Journal of Petroleum Exploration and Production Technology (2021) 11:109–115
https://doi.org/10.1007/s13202-020-01061-6

ORIGINAL PAPER-EXPLORATION ENGINEERING

Improved ST-FZI method for permeability estimation to include the impact of porosity type and lithology

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Received: 21 June 2020 / Accepted: 27 November 2020 / Published online: 7 December 2020

Abstract

Permeability represents the flow conductivity of a porous media. Since permeability is one of the most vital as well as the complex properties of a hydrocarbon reservoir, it is necessary to measure/estimate accurately, rapidly and inexpensively. Routine methods of permeability calculation are through core analysis and well tests, but due to problems and weaknesses of the aforementioned methods such as excessive costs and time, these are not necessarily applied on neither in all wells of a field nor in all reservoir intervals. Therefore, log-based approaches have been recently developed. The goal of this research is to provide a flowchart to estimate permeability using well logs in one of Iranian south oil fields and finally to introduce a new algorithm to estimate the permeability more accurately. Permeability is firstly estimated using artificial neural network (ANN) employing routine well logs and core data. Subsequently, it is estimated using Stoneley-Flow Zone Index (ST-FZI) and is compared with the results of core analysis. Correlation coefficients in permeability estimation by artificial neural network and Stoneley-FZI are $R^2 = 0.75$ and $R^2 = 0.85$, respectively. On the next step, an improved algorithm for permeability prediction (improved ST-FZI) is presented that includes the impact of lithology and porosity type. To improve the permeability estimation by ST-FZI method, electro-facies clustering based on MRGC method is employed. For this purpose, rock pore typing utilizing VDL and NDS synthetic logs is employed that considers the porosity types and texture. The VDL log separates interparticle porosity from moldic and intra-fossil porosities and washes out and weak rock-type zones. Employing MRGC method, three main facies are considered: good-quality reservoir rock, medium-quality reservoir rock and bad-quality (non-reservoir) rocks. Permeability is then estimated for each group employing ST-FZI method. The estimated permeability log by improved ST-FZI method shows better match with the measured permeability ($R^2 = 0.93$). The average error between estimated and measured permeability for ANN, ST-FZI method and improved ST-FZI method is 1.83, 1.18 and 0.796, respectively. The increased correlation is mainly due to involving the impact of porosity types on improved ST-FZI method. Therefore, it is recommended to apply this algorithm on variety of complicated reservoir to analyze its accuracy on different environments.

Keywords Permeability estimation · Artificial neural network (ANN) · Stoneley-FZI · Rock pore typing

Introduction

Improved production from oil and gas reservoirs requires accurate and precise understanding about reservoir properties such as permeability. Permeability is one of the most fundamental reservoir parameters with significant impact on production (Ranjbar et al. 2016; Rezaei and Chehrazi 2010). It is of the most complex petrophysical parameters during reservoir characterization. Variety of methods have been proposed for its measurement and assessment. Direct measurement of core in laboratory, experimental correlation, well test, nuclear magnetic resonance (NMR) log and the Stoneley velocity of Dipole Shear Sonic Imager (DSI) log or the combination of the aforesaid methods with multivariable analysis or intelligent algorithms can be mentioned (Ranjbar et al. 2016; Rezaei and Chehrazi 2010; Arpat et al. 1998). Direct core permeability measurement is time-consuming and expensive. Experimental correlations rely on core information and are only applicable for a specific field and domain. These methods are case dependent too (Wyllie et al. 1950; Arpat et al. 1998). For well test, the

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production should be stopped for a while that may count as uneconomical method (Arpat et al. 1998). Although NMR log calculates the permeability accurately, it does not exist on all wells due to its costs. It also ends up with extra complication on the shaly reservoirs. To overcome at these problems, various methods were proposed to estimate permeability from routine logs (Mohaghegh et al. 1997). With advent of intelligent methods, clustering and new instrument such as DSI, the routine log-based methods might count in the same level as laboratory measurements of permeability. Arbogast and Franklin (1999) and Wong et al. (2000) demonstrated the ability of neural network-based methods for estimating petrophysical features of reservoir rocks. Labani et al. (2010) estimated the effective porosity and permeability using core-intensified magnetic logs in Southern Pars oil field by a complex machine and smart methods. Elkatatny et al. (2018) predicted permeability of a carbonate heterogeneous reservoir by developing a neural network model that uses resistivity, density and neutron-porosity logs. In addition, they developed a mathematical equation employing artificial neural network.

