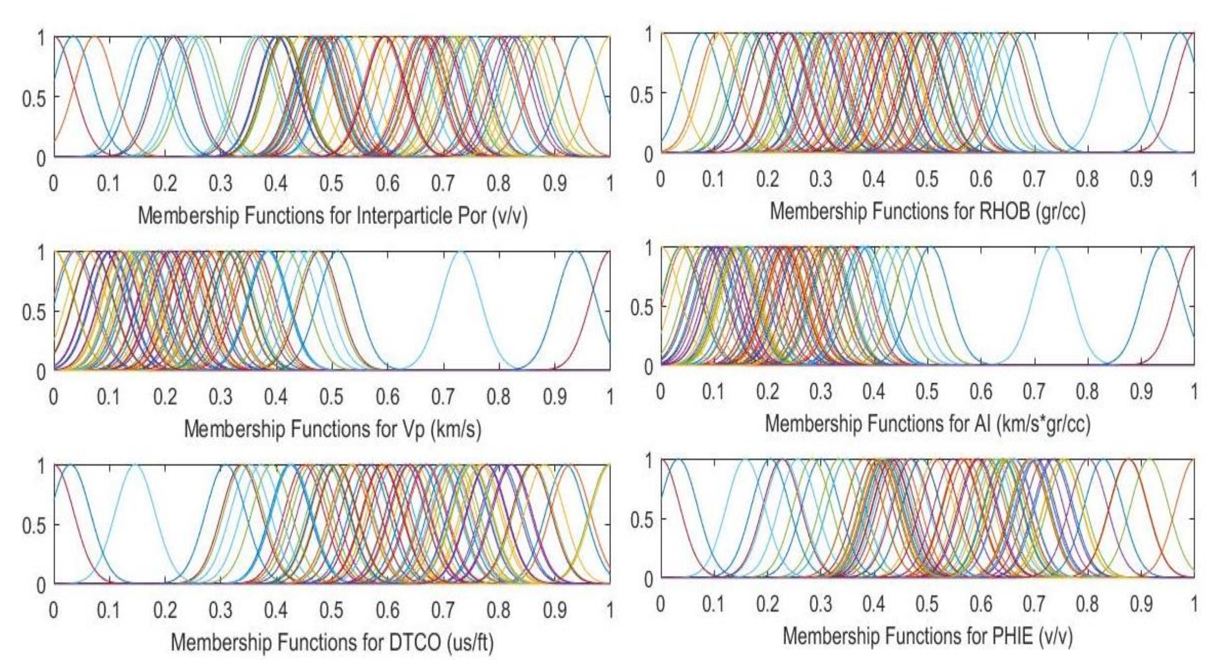

Figure 4: Fuzzy Inference System Membership Function for 6 input in ANFIS Algorithm.

