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TOC determination of Gadvan Formation in South Pars Gas field, using artificial intelligent systems and geochemical data

Mehdi Khoshnoodkia [a,*], Hassan Mohseni [a], Omeid Rahmani [b], Akbar Mohammadi [a]

[a] Department of Geology, Faculty of Science, Boo-Ali Sina University, Hamadan, Iran
[b] Mahabad Branch, Islamic Azad University, Mahabad, Iran

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ABSTRACT

Potentially, TOC content is affected by logging data in a source rock (density, sonic, neutron and resistivity logs). Hence, to analyze these logs, which we make a quick and reliable assessment of a source rock. So, it is a quick and economically cheaper method rather than direct geochemical analysis. A source rock interval poses to less density, lower velocity, higher sonic porosity, higher gamma ray values and increase in resistivity. In this research, Gadvan Formation was studied in two boreholes as potential of source rock. The log data of two wells were used to construct of intelligent models in a source rock of the South Pars Gas field in southwest of Iran. A suite of geophysical logs (neutron, density, sonic and resistivity logs) and cutting chip data samples data were applied for determining TOC content of this formation. Rock-Eval pyrolysis data reveal that Gadvan Formation is poor source rock (less than 0.5%). Hence we attempted a correlation between geophysical data and direct TOC content measurements of using Δ Log R, Rock-Eval, neural network and fuzzy logic techniques. The results showed that intelligent models were successful for prediction of TOC content from conventional well logs data. Meanwhile, similar responses from other different intelligent methods indicated that their validity for solving complex problems.

1. Introduction

The source rock mostly is defined as fine grained (e.g. Shale or Mudstone). The source rock contains significant amount of organic matter which commonly is quantified as Total Organic Carbon "TOC" and could produce hydrocarbon during thermal maturation (Bordenave, 1993; Tissot and Welte, 1984). So, producing hydrocarbon depends on type of kerogen, burial history and geothermal gradient. Various techniques are used for source rock evaluation, which is common to use organic matter petrography and Rock-Eval pyrolysis among geochemistry analyses (Waples, 1985). The most commonly well logs were used for source rock evaluation, including density, sonic, gamma ray, neutron and resistivity logs. So, a feasibility study to interpret organic matter from wire logs comes from its physical properties. These physical properties include lower density, slower sonic velocity or higher sonic transit time, higher resistivity and higher hydrogen in host rock (Luffel, 1992; Serra, 1986). Schmoker (1981) and Hertzog et al. (1989) determined source rock intervals base on spectral gamma ray (SGR log). Furthermore, different authors investigated source rock to made use of geophysical logs, including resistivity laterlog deep log [Rlld], sonic log [Δt], formation density compensated log [FDC (ØD)], neutron log [NPHI (ØN)] and gamma ray log [GR] (e.g. Dellenbach et al., 1983; Hussain, 1987; Meyer and Nederlof, 1984). Passey et al. (1990) devised a Δ Log R method as a combination of porosity logs (Δt, ØD, ØN) and resistivity log in recognition and detailed calculations of TOC content in a source interval. Kamali and Mirshady (2004) applied Δ Log R method in Combination with Neuro- Fuzzy approaches for determining of TOC Content of Gurpi and Pabbdeh Formations in Dezful Embayment (Zagros Basin). Moreover, geochemical methods (e.g. Rock- Eval pyrolysis) take much more time and cost than Δ Log R method.

Disadvantage of geochemical methods includes sample's dimension that can't be a real representative of the whole interval. Geochemical methods are less representative than log based methods; however, log based methods usually require calibration using measured data and often are more erroneous when based on poor quality measurements. So, in the present research, we tend to determine on TOC content of this formation from Δ Log R method and validate the results with artificial neural network and fuzzy logic approaches.

Gadvan Formation is known locally as richness and an effective source rock in the Dezful Embayment (Ala et al., 1980; Bordenave and Burwood, 1990, 1995; Kamali and Mirshady, 2004). Geological and reservoir explorations proved the presence of hydrocarbon in Cretaceous intervals in southern South Pars Gas field (known as North Dome in Qatar) and Gadvan Formation deposited among two

* Corresponding author.
E-mail address: m_khoshnoodkia@yahoo.com (M. Khoshnoodkia).

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reservoirs rock (Dariyan Formation (Shuaiba Formation) and Sarvak Formation (Mishrif Member)) in this field. So, it is possible that this organic facie to be source (kitchen) of already trapped hydrocarbon in Cretaceous intervals.

2. Geological setting

South Pars Gas field is the world's largest non-associated gas reservoir located in territorial water of Persian Gulf between Iran and Qatar (Fig. 1). South Pars Gas field is the northern extension of North Dome structure in Qatari part. The South Pars field is under development by the Pars Oil and Gas Company (POGC) of Iran.

The regional geology of the Persian Gulf and adjacent area has been discussed in numerous publications (Bordenave and Burwood, 1990; James and Wynd, 1965; Ziegler, 2001). However, the geological history of Gadvan and Fahliyan Formations is summarized here. In this study, Gadvan Formation in two wells (B and C) was sampled for geochemical analysis (Fig. 1).

Gadvan Formation (Lower Cretaceous) is 73 m thick in boreholes (B and C), and Composed of interbedded green gray to brown shale beds, marls, and brawn limestones. Both lower and upper contacts are transitional with Dariyan and Fahliyan Formations respectively (Fig. 2). Fahliyan Formation composed of massive oolitic-peloidal limestones during progressive of sea level formed a shallow shoal passage from the Fars province of Iran and SW of Zagros Basin to the southern Persian Gulf which changes to deep marine mudstone facies (Ziegler, 2001). Upper contact of Fahliyan Formation consisted of sandstone, siltstone, and glauconitic which indicated a regressive and erosion phase. After this phase, Gadvan Formation deposited during progressive phase. Gadvan Formation as a shale facies indicates somewhat deeper-water intrashelf conditions (Ziegler, 2001). Gadvan Formation as a shale facies indicates somewhat deeper-water intrashelf conditions (Ziegler, 2001). Although Gadvan Formation deposited in euxinic environment, it is weak in view of organic matters in Zagros Basin. However, richness of organic matters is locally in Dezful Embayment (Bordenave and Burwood, 1990). These rocks appear to grade laterally into the long-lasting Garau Formation that consists of gray-black carbonaceous shales and argillaceous limestones of deep,

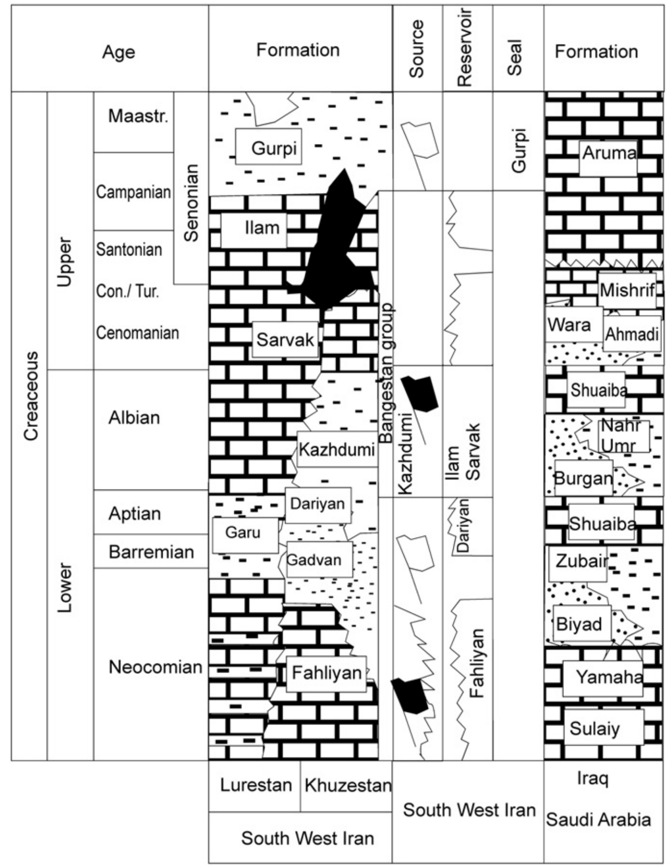

Fig. 2. Stratigraphic chart for Cretaceous system of southwest Iran and adjacent area (After Bordenave, 2002).

open-marine conditions in Kuzestan area, whereas In the north west of Zagros changes to shallow marine facies. Gadvan Formation interchanged to Fahliyan Formation in coastal Fars area (James and Wynd,