Permeability calculation from the Stoneley wave might be counted as a direct permeability estimation compared with other logs. The Stoneley wave estimates the permeability with high accuracy and is also inexpensive, accessible and continuous (Brie et al. 1998; AL-Adani and Barati 2003; Kumar et al. 2008; Soleimani et al. 2018). Al-Adani et al. 2003 investigated on permeability effects on slowness of the Stoneley wave and estimated the permeability log, successfully. Soleimani et al. (2018) used the Stoneley wave to estimate the permeability on various rock facies in an oil field in 2018. They employed the acoustic dipole apparatus. The estimated permeability shows a good agreement with core permeability. Rafik et al. (2017) introduced electro-facies characteristic in permeability estimation using cluster analysis. The goal of this research is to apply a Stoneley-based method for permeability estimation and to improve its accuracy by including the impact of geological heterogeneity on the permeability estimation. A real case study is employed in this research, too.

Case study

Our case study is an oil field in southwest of Iran. Ilam (contains more than 80% oil reserve), Sarvak, Gadvan and Fahlian formations are the most important hydrocarbon layers in this field. Ilam formation belongs to the Mesozoic period and is made of Limestone, Shale and Dolomite (Motiei 1993). Ilam formation is the most prominent late Cretaceous reservoir in Iran that often adjoins with lower Sarvak formation (Aghanbati 2004). The permeability range of this reservoir is from 0.04 to 13.25 mili-darci. There is a good relationship between porosity and permeability; however, existence of variety of pore types breaks the general trend in some extent. The full log set and output of core analysis of well A in Ilam formation are being used in this study. Core samples in well A were available from 2904 to 3028 m of Ilam formation. In the laboratory, the prepared core samples are taken under the reservoir conditions, and subsequently the permeability is measured by field operator utilizing of fluid injection and Darcy equation in 17 core samples.

Methodology

Permeability is estimated by 3 methods in this article. At first, permeability is calculated using artificial neural network (ANN) employing routine logs and core data. On the second step, due to dependency of Stoneley log to permeability, ST-FZI method is used to estimate permeability. On the third step, an algorithm is presented in this work to include the impact of lithology and porosity type on the ST-FZI method. Details about each method will be being discussed on the following sections.

Permeability estimation using artificial neural network method

On the first step, a series of data including well logs and core permeability are introduced to the network as training data. ANN Geolog 7.4 module is used for this purpose that provides a model to estimate the permeability by artificial neural network. DT, NPHI, RHOB and PHIE logs plus measured permeability of core analysis are used as input. Employing step-by-step regression, the best input variables were selected to build artificial neural networks model. The input and output data were subsequently normalized. Moreover, the model inputs were controlled by cross-plots. Finally, through trial and error, the optimum parameters of the neural model (number of neurons and repeats) were obtained. Final weight and bios are calculated after optimizing the network and the output (Balan et al. 1995; Mohaghegh et al. 1995; Ameri et al. 2001; Tahmasebi and Hezarkhani 2012). The measured permeability values in 17 core samples and 3424 number of log data point were used for model training and validation. Seventy percent of this is employed for training and 30 percent for validation.

Figure 1 shows the correlation between core and estimated permeability using ANN method ($R^2 = 0.75$). Figure 2 (first panel from the right-hand side) shows the estimated permeability log using ANN (red curve) with the core permeability (blue points). The mean error between the estimated and measured permeability is 1.83. As it is seen, the permeability estimation is fair by this method. There are