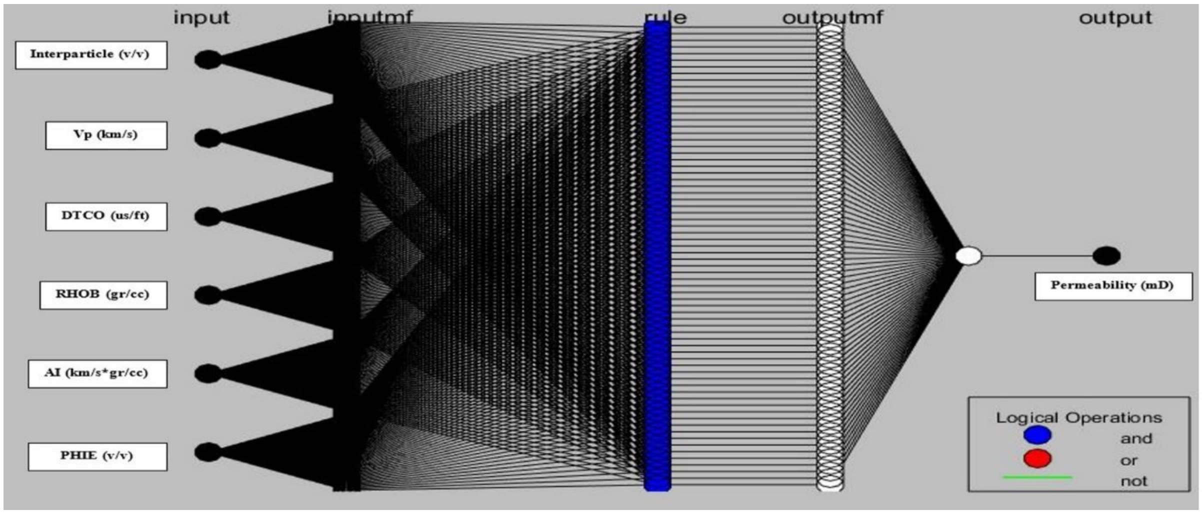

Figure 5: Structure of Neuro-Fuzzy Model for Permeability Prediction.

Result and Discussion

The primary and secondary pore type value using DEM method in this well is calculated. DEM method is used to make models of porous rocks. From this method the type of pores could be calculated. To determine what kind of pore type, the inclusion must be added to the models, and then to compare *V*p reference by *V*p measurement. To calculate *V*p reference we have to make rocks model which has 100% interparticle (dry rock) pores and then the secondary pore type will add step by step with inclusion add each 1% to the dry rock model until *V*p model approach *V*p measurement.

We can calculate *V*p model from DEM equation by extracting effective bulk and shear modulus value to *V*p model equation to ensure that the inclusion we add is appropriate like we can see in the several figure 6 and 7. As we can see in Fig. 6 error value decreases and the trend of cross plot tend to be more linear in DEM method because we have used more accurate input parameters. The more accurate input parameters that we use then RMS error value will decrease and the quantity calculation of secondary pore type will more accurate in each well.

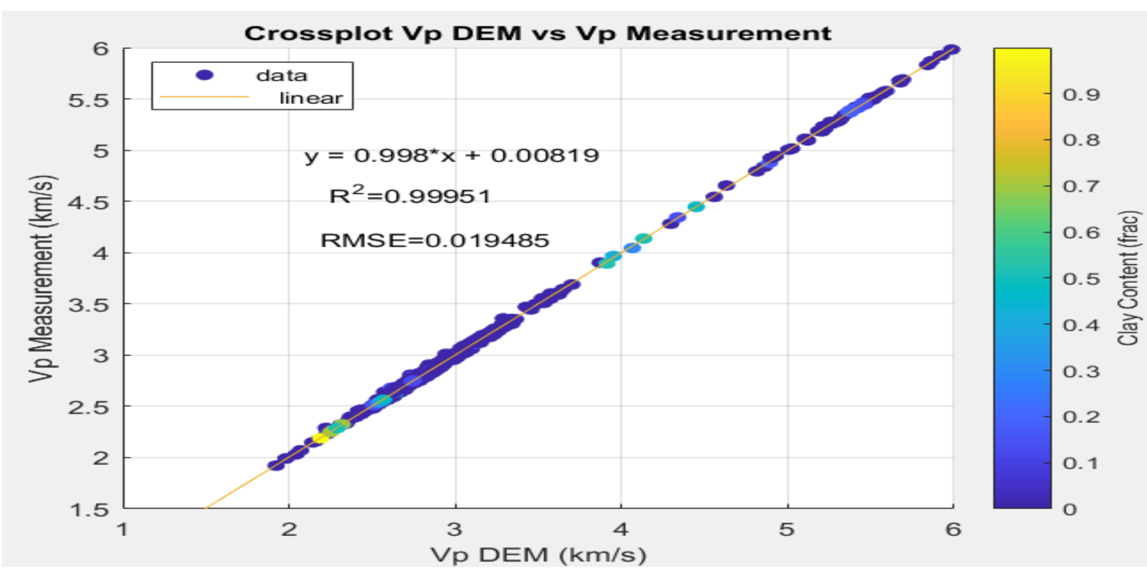

Figure 6: Cross Plot *Vp DEM* vs *Vp Measurement*.