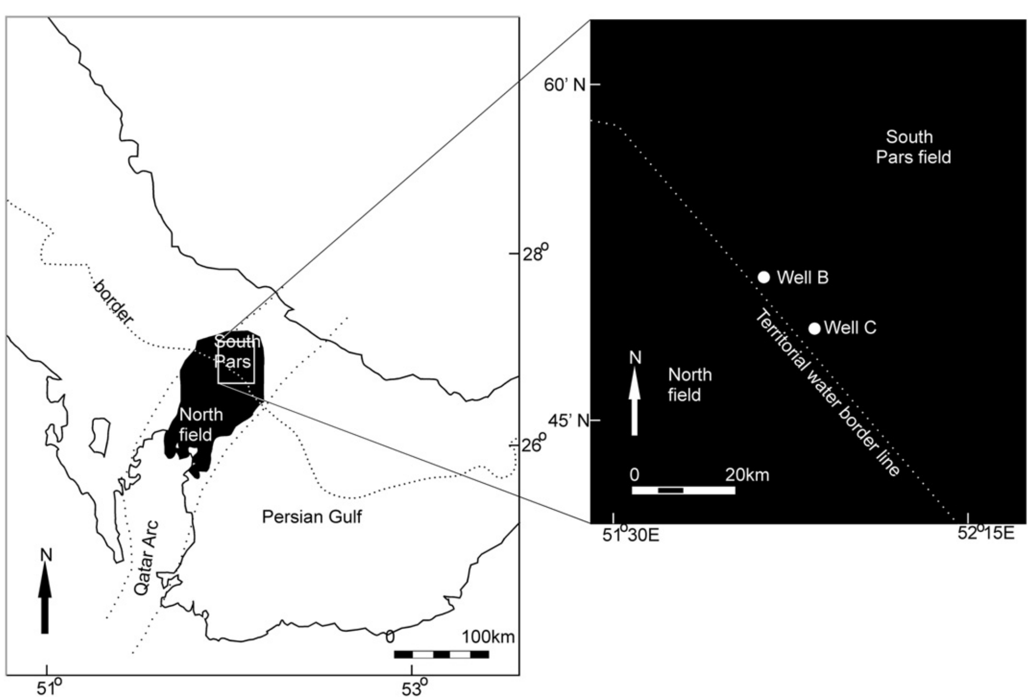

Fig. 1. Location map of studied boreholes (B and C) in South Pars Gas field (After Aali et al., 2006).

1965) and Dariyan Formation overlaid on Fahliyan Formation. Fahliyan Formation is intrashelf basin in north and south of Persian Gulf, which deposited deep mudstone. However, there are reef structures surrounding of intrashelf basin that developed as good reservoir for Qatar-Fars hinterland.

Moreover, some oil has been discovered in the Cretaceous successions in the South Pars field. Considerable oil volume has been reported from Upper Dariyan (Shuaiba) Formation and upper part of the Sarvak Formation (Mauddud member), which underlying Gadvan and Kazhdumi Formations, respectively (Rahmani et al., 2010).

3. Methods used

3.1. Geochemistry analysis

Pyrolysis of organic matter is a thermal method, which has commonly been applied for evaluation and thermal maturity of source rocks, especially to determine of the source rock richness. Also, it can be used for determining of hydrocarbon generating rock (Page and Kuhnel, 1980). These analyses have been performed by Rock-Eval Pyrolysis apparatus and can obtain information such as; quantity, quality, thermal maturity, type, genetic potential, production index, hydrogen index, and oxygen index of organic matter. In this research 14 samples were took from boreholes B and C cutting chips (from Gadvan Formation) for Rock- Eval III pyrolysis and analyzed in Research Institute of Petroleum Industry (R.I.P.I) of Iran. Results are summarized in Table 1.

3.2. Δ Log R

Δ Log R is a practical method, for identifying and calculating total organic carbon in organic-rich rocks which has been developed by using well logs. The method employs the overlapping of a properly scaled porosity log generally sonic transit time curve with one of these logs, including neutron, density and resistivity logs (Passey et al., 1990). In water-saturated, organic-lean rocks, the two curves are paralleled each other and can be overlain, since both logs respond to variations in formation porosity. However, in either hydrocarbon reservoir rocks or organic rich non-reservoir rocks, a separation between the curves occurs (Passey et al., 1990). Using the gamma-ray curve, the reservoir intervals can be identified and illuminated from the analysis. The separation in organic rich interval results from two effects: the porosity curve responds to the presence of low-density, low-velocity kerogen, and the resistivity curve responds to the formation fluid. In an immature organic-rich rock, where no hydrocarbons have been generated, the observed curve separation is due solely to the porosity curve response. In a mature source rocks, in addition to the porosity curve response, the resistivity increases because of presence of generated hydrocarbons. The magnitude of the curve separation in non-reservoirs is calibrated to total organic carbon and maturity, and allows for depth profiling of organic richness in the absence of data samples. This method allows organic richness to be accurately assessed in a wide variety of lithologies and maturity by using common well logs (Passey et al., 1990). The following well logs (neutron, density, sonic and resistivity) were available for this research. We try to correlate the results of well logs data with direct TOC measured from cutting samples of this formation. Furthermore, we attempted to establish a quantity correlation between standard well logs and total organic carbon by means of Δ Log R methods which are vary base on porosity logs, including neutron/ resistivity, density/ resistivity and sonic/ resistivity.

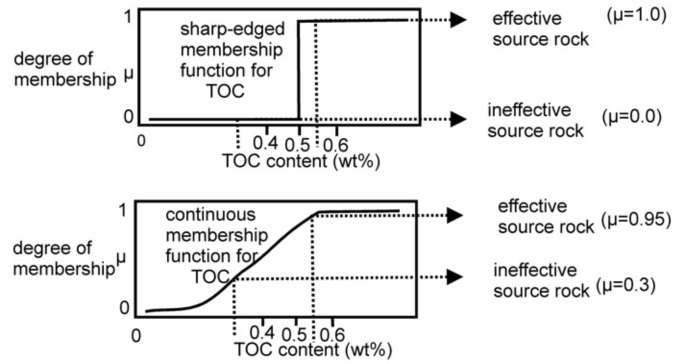

Fig. 3. Membership functions for TOC content of source rock in crisp logic (a) and fuzzy logic (b) methods.

3.3. Fuzzy logic

Preliminary fuzzy logic concept was introduced first by Zadeh in 1965. In crisp logic (CL), a value may or may not belong to one class, but in fuzzy sets allow partial membership. The membership or

Table 1
Geochemical data of Gadvan Formation in well B and C in South Pars field.

Sample No.	Depth (m)	S1	S2	S3	Tmax	HI	OI	TPI	TOC	MI
B-1162	1162	0.84	0.56	1.4	419	151	249	0.60	0.37	2.27
B-1174	1174	0.93	1.09	2.02	422	182	308	0.46	0.60	1.55
B-1182	1182	2.74	0.67	3.41	411	116	214	0.80	0.58	4.72
B-1192	1192	2.36	1.88	4.24	425	261	188	0.56	0.72	3.28
B-1212	1212	1.34	0.66	2	416	129	241	0.67	0.51	2.63
B-1220	1220	15.83	13.86	29.69	419	470	31	0.53	2.95	5.37
B-1230	1230	6.42	8.00	14.42	424	423	101	0.45	1.89	3.40
C-1162	1162	1.42	1.54	2.96	425	261	302	0.48	0.59	2.40
C-1174	1174	1.10	1.36	2.46	425	267	278	0.45	0.51	2.16
C-1182	1182	1.63	1.31	2.94	422	247	200	0.55	0.53	3.08
C-1192	1192	0.86	0.79	1.65	411	166	372	0.52	0.47	1.83
C-1212	1212	0.80	0.93	1.73	419	291	262	0.47	0.32	2.5
C-1220	1220	0.81	0.81	1.62	416	159	314	0.50	0.51	1.59
C-1230	1230	1.73	1.64	3.37	430	315	219	0.51	0.52	3.33

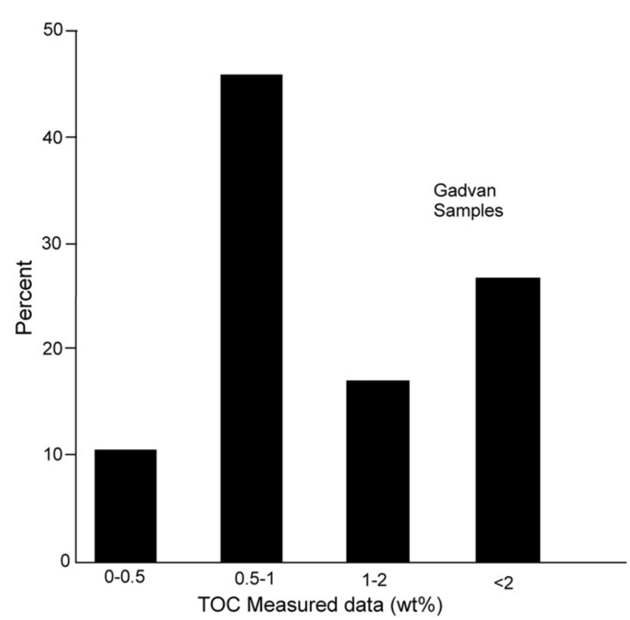

Fig. 4. Bar chart of percentage of measured TOC for Gadvan Formation in well B and C.