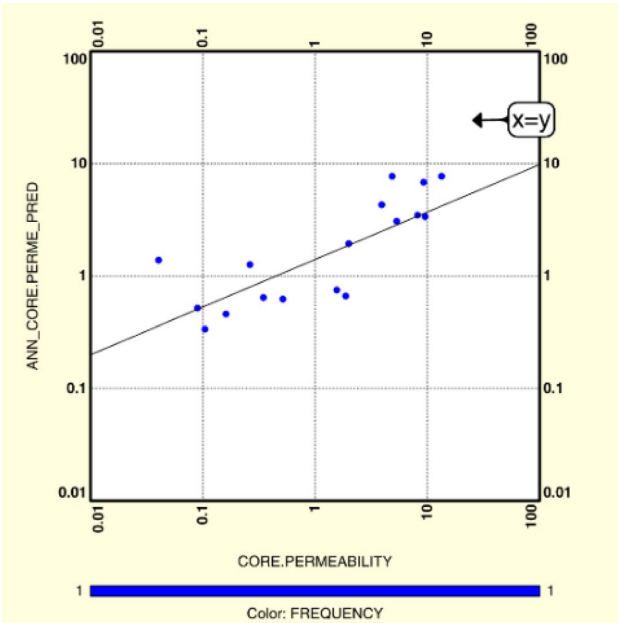

Fig. 1 The correlation between core and estimated permeability using ANN in well A

observed high permeability values on the non-permeable zones.

Permeability estimation using Stoneley-Flow Zone Index (ST-FZI)

Considering application of the Stoneley wave on the permeability estimation, special focus was paid on this log to enrich the permeability estimation methods. To do this, shear wave slowness, Stoneley wave slowness, impermeable Stoneley wave slowness, core permeability, effective porosity and volume of each mineral, bulk density and index matching factor of each mineral are necessary inputs to calculate the permeability (Winkler and Johnson 1989; AL-Adani and Barati 2003; Wu and Yin 2010). To estimate the impermeable Stoneley wave slowness, below two methods can be utilized:

1. Calculating average Stoneley wave slowness in impermeable zones (189 intervals are recognized in our case study).
2. Employ the Stoneley wave slowness value for low porosity (0–0.05%) zones.

Cross-plot of the Stoneley wave slowness versus the effective porosity was used in this research because of its high accuracy. Stoneley wave slowness in impermeable zone (DTSTE) is estimated as 187 (Fig. 3). Subsequently, Stoneley permeability index is calculated using Eq. (1).

$$\mathrm{KIST} = \frac{\mathrm{DTST}}{\mathrm{DTSTE}} \tag{1}$$

In the above equation, KIST is the Stoneley permeability index, DTST is the Stoneley wave slowness in entire formation, and DTSTE is the Stoneley wave slowness in impermeable zone (elastic). Flow zone index (FZI) and index matching factor (IMF) were calculated utilizing Eqs. (2) and (3) (Winkler and Johnson 1989; AL-Adani and Barati 2003; Wu and Yin 2010).

$$\mathrm{FZI} = \mathrm{IMF}(\mathrm{KIST} - 1) \tag{2}$$

where

$$\mathrm{IMF} = \sum \left(\mathrm{IMF}_i V_i\right) \tag{3}$$

where IMF is index matching factor, V_i is volume of each mineral, and i represents mineral.

IMF is obtained by summing the volume weighted IMF for each individual mineral in the model. Using Eq. 2, the total indexes match factor for various depths was calculated such that the best compatibility between permeability and flow zone was obtained. The index matching factor was set to zero in the shale zone, since it is a non-permeable zones. The value of IMF for major minerals on this field (calcite and shale) is calculated 8.94 and 0, respectively.

Finally, the Stoneley permeability can be obtained using Eq. (4) (Winkler and Johnson 1989; AL-Adani and Barati 2003).

$$K = 1014 \times \mathrm{FZI}^2 \times \left[\frac{\varnothing^3}{(1-\varnothing)^2}\right] \tag{4}$$

where K is the Stoneley permeability, $\varnothing$ is the effective porosity, and FZI is flow zone index. Figure 4 shows the correlation between core and estimated permeability using ST-FZI method ($R^2 = 0.85$). Figure 2 (second panel from the right-hand side) shows the estimated permeability log using ST-FZI (red curve) with the core permeability (blue points). The mean error between the estimated and measured permeability is 1.18. As it is seen, the estimated permeability matches with measured permeability compared with ANN method. It does worth to highlight that ANN method uses only routine logs.

