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Estimation of Total Organic Carbon from well logs and seismic sections via neural network and ant colony optimization approach: a case study from the Mansuri oil field, SW Iran

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Abstract

In this paper, 2D seismic data and petrophysical logs of the Pabdeh Formation from four wells of the Mansuri oilfield are utilized. ΔLog R method was used to generate a continuous TOC log from petrophysical data. The calculated TOC values by ΔLog R method, used for a multi-attribute seismic analysis.In this study, seismic inversion was performed based on neural networks algorithm and the resulting acoustic impedance was utilized as an important predictor attribute. Afterward, a probabilistic neural network was trained by using a set of predicting attributes derived from multiple regression. Subsequently, TOC was estimated by using seismic attributes with a correlation coefficient of 75%. In the next step of the study, the nonlinear ant colony optimization technique was utilized as an intelligent tool to generate a 2D TOC section from seismic attributes. Nonlinear ant colony optimization proposed an intelligently derived equation for which weight factors of each predictor seismic attribute in TOC estimation model were derived by using stochastic optimization. The results show that nonlinear ant colony equation (stochastic optimization) outperforms the probabilistic neural network model (gradient optimization).

Keywords: *Total Organic Carbon; Well Logs;seismic Inversion; Probabilistic Neural Network; Ant Colony Optimization*

Introduction

In the exploration of hydrocarbon resources, the detection of applicable methods can be effective help for decreasing the exploration costs and save time. One of the 5 main elements of a hydrocarbon system is source rock. Total organic carbon (TOC) is crucial indicator for evaluation of the hydrocarbon generation potential of source rocks and shale gas reservoirs. It is estimated by analyzing cores, cuttings or sidewall cores in the laboratory by using source rock evaluation instruments (e.g. Rock-Eval pyrolysis).Among researchers which have created a quantitative correlation between well log responses and primary parameters of source rocks can refer to Passey *et al.* (1990) and Kadkhodaie- Ilkhchi *et al*. (2009).

In recent years, the application of expert systems is noticed in various branches of science and engineering in order to decrease cost and time, increase the accuracy of measurements. One of the comparatively novel computational intelligent methods inspired byants observation is artificial ant colony optimization (ACO) approach.First, the ant colony optimization was presented by Dorigo and colleagues (Colorni *et al.,* 1991) and Dorigo and Gambardella extended the initial algorithm for ACO method (Dorigo & Gambardella, 1997).

By using geophysical exploration methods can obtain physical properties of the Earth function. Yilmaz (2000) explained the importance of inversion of post-stack seismic amplitudes in reservoir description, fluid assessment, and well placement. The two methods of attributes optimization are dimension reduction method (Roweis & Saul, 2000) and selection method (Tang *el at.*, 2009). For reservoir properties, theprediction from attributes can usually utilize methods such as an artificial neural network (Luo & Wang, 1997), none-liner regression (Xu, 2009), Kriging method (Krige, 1951) and support vector machine (Yue & Yuan, 2005). Among the performed case studies on the source rocks by multi-attribute analysis can refer to Jianliang *et al.* (2012). The aims of the present research are as follows.

Calculation of TOC from conventional well logs using the ΔLog R method (Passey *et al.,* 1990),

Estimation of TOC from seismic attributes using the Probabilistic Neural Networks (PNN) approach,

Prediction of TOC from seismic attributes using the Ant Colony Optimization (ACO) approach,

Comparing the results of the probabilistic neural network and ant colony optimization model for predicting TOC.

A general workflow of the methodology used for

TOC estimation from seismic attributes is shown in Fig.1.