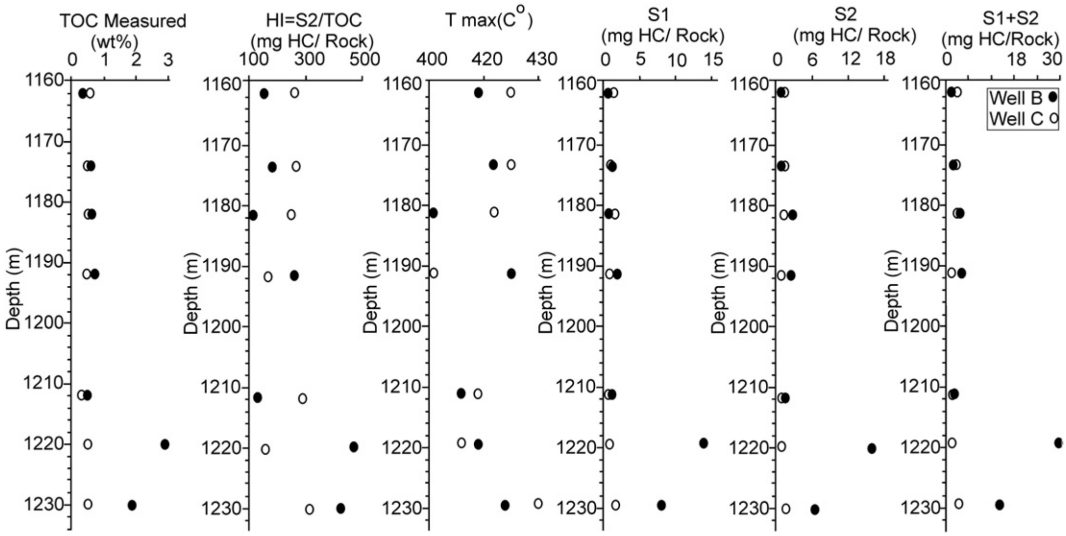

Fig. 5. Geochemical parameters (TOC, HI, Tmax, S1, S2, S1 + S2) vs. depth for Gadvan Formation in well B and C.

non-membership of an element X in crisp set C is described by a characteristic function of $\mu_C(x)$, where (1, 2):

$$\mu C(x) = \begin{cases} 1 & \text{if } X \in C \\ 0 & \text{otherwise} \end{cases}, \tag{1}$$

$$XA(X) : x \rightarrow \{0, 1\}, \tag{2}$$

Fuzzy set theory completed this concept by defining partial membership which can take values ranging from (3):

$$\mu_F(x) : X \rightarrow [0, \quad 1], \tag{3}$$

Where X refers to the universal set defined in specific problem and F is a fuzzy set (Yagar and Zadeh, 1992). The membership function

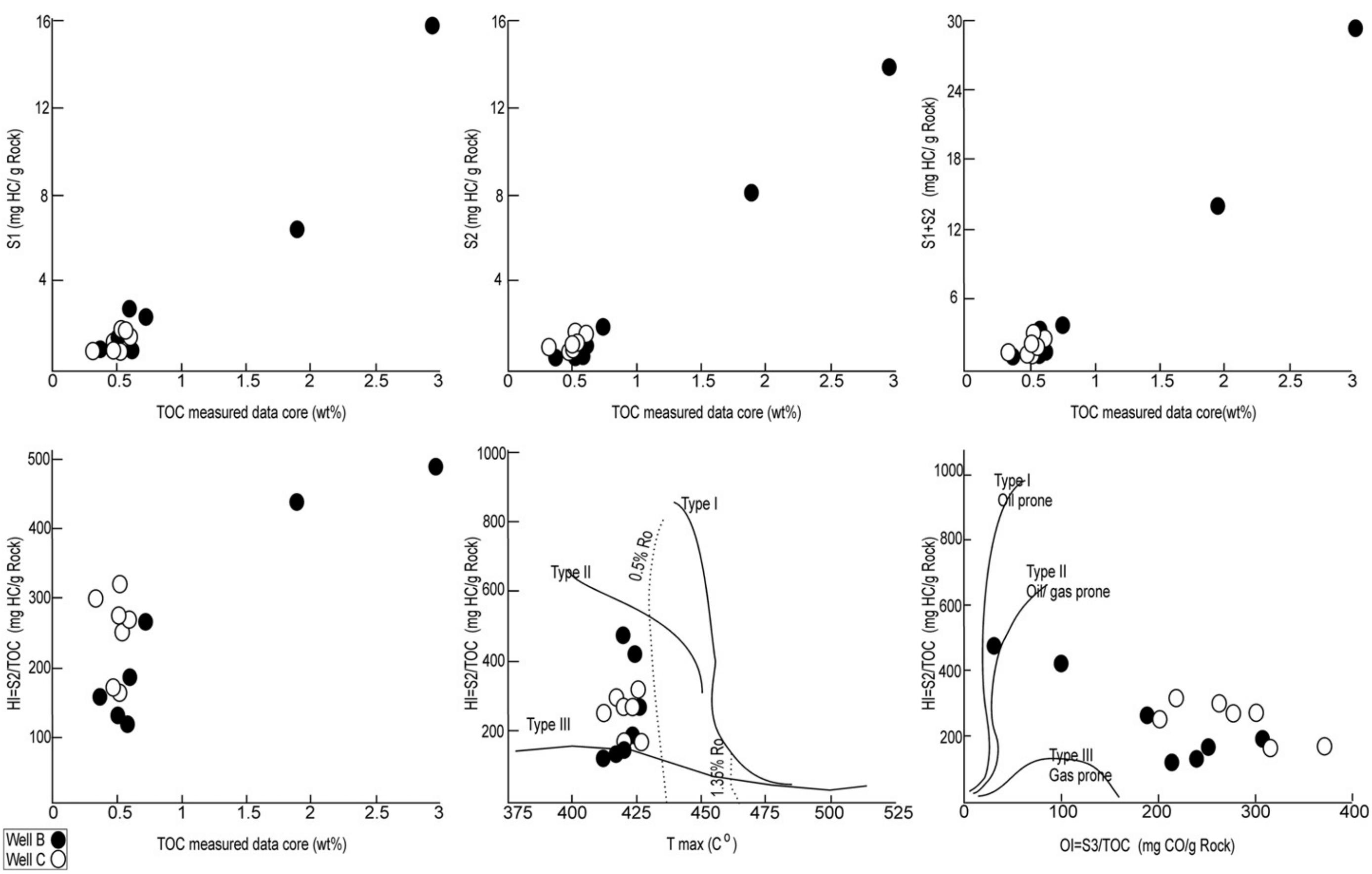

Fig. 6. Geochemical parameters (HI, S1, S2, S1 + S2) Vs. (TOC, Tmax and OI) for Gadvan Formation in well B and C.

illustrated for a crisp set C and fuzzy set F (Matlab user's guide, 2001a, 2001b).

3.3.1. Fuzzy inference system (FIS)

Fuzzy inference is a formulating process of mapping from input data to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned (Matlab user's guide, 2001a, 2001b). Fuzzy inference systems fall in to two categories; Mamdani-type (Mamdani and Assilian, 1975) and Sugeno-type (Takagi and Sugeno, 1985). These two types of inference systems vary somewhat of the way outputs are determined. The most commonly Mamdani's fuzzy inference method is seen fuzzy methodology and it is a set of linguistic control rules come from experienced-human operators. Mamdani's method was among the first control systems built using fuzzy set theory. These two methods are similar and there is a main difference in output membership functions (MFs). Sugeno-type introduces by constant (linear) of MFs and membership function determine by clustering process. A small cluster radius usually yields many small clusters. However, a large cluster radius yields a few large clusters in the data (Chiu, 1994). So, these clusters have an individual membership function. Each of membership function has a set of rules for formulating input data to achieve output data such as; (if, and, then rules). Here you can see a rule below;

If (Δt is high) and (FDC is low), then TOC is high.

Upper rule consists of two parts, including if and then part. When first part (if part) has multiple parts, fuzzy logic operators will connect (interpret) them. In Matlab user's guide, 2001a, 2001b were compared the operators from FL and CL approaches.

3.3.2. Why to use fuzzy sets?

Totally, geosciences knowledge to classify and get target and clear results associated with state of being uncertain and doubtful. As a result, it is appropriate to use fuzzy reasoning for solving problems.

Here, we can clarify TOC amount by the following simple example in basis of fuzzy logic and crisp logic. For being an effective source rock, particular formation should have minimum level of total organic carbon. This value defined about 0.5% as value of contain significant amount of organic matter in mud rocks and if it has good maturity and richness parameters, could produce hydrocarbon during thermal maturation (Tissot and Welte, 1984). However, amount of TOC alone does not qualify maturity of source rock. So, the richness amount of TOC is an important criterion. (I.e. Rock Eval parameters such as S2, S3, HI…). If a mudrock has lower than this range, is an ineffective source rock on basis of crisp logic. Conversely, it means if an interval has more than 0.5% TOC amount, it will be considered as an effective source rock.