Introducing clustering model based on rock pore typing to improve permeability estimation from Stoneley-FZI method

In order to overcome at the heterogeneity of the reservoir, an initial step is added at ST-FZI method. The flow units were determined at the first step, and then, the Stoneley-Flow Zone Index (ST-FZI) was calculated for each flow unit separately. In this method the porosity type and rock

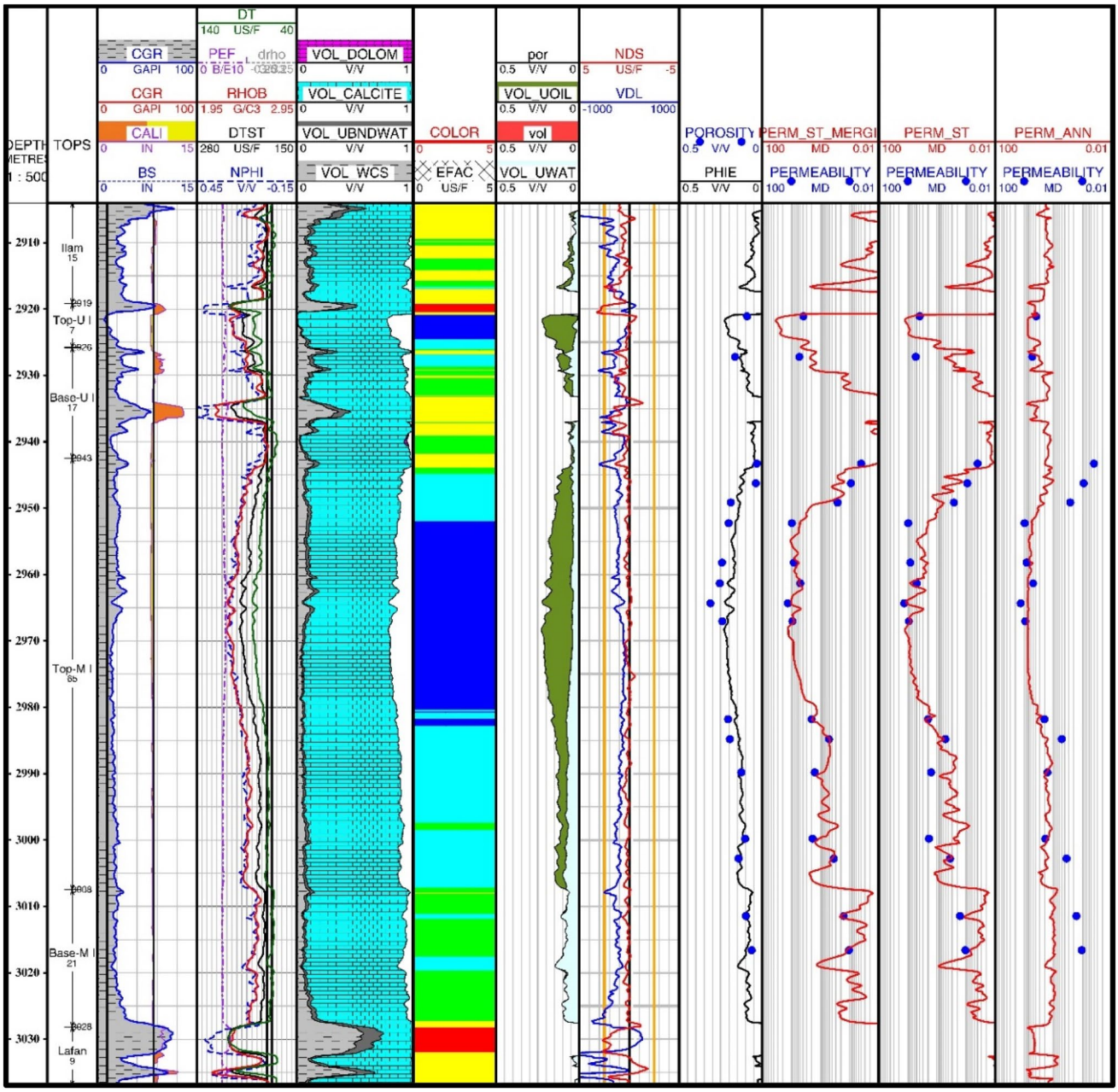

Fig. 2 The first, second and third panels from right to left: core permeability (blue points) and the estimated permeability using artificial neural network, the Stoneley-FZI method and the improved Stoneley-FZI method (all in red curve), respectively. Please note that the permeability is increased from right to left in each panel