Geological setting

Geologically, Dezful Embayment, owing to the essence of huge oil fields into it, is an important zone in Iran. This area has located in the folded Zagros. It is a foreland basin. The Mansuri is an anticline which has located within 45 kilometers of the southwest of Ahwaz city and the north of Dezful Embayment. This anticline has situated along fields of Ahwaz, Marun, and Abteymour. Fig. 2 shows the geological position of the Mansuri oil field. The length and width of this field with NW-SE trending at Asmari horizon is 42 kilometers and 4.5 kilometers respectively.James & Wynd (1965) are among people which have studied Pabdeh Formation.They explained that the type section of this formation is located in Tange-e-Pabdeh 32° 25'N, 49° 16' 22" E in the north of Lali oil field. Alizadeh *et al.* (2012) described that Pabdeh Formation in Mansuri oil field from geochemical aspects is divided into three divisions. Lower and Upper zones are containing fair to good hydrocarbon potential and Middle zoneis containing very good potential.

Methods and theories

Seismic inversion model

One of the useful data production tools of seismic data is inversion approach that can obtain acoustic impedance data from the seismic traces, so attention to this method has steadily been increased in the recent years. The existence of minimum differences between synthetic seismic and real seismic responses is the base of seismic inversion method. Synthetic seismic responses create by convolving wavelet and earth reflectivity.

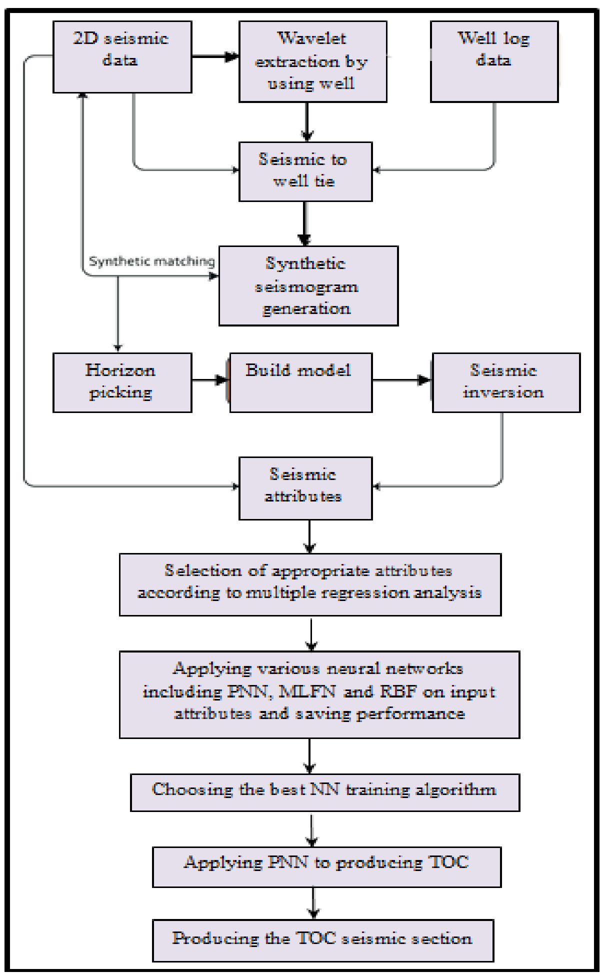

Figure 1. A general workflow of the methodology used for TOC estimation from seismic attributeS.