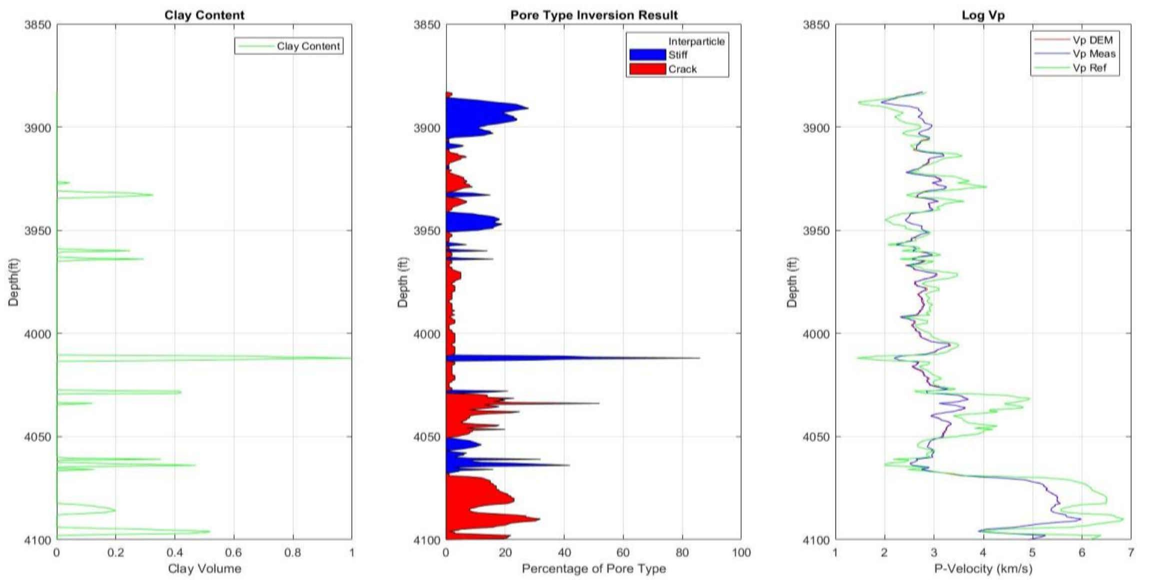

Figure 7: Pore type modelling result for all depth in the well.

From figure 7 in the second coulomb we can see the pore type quantity along the well depth which contain the Primary (Interparticle) and Secondary pore type (Stiff and Crack). We can rely this pore type modelling because we have validated the model quantitatively using P-Velocity which shown in the third coulomb. In the third coulomb we can see the P-Wave from modelling (Vp DEM) and P-Wave from well logging measurement (Vp Measurement) has match enough like we have shown in the figure 6 with the R^2=0.9995 and RMSE=0.01 (1%).

After this pore type modelling is done we have to run ANFIS algorithm to predict permeability in this well using the input that we have got in the feature engineering and augmentation using matrix Pearson correlation. The first step that we have to do is to train the data. In this research we use 100 data training and 36 data for testing from the 136 total data. If the training and testing data show us the minimum error and then we can denormalize the data to the real domain like we can see in the figure 8 and 9 below.