texture are considered that represent the impact of reservoir heterogeneity. On carbonate reservoirs, a few porosity types (e.g., interparticle, moldic, fracture) might be exist at a single lithology. Porosity types are the main controlling factor of permeability versus porosity relationships in a particular lithology. In order to classify different types of rocks based on hydraulic flow units, electro-facies were used to identify zones with different groups of permeability. To do this, 2 synthetic logs (velocity deviation log (VDL) and neutron density separation (NDS)) are generated. Velocity deviation log (VDL) is a synthetic log obtained by combining the sonic and neutron density logs. It is an important tool to recognize the porosity type in carbonate rocks (Anselmetti 1999). NDS log was artificially made of separation between the neutron and density logs in order to enhance the electrical facies identification in the lithology. The synthetic NDS is calculated using Eq. (5) (Ohen 1996).

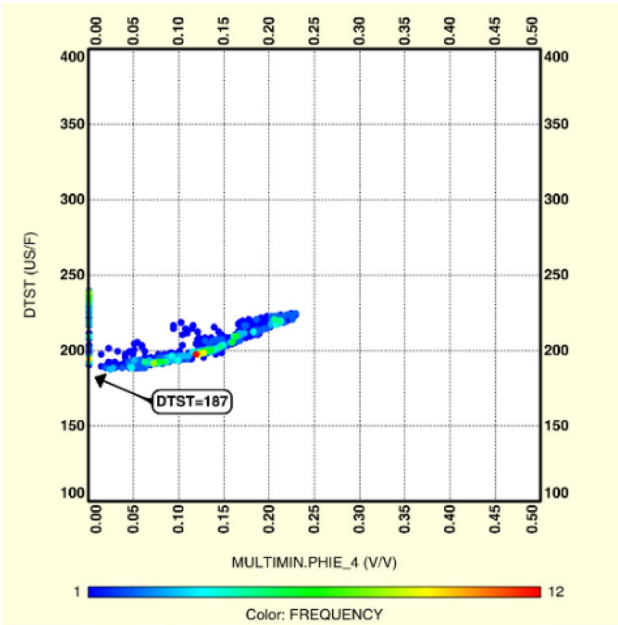

Fig. 3 Cross-plot of DTST versus effective porosity in well A

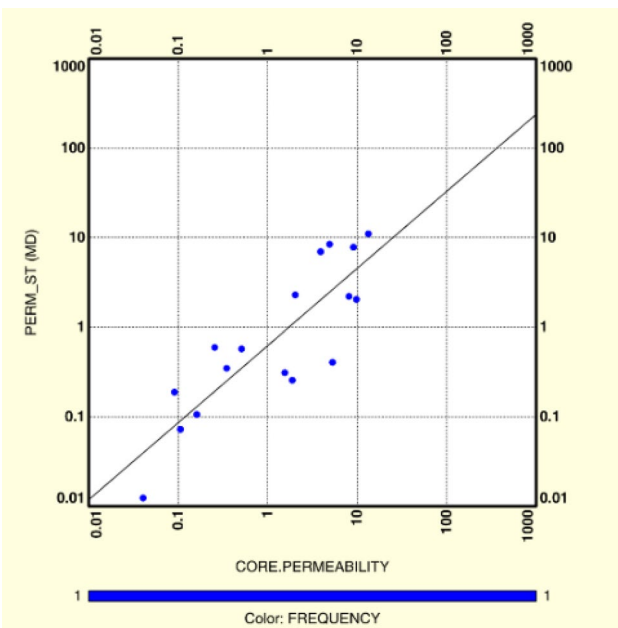

Fig. 4 Estimated permeability using ST-FZI versus core permeability in well A

$$\mathrm{NDS} = \left[\frac{(\mathrm{RHOB} - 1.95)}{(2.95 - 1.95)}\right] \times 10 - \left[\frac{(0.45 - \mathrm{NPHI})}{((-0.15) - 0.45)}\right] \times 10 \quad (5)$$

where RHOB is bulk density and NPHI is neutron porosity logs.