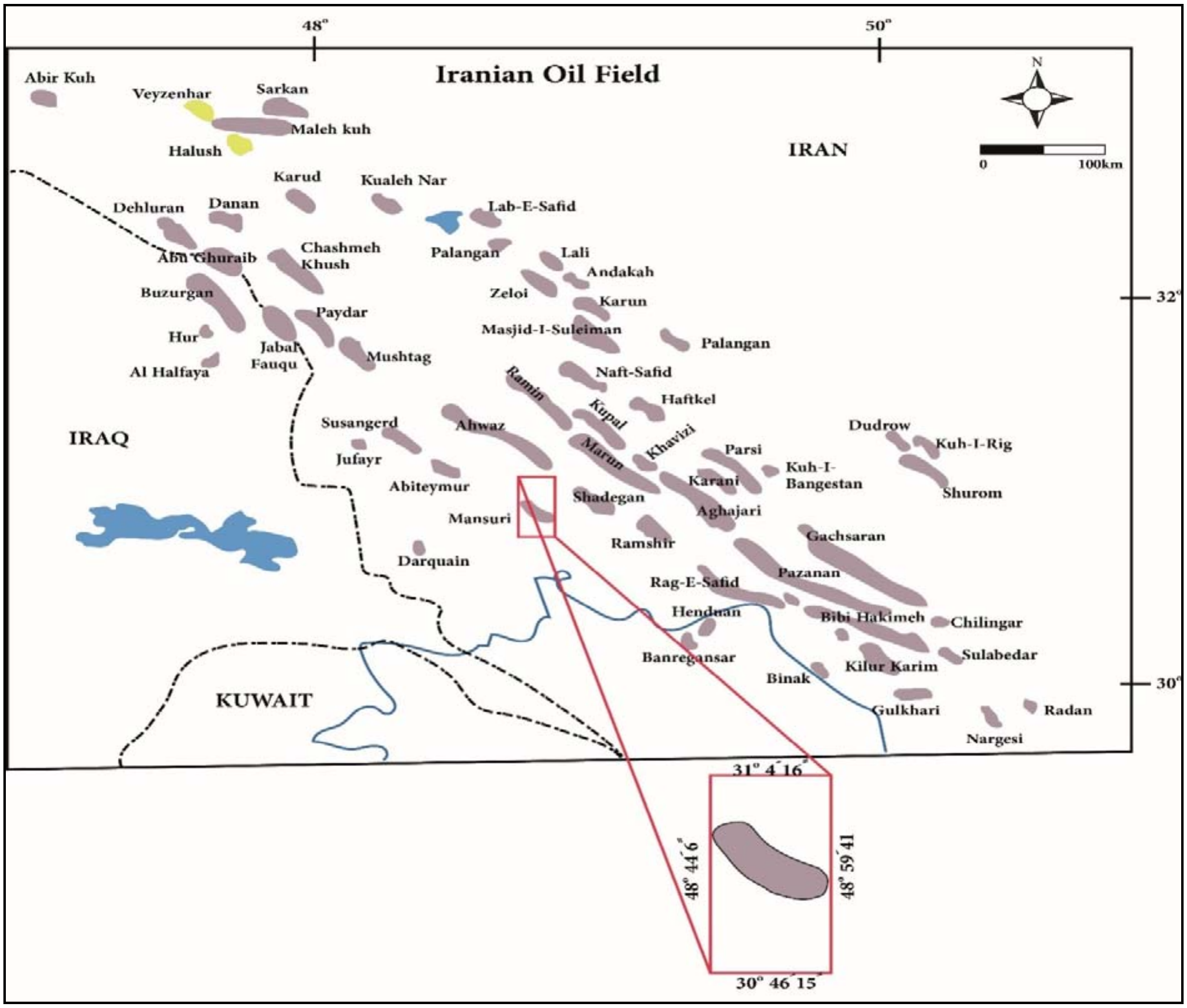

Figure 2. Geological position of the Mansuri oil field outlined by red rectangular (Modificated from KavianporSangno, 2015). The longitude and latitude range of the anticline are from 48º 44' 6" to 48º 59' 41" and from 30º 46' 15" to 31º 4' 16" respectively. The oil fields represented by gray color and the gas fields presented by light green color.

Earth reflectivity and Acoustic impedance are of the important rock properties. The calculation process of the subsurface impedance model using the post-stack seismic data is called inversion of post-stack. Yilmaz (1987) explained in the linear system theory, the seismic trace can be introduced as the result of the wavelet convolution with the impulse response of the medium, which is called reflectivity function. The seismic trace convolution model can retrieve the reflectivity function. Considering negligible the noise ηt, convolving the trace with the inverse filter can be restored the reflectivity function. So, the seismic trace is deconvolved. Mathematically expressed as,

$xt = p_t * rt + \eta t$,(1)

Where xt indicates seismic trace, pt indicates wavelet of every reflected event, rt indicates impulsive response or reflection function, n indicates the additive noise and the asterisk sign, *, represents the convolution operator.