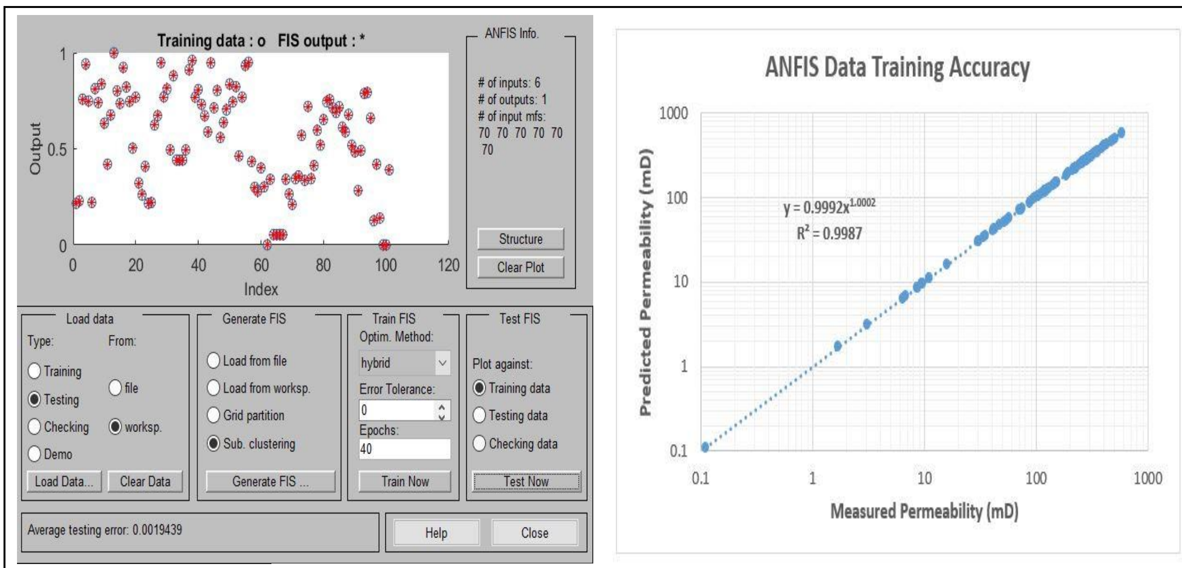

Figure 8: Training data result before denormalization (Left) and
After denormalization (Right)

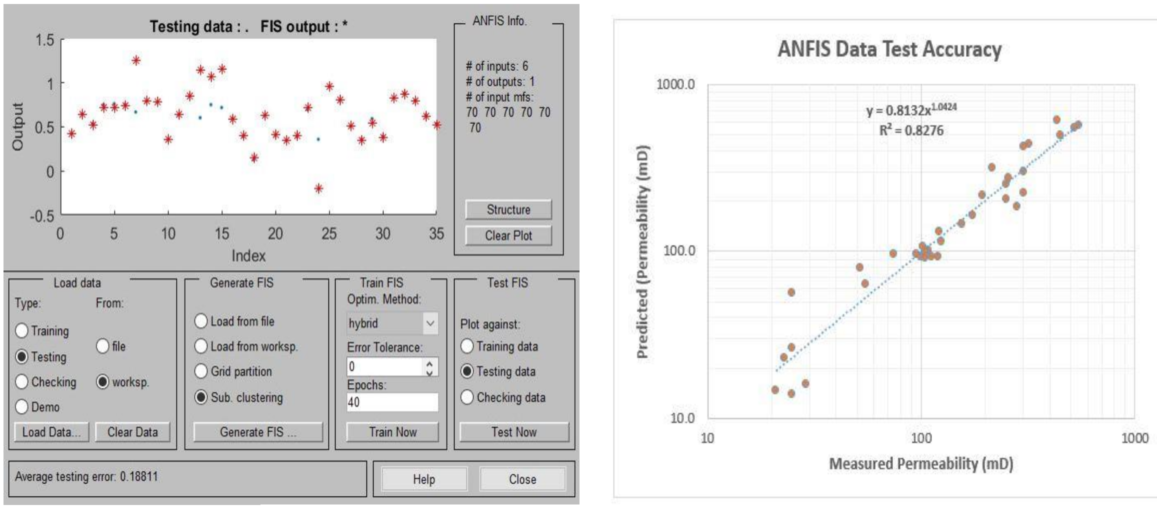

Figure 9: Testing data result before denormalization (Left) and After denormalization (Right)

From the figure 8 the result from training data show us Mean Absolute Percentage Error (MAPE) value 0.0019 with 40 epoch (iteration) that mean the training process has succeeded and the denormalize give us the good value for R^2= 0.9987. After we train the 100 data set we can continue for testing data. In the testing data we use 36 data set for testing. In testing result we got the good enough test result with MAPE value 0.18 and R^2= 0.8276 in figure 9 so we can use this algorithm to predict permeability along the well depth.