Table 1 Characteristics of clusters made of MRGC method in well A

	FACIES	WEIGHT	CGR	VDL	NDS	PHIE
1	1	238	18.23	-176.96	0.08	0.18
2	2	228	17.26	-188.26	0.19	0.13
3	3	152	21.21	-305.32	0.17	0.09
4	4	206	29.63	-341.28	0.64	0.04
5	5	31	64.16	99.58	2.08	0.00

Table 2 Index matching factor for each of flow units in limestone lithology

Color (class) in Table 1	IMF	EFACT
Dark blue (class 1)	12	1
Light blue and green (class 2 and 3)	10	2, 3
Red and yellow (class 4 and 5)	7.54	4, 5

On the next step, the number of electro-facies was calculated using multi-resolution graph-based clustering (MRGC) method. MRGC method is a powerful statistical-neural method that resolves the problem of next step (Ye and Rabiller 2000; Perez et al. 2005; Sfidari et al. 2012). In this study, the optimal number of electro-facies was obtained for well A. For clustering using MRGC method, CGR, PHIE, VDL, NDS are used as input. All input logs are initially normalized. Cross-plot analysis is also used to control the input logs. A known interval is employed to extract the cluster number and other setup parameter for the MRGC method. As Table 1 shows, 5 classes are identified in Ilam limestone reservoir in well A. The dark blue group represents the reservoir rock with high quality (relatively high porosity and permeability) and shows the main pay zone of Ilam reservoir. The light blue and green groups represent the reservoir regions with medium quality (medium porosity and permeability compared with dark blue group). These 2 groups contain higher water saturation compared with dark blue group. The yellow group indicates the impermeable reservoir rock, but the red group represents the shale (non-reservoir). Both later groups (yellow and red) might be counted as non-reservoir group.

To simplify the impact of reservoir heterogeneity and porosity types, the number of classes is reduced to 3 utilizing neutron density cross-plots. In fact groups 2 and 3 are counted as medium-quality reservoir rock, and groups 4 and 5 are considered as non-reservoir rocks. Table 2 shows the index matching factor (IMF) values for lime mineral in each of the flow units.

Subsequently, the permeability is estimated for each group employing ST-FZI method and using the specific characteristics of each group. The estimated permeability for each group is merged at the last step. There observed considerable improvement on the permeability estimation compared with the original ST-FZI method. The correlation

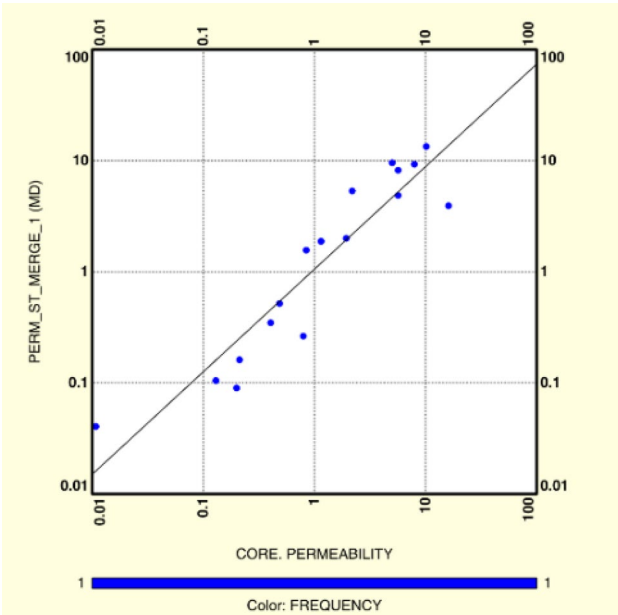

Fig. 5 Core versus estimated permeability using improved Stoneley-FZI method in well A

(R^2) between estimated and core permeability is 0.93 using this method (Figs. 2 and 5).