Ant Colony Optimization (ACO) model

The individual behavior of ants is simple but their swarm behavior is quite complex. Dorigo *et al.* (1996) exposed that swarms of ants working cooperatively can obtain the shortest route from the nest to a food source. ACO is a class of biologically inspired meta-heuristics algorithm. During trips of ants splash an odorous chemical liquid called pheromone. The role of pheromone is to find the shortest routes from food source to nest. Each ant selects the path according to the quantity of pheromone. In fact, by addition, the amount of pheromone in a route increases the probability selection that route. Toksarı (2006) showed that global pheromone updating rule is employed in the two phases. The first and second phase consists of the evaporation a fraction of the pheromone and the deposition of an amount of pheromone by each ant, respectively. The amount of pheromone is proportional to the fitness of its solution. This process is iterated until a stopping criterion.

ΔlogRmethod

ΔlogRmethod is proposed by Passey *et al.* (1990). They presented an adequate method for evaluation of potential source rocks and determination of the total organic carbon contentin organic-rich rocksusing well logs. The introduced technique creates by overlaying a properly scaled porosity log such as sonic, neutron or density on a resistivity curve and a separation between porosity log and resistivity log occurs in organic-rich rocks. The equation that was utilized for the estimation of ΔlogR from the sonic and resistivity logs is presented as follows:

$$\Delta \log R = \log 10(R/R\text{baseline}) + 0.02 \times (\Delta T - \Delta T\ \text{baseline}) \qquad (2)$$

where:

ΔlogR = the amount of curve separation between porosity log and resistivity log.

R = the measured resistivity in Ω m.

Δt = the measured transit time in us/m.

$R_{baseline}$ = the resistivity corresponding to the $\Delta t_{baseline}$ when the resistivity and sonic curves coincide in non-source rocks.

TOC is estimated from ΔlogR method by using the eq. 3.

$$TOC = (\Delta \log R) \times 10^{(2.297-0.1688\times LOM)} \qquad (3)$$

wherethe amount of level organic metamorphism is called LOM.In this study, the pyrolysis data from 14 cutting samples obtained from Pabdeh Formation of wells 6 and 20 were utilized. The samples were analyzed using Rock-Eval 6 apparatus. The Rock-Eval pyrolysis extensively is used to define theinitial evaluation of geochemical characteristics of source rocks.

Discussion

The recent study aims at estimating the Total Organic Carbonfrom seismic attributes in the Mansuri oil field. For this purpose, first, the ΔlogR method (Passey *et al.*, 1990) was used to determine the Total Organic Carbonof the source rock using the introduced well logs.After TOC calculation from the logs, for inversion and TOC estimation from the seismic data, the data regarding wells 14, 20, 25 and 28 of Mansuri oil field including well logs, well coordinates, depth and thickness of the understudy formation, check-shot data, and the geochemical data due to the ΔlogR method entered in the Geoview module of HRS software. The reason of selecting these wells was the availability of sonic and density logs of Pabdeh Formation. The applied seismic data includes the two-dimensionalpost-stack seismic data. The seismic data quality of this field is generally intermediate to good. The sample rate is 4 ms in this study. Seismic inversion and TOC prediction analysis were carried out using Strata and Emerge module of Hampson-Russell Software (HRS).