Fig. 3 illustrates the membership functions for TOC content from CL and FL methods, respectively. According to crisp logic, the TOC amount is not an effective source rock lower than 0.5%. However, fuzzy logic proposes that it will be effective up to the degree of numbers. Hence, it is necessary to obtain optimum number of membership functions [MFs] for particular interval of well that is 0.5 and 0.8 in well B and C, respectively. MF was obtained with specifying a set of values of range 0 and 1.

So, fuzzy reasoning is very similar to reality and it is suitable tool for prediction of TOC content in source rock. In Fig. 3*membership*

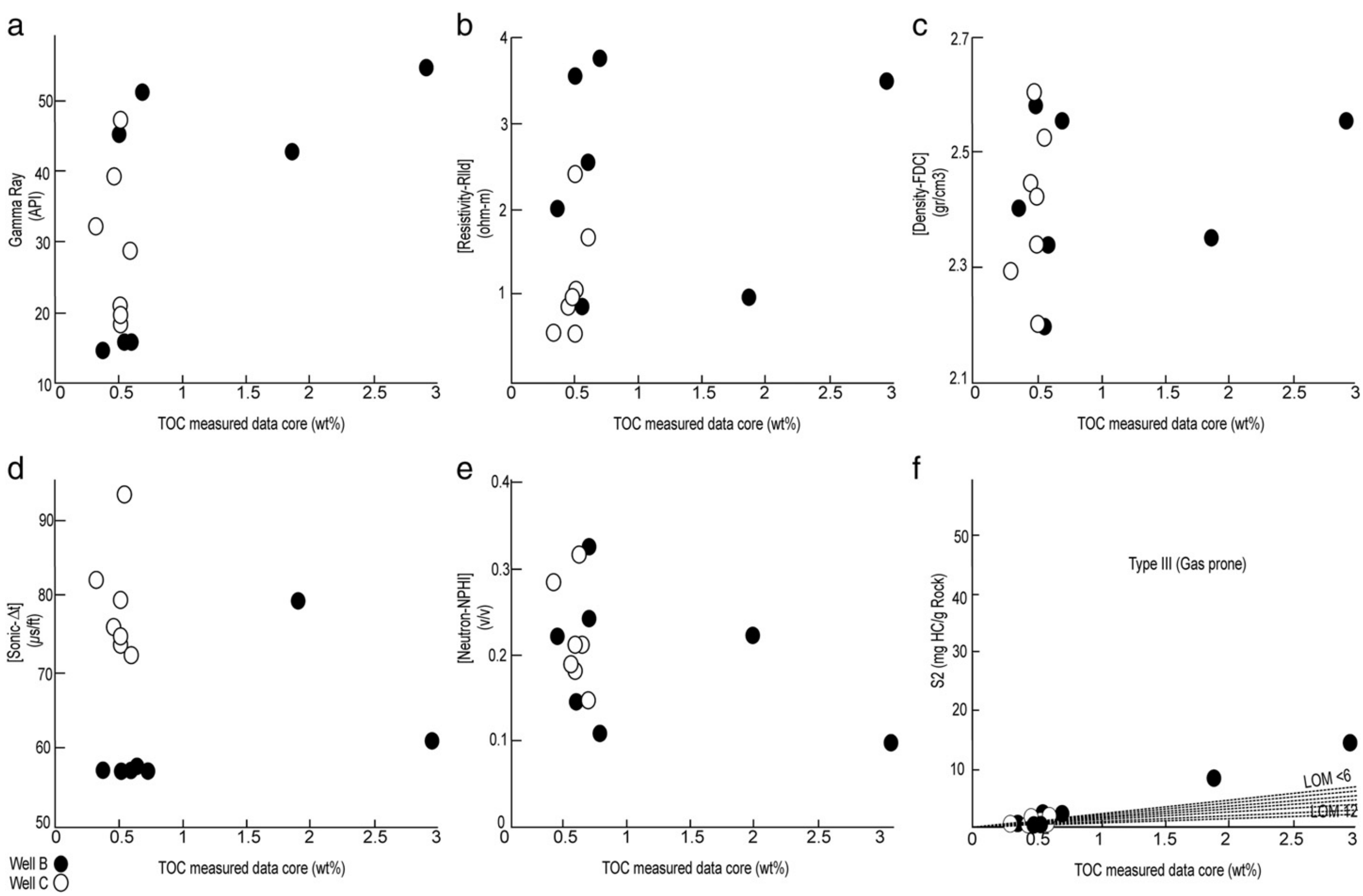

Fig. 7. Cross plots S2 and different logs values vs. TOC obtained from geochemical cutting samples in well B and C in South Pars field. (a) Plot of Gamma-Ray vs. measured TOC; (b) Plot of resistivity vs. measured TOC; (c) plot of bulk density vs. measured TOC; (d) plot of sonic vs. measured TOC; (e) plot of neutron porosity vs. measured TOC; (f) Plot of S2 vs. measured TOC.

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.

3.4. Back-propagation neural network

Neural network is composed of simple elements which operate in parallel. These elements are inspired by biological nervous systems. Neural nets contain no preconceptions of what model shape will be, so they are useful for production, system modeling where the physical processes are not understood or are highly complex in petroleum industry. Furthermore, a back propagation artificial neural network (BP-ANN) is a supervised training technique that sends input values forward through the network then computes the difference between calculated output and corresponding desired output from training dataset. The error is then propagated backward through the net, and the weights are adjusted during a number of iterations. The training process stops when the predicted output values gets best approximate of the desired values (Bhatt and Helle, 2002).

4. Modeling and prediction of TOC content

4.1. Geochemistry

In this research, 14 samples were taken from boreholes B and C cutting chips (in Gadvan Formation) for Rock- Eval III pyrolysis. Results are summarized in Table 1. Rock-Eval analysis indicated that more than half of samples which were taken from Gadvan Formation have TOC content less than 1% (Fig. 4), representing a poor source rock according to the Peters's (1986) classification. As it is shown in Fig. 6 (HI vs. OI) more than 92% of Gadvan Formation samples categorize as type III kerogen and the rest is type II kerogen. HI of about 93% of Gadvan samples is less than 300, that mean's these samples could produce oil/gas (Peters, 1986; Rahmani et al., 2010) (Figs. 5 and 6). However, HI-Tmax chart shows that they are mainly gas prone (Figs. 5 and 6). In addition, the average ratio S2/S3 of Gadvan Formation is 1.85. If ratio of S2/S3 is lower than 3, this formation could produce only gas hydrocarbon (Peters, 1986; Rahmani et al., 2010). So, this formation is not capable of oil production and only suitable for gas production with mainly type III kerogen. Based on Peters's (1986) classification T_{max} of Gadvan Formation is less than 430^{0}C (Rahmani et al., 2010) (Figs. 5 and 6), which according to Hunt (1996) falls within immature zone and doesn't reach to the thermal maturation of the oil window. Increase in TOC content of further samples, coincides with increase in S1, S1 + S2 and HI (Figs. 5 and 6) for Gadvan Formation.

4.2. Log respond in source rock

After calculation of TOC contents of the Gadvan Formation, we try to correlate the results with direct TOC measured from cutting