Discussion and results

To compare the above three permeability estimation methods, Fig. 2 is generated that to compare the core permeability with the estimated permeability using artificial neural network (first panel from right-hand side), Stoneley-FZI method (second panel from right-hand side) and improved Stoneley-FZI method (third panel from right-hand side). As it is shown, the correlation is significantly improved from ANN to Stoneley-FZI method and from Stoneley-FZI method to improved Stoneley-FZI method. The correlation (R^2) between the core and estimated permeability is 75, 85 and 93% for ANN, Stoneley-FZI method and improved Stoneley-FZI method, respectively. The mean error between estimated and measured permeability in 17 cored points is 1.83, 1.18 and 0.796 for ANN, Stoneley-FZI method and improved Stoneley-FZI method, respectively. As it is seen, ANN represents the low-quality estimation compared with other two. It does however worth to highlight that, similar to a normal practice in the oil and gas industry, we employed only routine logs for ANN. For improved Stoneley-FZI method, MRGC is employed that uses two synthetic log (VDL and NDS) for electro-facies clustering (Fig. 2, fifth panel from right-hand side). These 2 logs are sensitive to porosity types and rock texture. The investigation of VDL log represents three major groups: the neutral values that represent the interparticle porosity type, the positive values that are representative moldic and intra-fossil porosities and finally the negative deviations that are showing the wash-out zones (weak intervals. The second VDL group (positive values) represents the interval with high cementing that contains very low permeability zones with no connection between pore spaces. These observations match with the previous geological and thin section reports. There is no fracture nor gas traces in Ilam formation in this field.

Conclusion

In this study, permeability log is estimated using two advanced methods. In addition, a new algorithm is introduced to estimate permeability log. At the first step, permeability is estimated using artificial neural network method that employs routing log set as input. At the second step, permeability is estimated using ST-FZI method that employs Stoneley log. To include the impact of porosity type and lithology, electro-facies clustering based on rock pore typing method is added on ST-FZI method. This classification uses VDL and NDS logs besides routine logs and hence considers the impact of porosity type and lithology. The investigation of VDL log shows two positive and negative value groups besides a background neutral group. The background VDL value represents the interparticle porosity. The positive deviations are due to moldic and intra-fossil porosities that have lower permeability compared with its porosity value. The negative VDL value is correlated with wash-out zones that demonstrates the weak rock types. There is no fracture or gas traces in Ilam formation in this reservoir. The estimated permeability log is compared with the core permeability. The correlation for ANN, ST-FZI method and improved ST-FZI method is 75, 85 and 93 percent, respectively. The increased correlation is mainly due to involving the impact of porosity types on improved ST-FZI method. Therefore, it is recommended to apply this algorithm on variety of complicated reservoir to analyze its accuracy on different environments.

Compliance with ethical standards

Conflict of interest On behalf of all the co-authors, the corresponding author states that there is no conflict of interest.

Funding None.

References

Aghanbati A (2004) Geology of Iran. Geological Survey, 1st Edn, Tehran

Al-Adani N and Barati A (2003) New hydraulic unit permeability approach with DSI. In: SPWLA 9th formation evaluation symposium, Japan pp. 25–26.

Ameri S, Aminian K, Avary KL, Bilgesu HI, Hohn ME, McDowell RR, Matchen DL (2001) Reservoir characterization of upper devonian gordon sandstone, Jackonburg Stringtown Oil Field. West Virginia University, Northwestern Virginia

Anselmetti FS, Eberli GP (1999) The velocity-deviation log: a tool to predict pore type and permeability trends in carbonate drill holes from sonic and porosity or density logs. AAPG Bull 83(3):450–466

Arbogast JS, Franklin MH (1999) Artificial neural networks and high speed resistivity modeling software speeds reservoir characterization. Pet Eng Int 72(05):57–61

Arpat GB, Gümrah F, Yeten B (1998) The neighborhood approach to prediction of permeability from wireline logs and limited core plug analysis data using backpropagation artificial neural networks. J Pet Sci Eng 20(1–2):1–8

Balan B, Mohaghegh S. and Ameri S. (1995) State-of-the-art in permeability determination from well log data: part 1-A comparative study, model development. In: SPE Eastern Regional Meeting. Society of Petroleum Engineers