Seismic-well calibration

Connecting seismic data to well log is an elementary procedure in all interpretation projects which is accomplished by creating synthetic seismogram and matching geological marker with the correct seismic reflector. The synthetic seismograms for all the wells with DT and density logs were prepared which were essential to knot seismic to well. Impedance log is generated by combining the density and sonic logs. Afterward, reflectivity is produced by inverting the acoustic impedance log and it is inverted from depth to time using a suitable time–depth relationship. Finally, the synthetic seismogram is created by twistingthe reflectivity and wavelet.In this step, by using well extraction method extracted a wavelet from the seismic data. The well data is inverted from depth domain into time domain. The depth to time conversion model in the well location has provided by applying check-shot data supplied for wells 14, 20 and 28.This process was essential to create synthetics and extract the wavelets iteratively for the placement of the log data in time. The depth to time conversion model is performed for a comparison of the well logs, and their associated tops, with the seismic data in time. Horizon interpretations and geologic well tops are utilized as assistance in determining a time–depth relationship for deviated wells. The result of well to seismic tie for well 14 is shown in Fig. 3. As it has shown, the correlation factor between synthetic seismogram and composite seismic, at the well location, is 0.87%. Owing to the existence of high correlation (0.87%) between synthetic seismogram and composite seismic, parameters selected for the inversion analysis can be utilized to invert the whole volume.

Selection of optimum seismic attributes

The multiple regression analysis is a stepwise regression approach that can determine the strongest inputs and to predict target parameter. The choice of the optimal number of attributes is very important subject for multi-regression analysis. Accordingly, for all of the produced attributes of wells executed a multi-regression analysis and then a validation prediction error curve produced. The results revealed to ameliorate data prediction and arriving at the target logwill benefit the increase of attributes number. Of course adding more attributes in the multi-regression analysis always is not useful for the true signal prediction and may have the bad influence on the predicted target. Russell (2004) introducedthe validation error as a standard that can ascertain the stop of adding attributes to the input set. Validation versus prediction error curve for the used seismic attributed is shown in Fig. 4. The bottom black curve shows the total error and top red curve shows the validation error.Accordingly, four attributes composed of Dominant Frequency, Integrated Absolute Amplitude, Inversion Result and Amplitude Envelope were introduced as the optimal inputs set for predicting TOCusingProbabilistic Neural Network. The physical relationships between input data and output data can be stated as below.