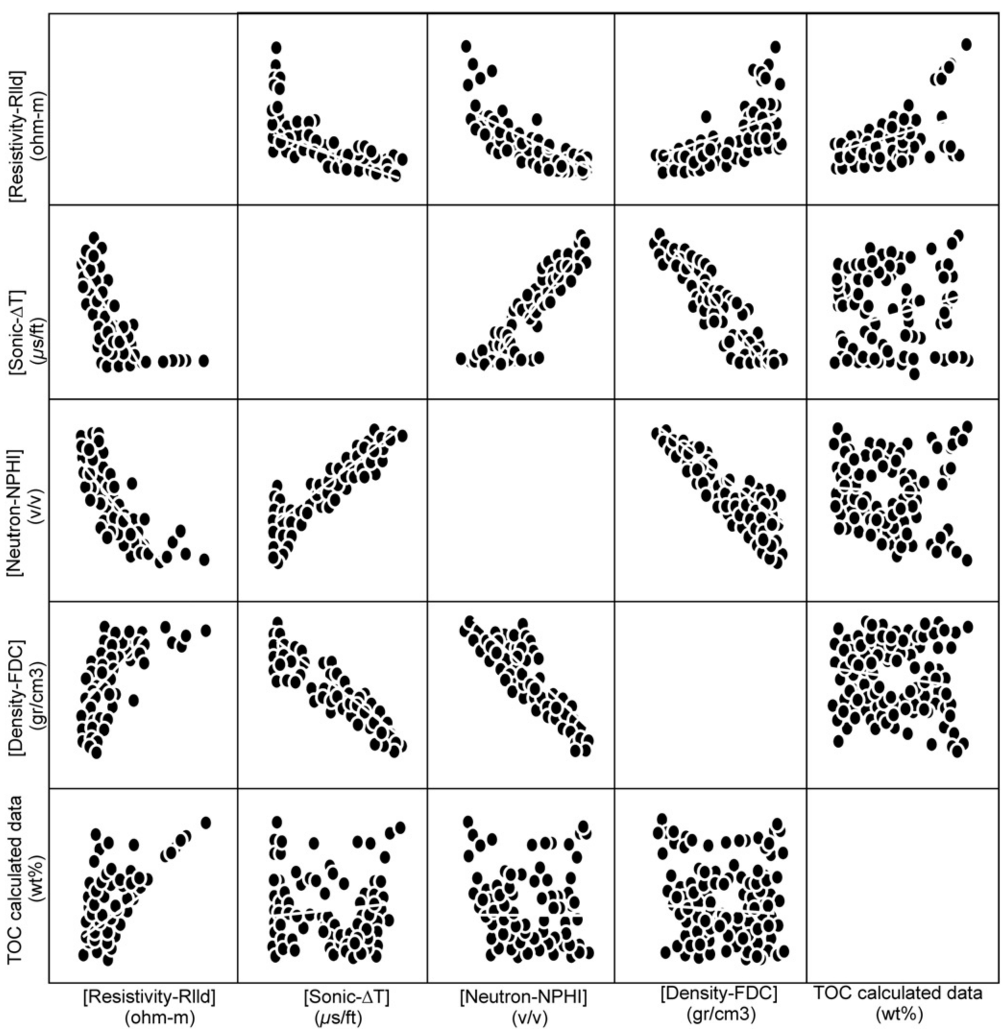

Fig. 8. Nonlinear relationship logs Vs. TOC calculated by Δlog R technique for Gadvan Formation in well C in South Pars field.

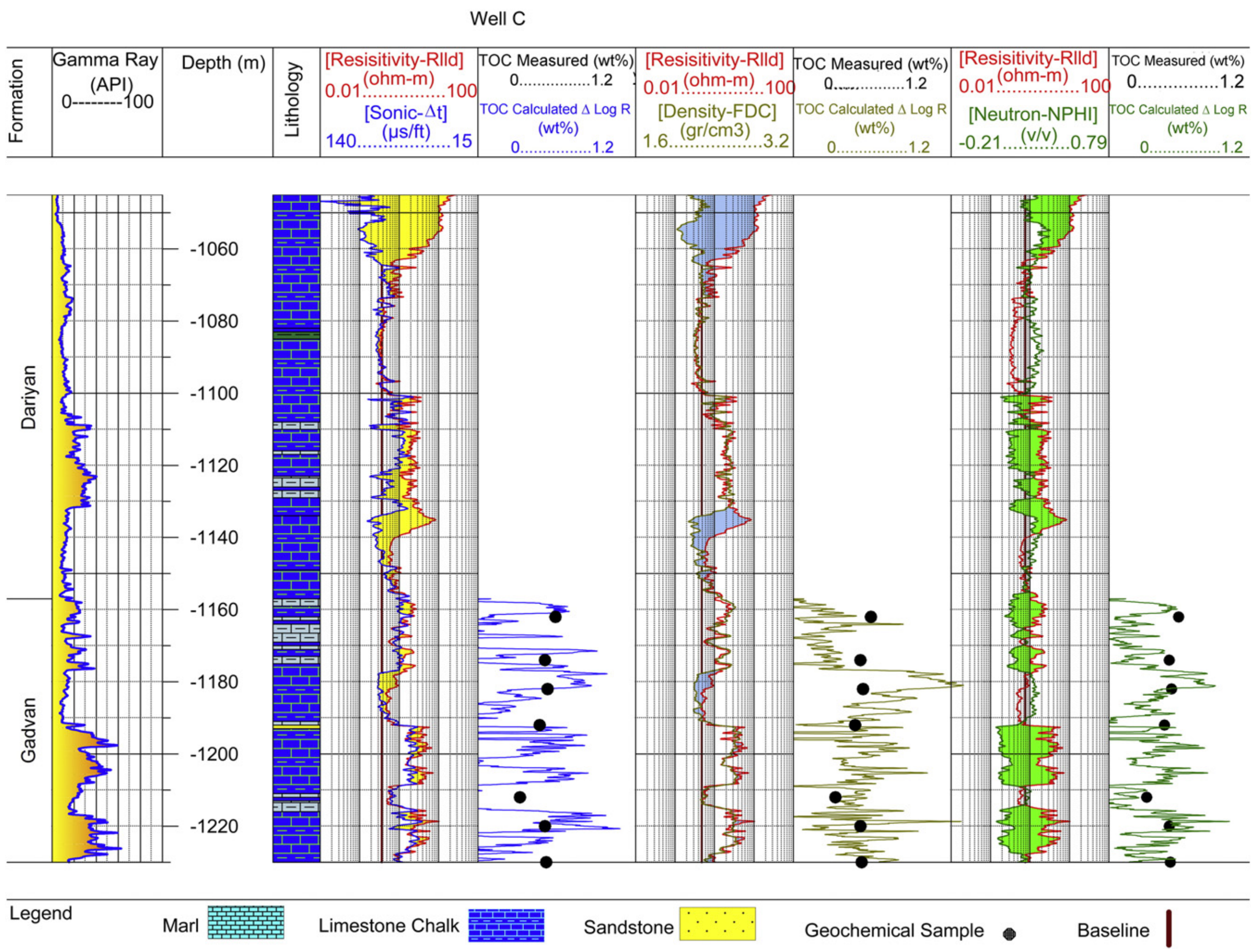

Fig. 9. Isoscaling sonic, density, neutron, and resistivity logs for calculation TOC content of Gadvan Formation.

samples of this formation and log data. Here is a brief description of different logs of boreholes B and C.

A source rock is defined by high gamma-ray intensity (Dellenbach et al., 1983). The gamma ray tool measures natural radioactivity that issues from the potassium, thorium, and uranium found in clay minerals that are commonly incorporated in shales and mudrocks (Ahr, 2008).As it is evident in Fig. 7a maximum gamma ray value of Gadvan Formation is 60 API units, which means Gadvan Formation is not good source rock.

The response of the resistivity log to organic matter content has received considerably less application, probably because the physical relationships are not well understood; however, the observations by Nixon (1973), Schmoker and Hester (1989) and Meissner (1978) that the resistivity increases dramatically in mature source rocks is an important observation, and presumably is related to generation of no conducting hydrocarbons. Resistivity response of a source rock is dependent on type of fluid in it and level of organic matter maturity. An immature source rock will shows low resistivity as the pore fluids are filled with interstitial water, whereas in a mature source interval, the pores are filled with hydrocarbons, hence high resistivity will be recorded (Nixon, 1973). Rlld record of both B and C boreholes are relatively low values (Figs. 7b and 8).

The TOC content of a source rock will affect on its bulk density because solid organic matter is less dense than surrounding rock matrix which are proposed that the use of the density log for estimating at organic matter content (Schmoker, 1979). Evidently, the density response is high in Gadvan Formation (Fig. 7c). This means, Gadvan Formation probably contains less TOC content, whereas density log has scattered pattern in low and high TOC (Fig. 8).

Sonic velocity in an immature source rock is higher than a mature interval (Dellenbach et al., 1983). In the Fig. 7d, sonic log drive porosity is plotted against TOC contents in both boreholes B and C. Apparently, Δt values of Gadvan Formation are higher and are more scattered (Figs. 7d and 8).

Table 2
Content of organic matter by Δ Log R and geochemical data.

Wells	*P*: Resistivity-Sonic	Sonic [Δt] $_{baseline}$	Resistivity [Rlld] $_{baseline}$	*P*: Resistivity-Density	Density [FDC] $_{baseline}$	Resistivity [Rlld] $_{baseline}$	*P*: Resistivity-Neutron	Neutron [NPHI]$_{baseline}$	Resistivity [Rlld] $_{baseline}$	TOC sampling	TOC Δ Log R (sonic)	TOC Δ Log R (density)	TOC Δ Log R (neutron)
B	0.03	93.1	0.35	2.5	2.2	0.3	4	0.25	0.7	0.55	__	0.5	0.47
C	0.03	89.2	0.5	2.5	2.3	0.35	4	0.25	0.6	0.49	0.3	0.47	0.33

Hydrogen index of a neutron log will increase in mature and rich source rock. The advantage of this tool includes the sensitivity to low amounts of organic carbon (Passey et al., 1990). TOC vs. neutron porosity (NPHI) in Figs. 7e and 8 reveals that the Gadvan Formation has not high porosity by increasing TOC.

Cross plot of S2 vs. TOC gives evidence that this formation has poor source potential (peters, 1986) because all samples fall bellow the limit of 5 of S2 amount in this figure (Fig. 7f).