After we got the good training and testing score we will calculate the reservoir permeability value for all depth in this well and we will plot it together with pore type result and core data which we got from the laboratory measurement. We can see the final result in the figure 10 which describe the relation of pore type and permeability value in this well. From this final result we can make several decisions for improving our well performance such as where we should decide perforating zone and avoid the wash out zone which relate to the stiff pore.

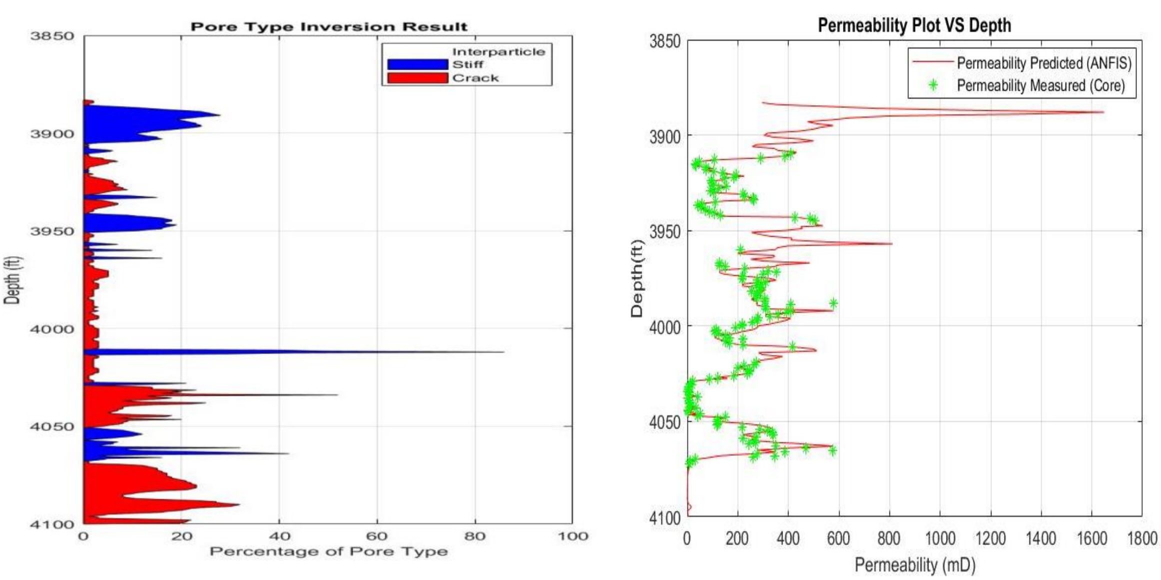

Figure 10: Pore Type Modelling Result (Left) and Permeability Predicted & Measured (Right)

Conclusion

1. Differential Effective Medium (DEM) is a good method for pore type modelling and give us the value of **R^2=0.99951** & **RMSE=0.019485** for X-plot Vp Model against Vp Measured validation.
2. ANFIS algorithm approach in this research has been successfully applied for the prediction of permeability value in carbonate reservoir with value of **R^2=0.9987** for training data and **R^2=0.8276** for testing data.
3. From this research we can see at **figure 10** that Stiff pore (Secondary Porosity) + Interparticle pore (Primary Porosity) has the highest permeability value at **3870 ft - 3900 ft = ± 1600 mD.**
4. Crack pore (Secondary Porosity) + Interparticle pore (Primary Porosity) has the highest permeability value at **4025 ft - 4050ft = ± 20 mD** and at **4075 ft - 4100ft = ± 15 mD.**

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