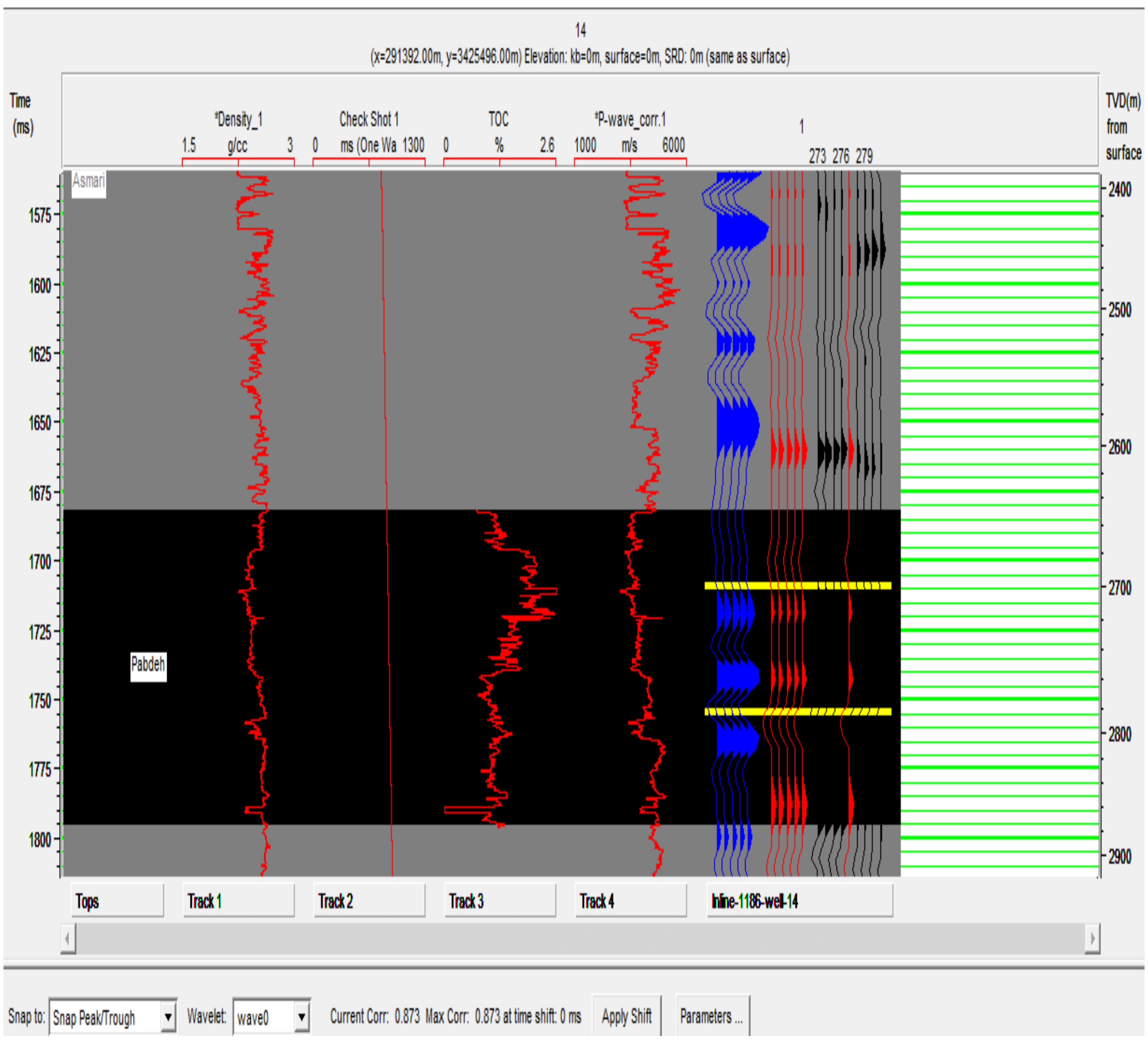

Figure 3. The synthetic seismogram and real seismic traces captured at well 14 location, the correlation coefficient is 0.873. The yellow lines mark the correlation window extents.

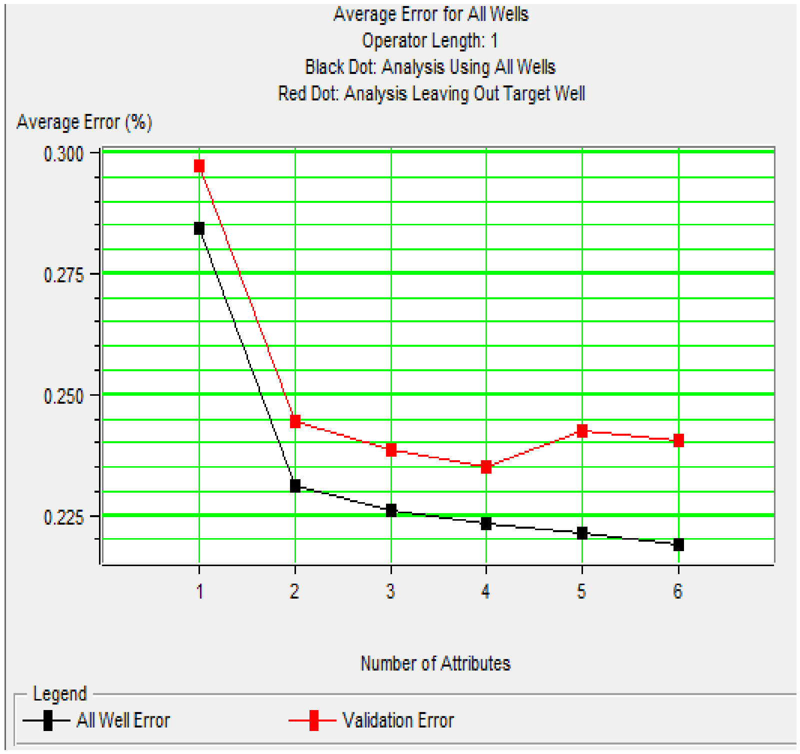

Figure 4. Validation vs. prediction error curve. The bottom black curve shows the total error and top red curve shows the validation error.