4.3. Δ Log R

Normally, Δ Log R method is used as a variation on porosity logs, including neutron/ resistivity, density/ resistivity and sonic/ resistivity. For calculation of TOC, LOM (level of organic maturity) should be defined with a chart for TOC to S2 via maturity diagram for type III kerogen. Also calculation of LOM can be defined by the sketch that is about comparison of several of maturity indicators based on range of Ro, and Tmax (Hood et al., 1975; Tissot and Welte, 1984).

In both boreholes B and C, a LOM of 6.5 was considered for this purpose (Fig. 8f). At last calculated TOC are compared with direct measured TOC contents of cutting samples (Fig. 9).

Determination of Δ Log R on the basis of sonic- resistivity method were applied and explained in the following section. So, at first these two logs were rescaled, and then a baseline was extracted through the most overlapping with Δt and resistivity logs (Table 2 and Fig. 9). Then, EXXON equation (Eq. (4)) was used for Δ Log R calculation:

$$\Delta LogR = log10(R/R_{baseline}) + P(\Delta t - \Delta t_{baseline}), \tag{4}$$

In which $\Delta t_{baseline}$ and R_{baseline} are read from an interval that logs overlap with each other in Fig. 9 and P is ratio transit time cycle per of resistivity cycle. In well B, $\Delta t_{baseline} = 93.12\ \mu s/ft$ and $R_{\text{baseline}} = 0.35\ \Omega$ and in well C, $\Delta t_{baseline} = 89.22\ \mu s/ft$ and $R_{\text{baseline}} = 0.5\ \Omega$ were measured. Hence, P was calculated as 0.03 (Table 2). We used the following equation (Eq. (5)) after EXXON for calculation of TOC in a source rock (Table 2) and assuming LOM = 6.5. So, we calculated TOC contents of Gadvan Formation (Fig. 9).

$$TOC = \Delta LogR * 10^{(2.297 - 0.1688\ LOM)}, \tag{5}$$

The same procedure was used for well B. The other methods (resistivity/ neutron log and resistivity/ density log) also were applied (Eqs. (6) and (7)) and the results are presented in Table 2.

$$\Delta LogR = log10(R/R_{baseline}) + P(\Phi N - \Phi N_{baseline}), \tag{6}$$

$$\Delta LogR = log10(R/R_{baseline}) - P(pb - pb_{baseline}), \tag{7}$$

A comparison between these results reveal that resistivity/ sonic combination gives the least error in the least square mean method, in compared with direct measurement of TOC from cutting samples.

4.4. Fuzzy logic

Here, Takagi–Sugeno fuzzy inference system (TS-FIS) was applied to estimate TOC content from well log data using Matlab software. For this target, logging data of intervals of wells B and C of Gadvan Formation was selected to construct TS-FIS model. Four logs include sonic log (Δt), resistivity (Rlld), bulk density (FDC) and neutron porosity (NPHI) were considered as inputs and TOC of Δ Log R estimation as output of the fuzzy model.

A comparison between input data and TOC content of Δ Log R in well C showed that the best method for estimation of TOC content is Δt and resistivity logs (Figs. 8 and 9). To generate TS-FIS for estimation of TOC content, it is important to get optimum number of MFs and fuzzy if-then rules. The fewer rules cannot cover behavior system completely and also more rules will complicate the system. In this method, subtractive clustering was selected and each point in subtractive clustering is used for a potential cluster center (Chiu, 1994). Where is for n data point;

$$D_i = \sum_{j=1}^{n} e^{-} |x_i - x_j||^2 / (r_a / 2)^2, \tag{8}$$

Here, a term equals with $4/ra^2$ and ra is a positive constant. Hence the criterion for measuring a data point is a function of its distance to all other data points. It is clear that data point has many neighboring points and also has high potential of cluster center. The ra constant is radius of neighborhood or cluster radius, this value has a range between [0, 1]. Picking up the best ra is crucial role in determining the number of clusters. Clearly describe a smaller cluster radius will usually depend on more and smaller clusters in the data and results with more rules. A large cluster radius depends on a few large clusters in the data (Chiu, 1994). First cluster center is selected to be the data point has the highest measure. If $x1$ is selected as a cluster center, $P1$ is assumed a new criterion of cluster. New criterion cluster is calculated for all points except first cluster center (9).

$$P_i \underline{\leftarrow} P_i - P_1 e^{-\beta} | x_i - x_1 |^2 \tag{9}$$

Where $\beta = 4/rb^2$ and rb is constant number. To avoid closer space cluster center, rb should be designed higher than ra and is set to 1.5 ra (Chiu, 1994). After the first cluster, the next cluster center is chosen and the density measure is reduced again. This process continues until a sufficient number of clusters are attainted (10).

$$P_i \underline{\leftarrow} P_i - P_k e^{-\beta} | x_i - x_k |^2, \tag{10}$$

The optimum number of rules and MFs were obtained with specifying a set of values of range 0 and 1 for ra. Performance of model was calculated for the test well. Choose ra with value of 0.5, 0.8 in well B and C, respectively. Also, four rules associated with four Gaussian type membership functions for each of the input data set which were

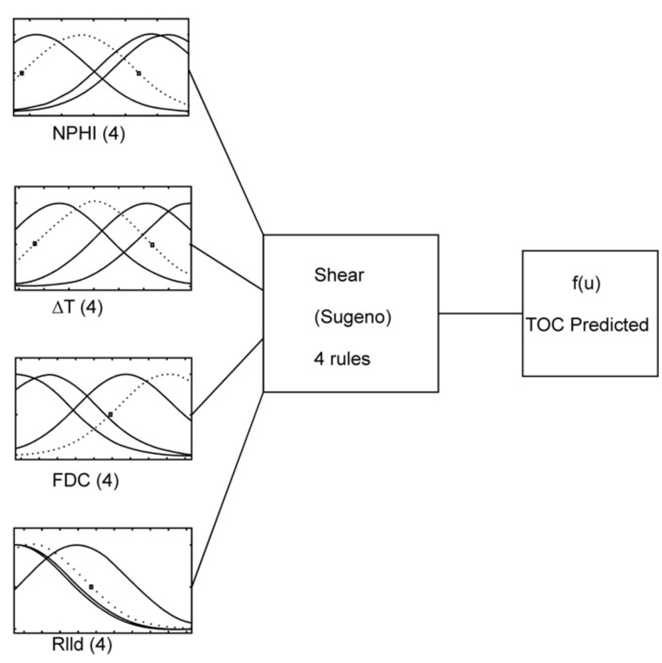

Fig. 10. Fuzzy formulation with well log data (inputs) to predicted TOC content (output) using the TS-FIS.

captioned by low, moderate, high, and very high, respectively (Figs. 10 and 11). TS-FIS the output MFs (TOC content) is linear values and will have following parameters.

Output MF1: [0.5203 0.04968 1.738 -0.04783 -4.522] (low)
Output MF2: [0.1463 0.05197 -1.773 0.3867 -4.478] (moderate)
Output MF3: [0.2112 0.003711 1.752 -1.944 3.776] (high)
Output MF4: [1.83 0.1144 -2.45 0.5946 -11.95] (very high)

Here, there are fuzzy if-then rules for input data (well logs) and output data (TOC content).

1) If (Rlld is high) and (Δt is moderate) and (NPHI is moderate) and (FDC is high), then (TOC is low).
2) If (Rlld is very high) and (Δt is low) and (NPHI is low) and (FDC is very high), then (TOC is high).
3) If (Rlld is low) and (Δt is high) and (NPHI is high) and (FDC is moderate), then (TOC is moderate).
4) If (Rlld is moderate) and (Δt is very high) and (NPHI is very high) and (FDC is low), then (TOC is very high).

In Fig. 12 illustrated the procedure of fuzzy logic methods. Fuzy logic has four steps; First step are called Fuzzify inputs, which takes the inputs data and define degree of inputs data with membership function. The second step is the use of fuzzy operator for applying rules. In the third step, this is an aggregation method for fitting output with fuzzy set. Finally in the last step, Defuzzify process will be done