Brie A, Endo T, Johnson DL and Pampuri F (1998) Quantitative formation permeability evaluation from Stoneley waves. In: SPE annual technical conference and exhibition. Society of Petroleum Engineers

Elkatatny S, Mahmoud M, Tariq Z, Abdulraheem A (2018) New insights into the prediction of heterogeneous carbonate reservoir permeability from well logs using artificial intelligence network. Neural Comput Appl 30(9):2673–2683

Kumar A, Klimentos T, Sarkar A, Sinha A and Nath G (2008) Permeability determination from stoneley waves in gas saturated sands, India: a case study. In: SPWLA 49th annual logging symposium. Society of petrophysicists and well-log analysts

Labani MM, Kadkhodaie-Ilkhchi A, Salahshoor K (2010) Estimation of NMR log parameters from conventional well log data using a committee machine with intelligent systems: a case study from the Iranian part of the South Pars gas field, Persian Gulf Basin. J Pet Sci Eng 72(1–2):175–185

Mohaghegh S, Arefi R, Ameri S, Rose D (1995) Design and development of an artificial neural network for estimation of formation permeability. SPE Comput Appl 7(06):151–154

Mohaghegh S, Balan B, Ameri S (1997) Permeability determination from well log data. SPE Form Eval 12(03):170–174

Motiei E (1993) Geology of Iran, Zagros stratigraphy. Geological Survey, 1st Edn, Tehran

Ohen HA, Ajufo AO and Enwere PM (1996) Laboratory NMR relaxation measurements for the acquisition of calibration data for NMR logging tools. In: SPE Western Regional Meeting. Society of Petroleum Engineers

Perez HH, Datta-Gupta A, Mishra S (2005) The role of electrofacies, lithofacies, and hydraulic flow units in permeability predictions from well logs: a comparative analysis using classification trees. SPE Reserv Eval Eng 8(02):143–155

Rafik B, Kamel B (2017) Prediction of permeability and porosity from well log data using the nonparametric regression with multivariate analysis and neural network, Hassi R'Mel Field, Algeria. Egypt J Pet 26(3):763–778

Ranjbar RR, Bonab H, Mehdipour V (2016) Geology of carbonate reservoirs. Aij Publications, Tehran

Rezaei MH, Chehrazi A (2010) Principles of implantation and interpretation of well surveyors. Tehran University Press, Tehran

Rosenbaum JH (1974) Synthetic microseismograms: Logging in porous formations. Geophysics 39(1):14–32

Sfidari E, Kadkhodaie-Ilkhchi A, Najjari S (2012) Comparison of intelligent and statistical clustering approaches to predicting total organic carbon using intelligent systems. J Pet Sci Eng 86:190–205

Soleimani B, Moradi M, Ghabeishavi A (2018) Stoneley wave predicted permeability and electrofacies correlation in the Bangestan Reservoir, Mansouri Oilfield. SW Iran Geofísica Internacional 57(2):107–120

Tahmasebi P, Hezarkhani A (2012) A fast and independent architecture of artificial neural network for permeability prediction. J Pet Sci Eng 86:118–126

Winkler KW, Liu HL, Johnson DL (1989) Permeability and borehole Stoneley waves: comparison between experiment and theory. Geophysics 54(1):66–75

Wong PM, Tamhane D and Aminzadeh F (2000) A soft computing approach to integrate well logs and geological clusters for petrophysical prediction. In: Proceedings 3rd international conference on petroleum geophysics. New Delhi, India

Wu X and Yin H (2010) ExxonMobil Upstream Research Co. Method for determining reservoir permeability form borehole Stoneley-wave attenuation using Biot's poroelastic theory. U.S. Patent 7,830,744

Wyllie MRJ, Rose WD (1950) Some theoretical considerations related to the quantitative evaluation of the physical characteristics of reservoir rock from electrical log data. J Pet Technol 2(04):105–118

Ye SJ and Rabiller P (2000) A new tool for electro-facies analysis: multi-resolution graph-based clustering. In: SPWLA 41st annual logging symposium. Society of Petrophysicists and Well-Log Analysts