Dominant frequency indicates unnatural frequency weakening and, thereby, can display the essence of hydrocarbon in zones. Integrated Absolute Amplitude is known as the sum of all the trace amplitudes within the window interval. It can indicate amplitude anomalies owing to lithology and porosity variations. Acoustic impedance generates by the product of sonic velocity and bulk density. Sonic velocity with bulk density has an inverse relationship. Accordingly, Total Organic Carbonis an inverse function of acoustic impedance. Taner *et al.* (1994**)** introduced Amplitude Envelope as an indicator of the major lithology changes and of gas and liquid accumulations. In this study, the operator length 1 is considered as the best results with the least amount of error through examining the amount of different operator length.

Design of a Probabilistic Neural Network for the prediction of TOC

Artificial neural networks are a kind of fast and efficient nonlinear models which have utilized in many bases of prediction, process control and classification. This method can map a set of input data to their outputs. For this purpose, to investigate the available nonlinear relationships between input and output data, a probabilistic neural network model was manufactured using the chosen seismic attributes from the multi-regression analysis. Afterward, the entire seismic section was converted into the Total Organic Carbonvalues by using the developed probabilistic neural network model and the optimal seismic attributes.

Design of a nonlinear ACO for the prediction of TOC

In this part of the research, a general design was presented to estimate the Total Organic Carbonand to generate a seismic section using nonlinear ant colony method. In so doing, first, in Emerge part of HRS software, the training data for ant colony in ASCII format was obtained utilizing the probabilistic neural network. To build the model, the set of the 391 training data from wells 14, 20, 25 and 28 were employed. Normalization is important enough to be applied to produce better data. After the input data selection, the data were normalized between 0 and 1 based on the following equation.

$$\mathrm{Xnorm} = \frac{\mathrm{X-Xmin}}{\mathrm{Xmax-Xmin}} \qquad (4)$$

where x is the data which needs to be normalized.x_{max} and x_{min} are the maximum and minimum of the original data, respectively. Assuming that there are ninputs parameters xiwhich are utilized to predict the Total Organic Carbon, then the targetparameterprediction could be written in the nonlinear form as follows:

$$t(x_1, x_2, \dots, x_n)_{(nonlinear)} = \alpha_1 . x_1^{\beta 1} + \alpha_2 . x_2^{\beta 2} + \cdots . + \alpha_n . x_n^{\beta n} + \alpha_{n+1} \quad (5)$$

wheret is the targetparameter prediction, parameters α_1, α_2, … α_n, are coefficients of the equation, and α_{n+1} is constant. Parameters β_1, β_2, β_n are exponents of the nonlinear equation. Fitness function that should be optimized with ACO, is defined as follows.

$$MSE = \frac{1}{m} \sum_{j=1}^{n} \left(TOC_{ACO(nlin)} - TOC_{real}\right)^2 \quad i = 1,2, \dots n \quad (6)$$

where MSE is the mean square error, m is the number of model data and n is the number of input parameters for TOCprediction. $TOC_{ACO\ (nlin)}$ is the estimated TOC for the nonlinear ACO model.

Results

The values of total organic carbon from Rock-Eval pyrolysis are shown in Table 1. The data show that the total organic carbon values are between 0.41 and 3.17 wt%, with an average of about 0.99 wt%. A graphical comparison between the measured and simulated TOC values using the ΔLogR method is shown in Fig. 5.

Table 1. The result of Rock–Eval pyrolysis of samples for Pabdeh source rock.