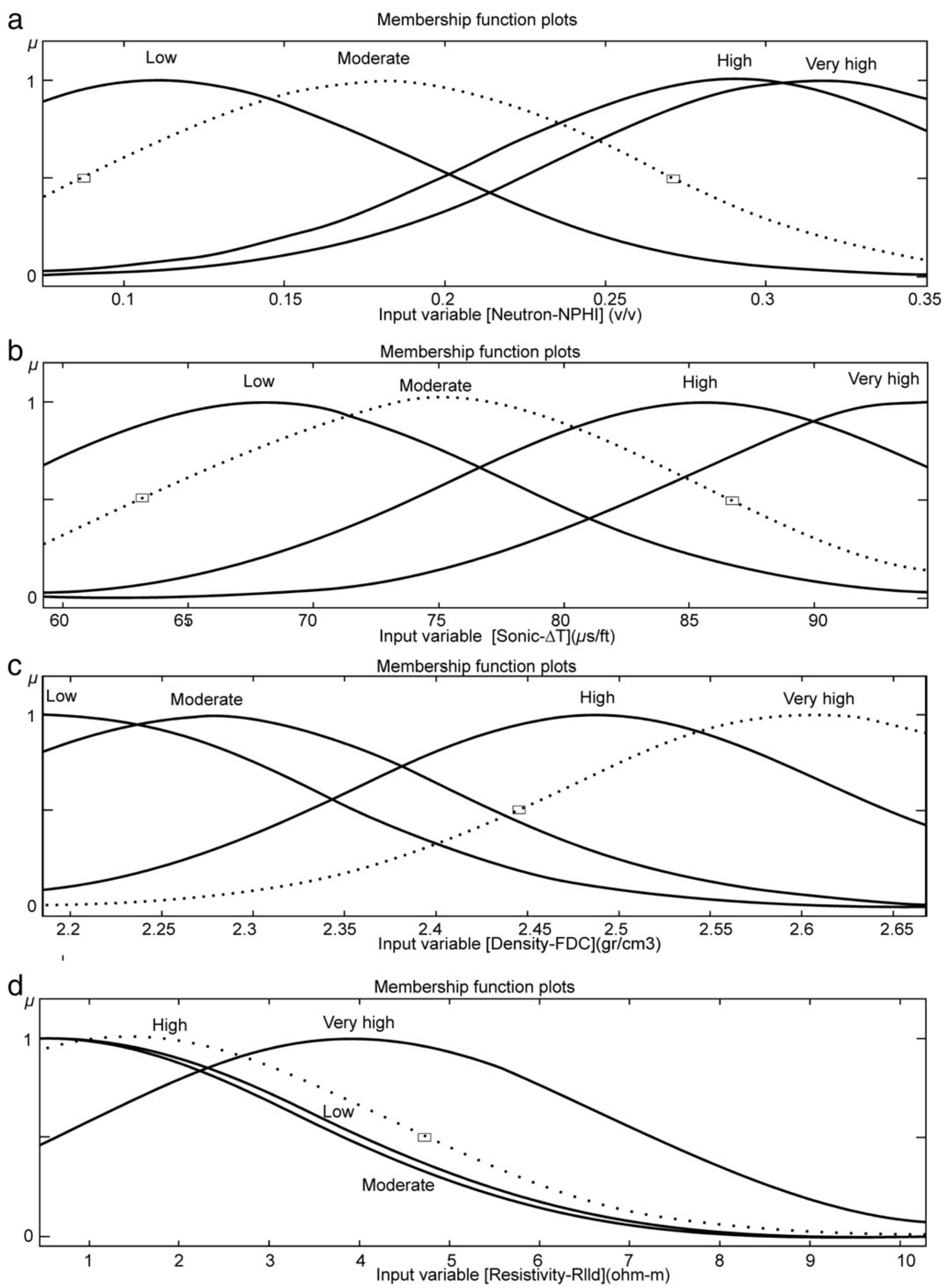

Fig. 11. Membership functions with subtractive clustering (cluster radius = 0.8) for NPHI (a), Δt (b), FDC (c), Rlld (d) for Gadvan Formation in well C.

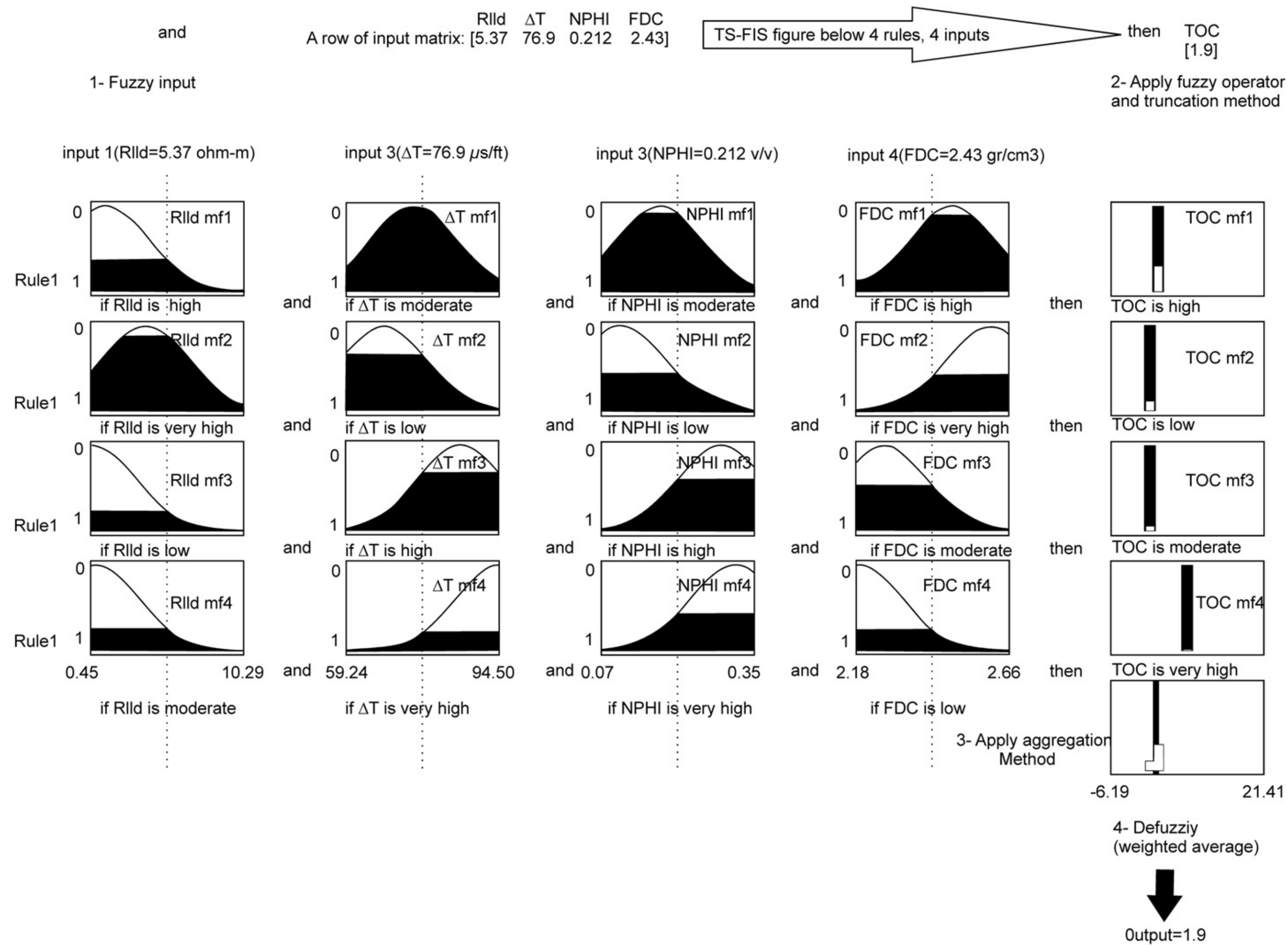

Fig. 12. A graphical illustration showing formulation of well log inputs to predicted TOC using four fuzzy if-then rules generated by TS-FIS. Each input is covered by four Gaussian membership functions (for example, Δt mf1, Δt mf2, Δt mf3, Δt mf4 which are captioned by very high, high, moderate, and low, respectively). By passing a row of the inputs matrix including Rlld = 5.37 (Ohm.m), Δt = 76.9 (*μs/ft*), NPHI = 0.212 (V/v), and FDC = 2.43 (gr/cm3) from the FIS, its related MFs are affected in each rule.

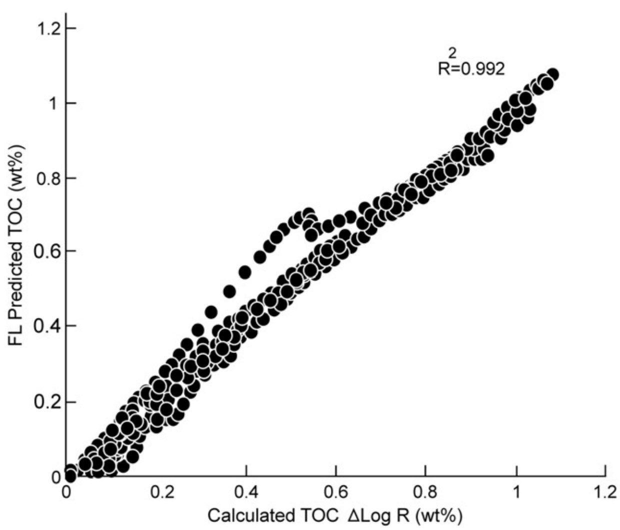

Fig. 13. Cross plot showing correlation coefficient between calculated and predicted TOC content using FIS (All of samples are in well C).

with result of aggregation method. So, TOC content was achieved in Gadvan Formation of well C (Fig. 12).

Measured error using MSE function is 0.001 and correlation coefficient between real and FL predicted TOC (2875 data points) is about 0.989 (Fig. 13).

4.5. Artificial neural network

In this research were applied three layers feed forward back propagation neural network were applied to calculate content of organic matter in source rock hydrocarbon (Fig. 14). Both the first and the second layer designed to have four and five neuron in Gadvan Formation. The end layer has only one neuron because there is only one out put (total organic carbon) (Fig. 14). These neurons were picked by guesswork and experience. All of the chosen logs as input data were separately normalized in range between 0 and 1. Chosen normalization method has been linear method. To achieve the best network, combination of inputs, activation function of hidden layer and number of neurons in hidden layer were changed.

Calculation of TOC via Matlab environment software was computed. The obtained data from neutron, density, sonic and resistivity logs was inputs and calculated TOC was output of the system (Fig. 14). Measured TOC from well cutting aren't enough, because seven sample points were taken from every borehole cutting chips (from Gadvan

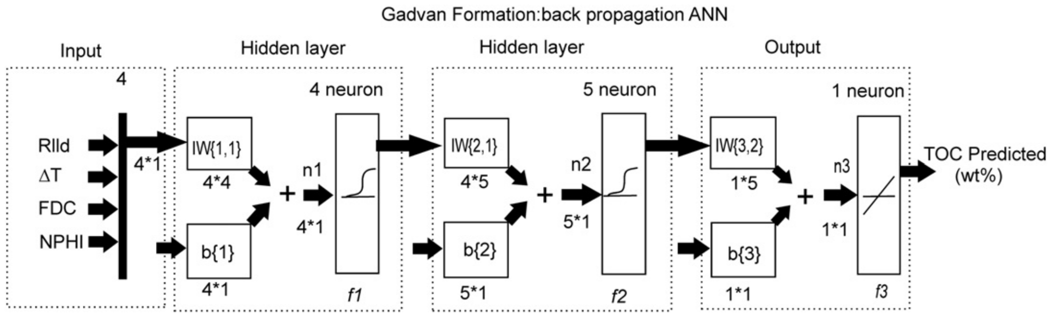

Fig. 14. A schematic structure of back propagation artificial neural network (BP-ANN) constructed for present study.

Formation). So, seven sample points of geochemical data can't be a real representative of the whole interval for seeing range of TOC content change. Hence, for using geochemical data, neural network needs more statistical data of sample points for processing operation.

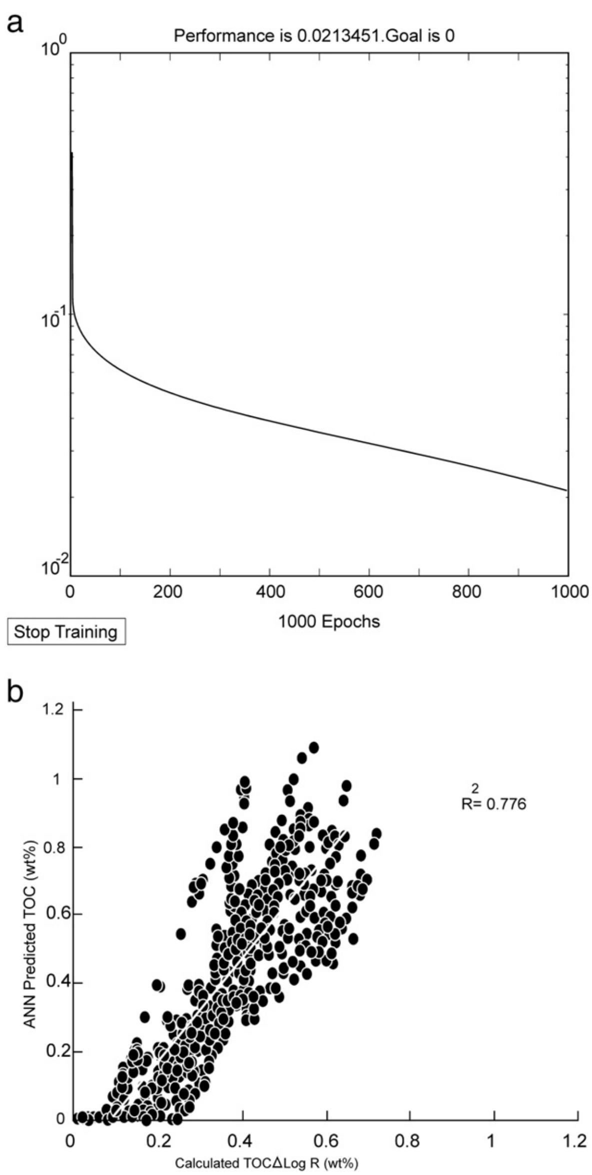

Fig. 15. (a) Mean square error (MSE) vs. training for each epoch, Gadvan Formation (0.0206092), (b) cross plot showing correlation coefficient between calculated and predicted TOC content using BP-ANN (All of samples are the test well C).

As measured TOC from well cutting was not enough, calculated TOC from Δ Log R method (sonic/ resistivity logs) are used for neural network training. Data point of Gadvan Formation (2875) also was divided into two independent data sets as a training data set (1194) and test data set (961). This procedure also was applied for well B. MSE performance function was used to optimize weights and default bias values. The applied transfer function from first layer to second layer is LOGSIG and from second layer to third layer is PURELIN. After 1000 epochs of training, MSE performance function of Gadvan Formation was 0.02 in well C (Fig. 15a). The correlation coefficient between Δ Log R and predicted ANN is 0.78 in Gadvan Formation of well C (Fig. 15b) and therefore ANN verifies their reliability.

5. Conclusions

Intelligent systems, which are BP-ANN, TS-FIS are effective methods and have been successful for data assessment which obtained from Δ Log R method and direct analytical measurement of TOC.

Both calculated (Δ Log R method) and predicted TOC content by TS-FIS and BP-ANN methods of Gadvan Formation reveal an average TOC of less than 0.5% which mean a very poor source rock for well C (Fig. 16a and b).

The measured TOC from samples in Rock- Eval pyrolysis, and calculated data based on Δ Log R method and predicted data versus depth shows a good agreement for two intelligent systems.

Measured error uses MSE performance function of Gadvan Formation is 0.02 in well C with BP-ANN. However, this value is 0.001with TS-FIS method in well C.

Gadvan Formation has TOC content less than reported from Dezful Embayment in South Pars Gas field.

Each of intelligent systems used for TOC prediction have different concepts to solve problem; however, the results of research are close to each other for verifying their concepts to solve problem.

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Appendix A

A. LOGSIG: LOGSIG is a log sigmoid transfer function. This log sigmoid transfer function calculates a layer's output from its net input.

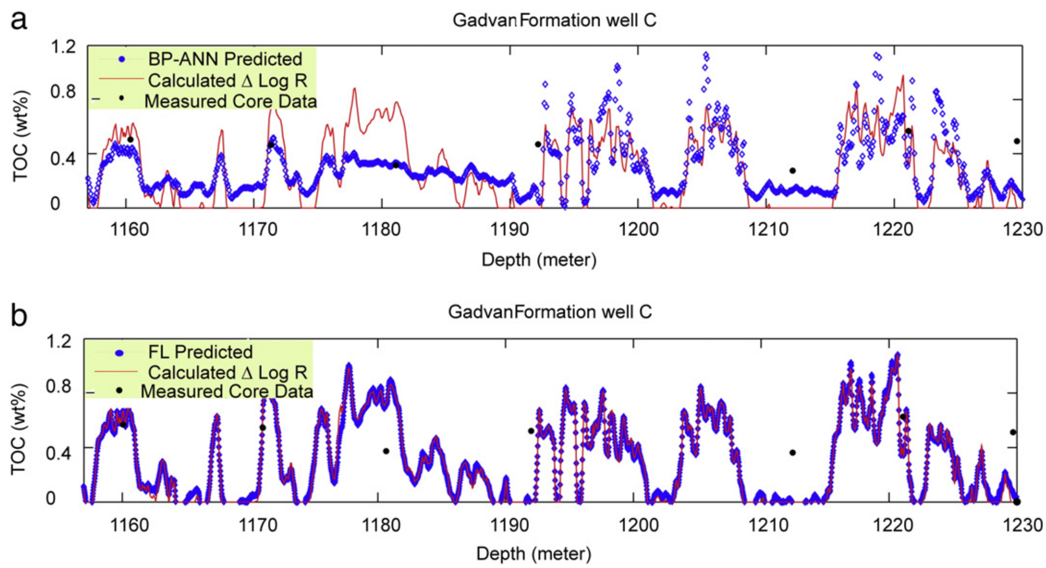

Fig. 16. Calculated ΔLog R, measured core data and Output predicted data of TOC content by BP-ANN (a) and FIS (b), Gadvan Formation in well C.

LOGSIG takes one input data, and returns each element squashed between 0 and 1 as normalized data.

B. PURELIN: PURELIN is a linear transfer function. This linear transfer function calculates a layer's output from its net input. PURELIN takes one input, returns useful information for neural network as real data.

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