Formations-Well name	Depth (m)	S_1 (mgHC/g Rock)	S_2 (mg HC/ g Rock)	S_3 (mg HC/ g Rock)	HI (mg HC/ g TOC)	OI (mg CO_2/ g TOC)	T_{max} (°C)	TOC (wt.%)
Pabdeh-6	2680	0.72	1.01	1.33	126	166	425	0.8
Pabdeh-6	2690	0.75	0.96	1.43	120	179	421	0.8
Pabdeh-6	2730	0.82	10.45	2.12	452	92	426	2.31
Pabdeh-6	2794	0.26	3.07	1.5	341	167	433	0.9
Pabdeh-6	2814	0.21	0.83	1.39	202	339	433	0.41
Pabdeh-6	2830	0.33	0.64	1.48	142	329	433	0.45
Pabdeh-6	2848	0.35	0.43	1.42	102	338	432	0.42
Pabdeh-6	2868	0.51	0.57	1.62	114	324	423	0.5
Pabdeh-6	2890	0.68	0.1	2.24	23	521	463	0.43
Pabdeh-20	2680	2.33	11.43	2.07	361	65	421	3.17
Pabdeh-20	2750	1.82	2.91	2.84	219	214	426	1.33
Pabdeh-20	2820	1	0.7	1.23	130	228	435	0.54
Pabdeh-20	2869	0.6	0.94	0.94	145	145	435	0.65

The results of application of Probabilistic Neural Network to predicting TOC

After determiningthe optimal seismic attributes from the multi-regression analysis,in order to predicting TOC, a probabilistic neural network model was constructed. According to Fig. 6, the correlation coefficient between the measured and predicted TOC values and the mean error of validation using probabilistic neural network model are 0.75 and 0.23 weight percent, respectively. The seismic section of the estimated TOC distribution from the PNN method in the well 14 location is demonstrated in Fig. 7.The results showed that PNN was successful for converting seismic data to TOC.

The results of application of nonlinear ACO to predicting TOC

In this part of the study, firstly, 100 ants were produced and the initial pheromone value was set to 0.2. The equation 7 utilized for final estimation of TOCfrom seismic attributes by using nonlinear ACO model:

$$TOC_{ACO(nlin)} = \alpha_1 . \text{Dominate Frequency}^{\beta 1} + \alpha_2 . \text{Integrated Absolute Amplitude}^{\beta 2} + \alpha_3 . \text{Inversion Result}^{\beta 3} + \alpha_4 . \text{Amplitude Envelope}^{\beta 4} + \alpha_5 \quad (7)$$

$TOC_{ACO(nlin)}$ is the estimated TOC from the nonlinear ACO model. In this equation, parameters α_1, β_1, α_2, β_2, α_3, β_3, α_4 and β_4 are coefficients and exponents corresponding to Dominate Frequency, Integrated Absolute Amplitude, Inversion Result and Amplitude Envelope inputs, respectively. Parameter α_5 is constant for the equation. The ACO derived values for α_1, β_1, α_2, β_2, α_3, β_3, α_4 and β_4 corresponding to Dominate Frequency, Integrated Absolute Amplitude, Inversion Result and Amplitude Envelope data are (1.086), (0.989), (-0.885), (0.947), (-0.313), (0.356), (0.357) and (0.706), respectively. Constant α_5 is derived as 0.345. Comparison between the measured and predicted TOC values for the input data using the nonlinear ACO model is shown in Fig. 8.

According to this figure, MSE of the ACO model for the input data is 0.02 which corresponds to the R^2 value of 0.804. The results indicated that the correlation coefficient between seismic attributes and TOC resulting from the ant colony model is more than of the probabilistic neural network model.

In the next step, to produce a seismic section of nonlinear Ant Colony, first, in ProMc part of HRS software, the four attributes of Dominant Frequency, Integrated Absolute Amplitude, Inversion Result and Amplitude Envelope with SEGY format were obtained. Afterward, by using VISTA software, an advanced software for seismic data processing, the seismic attributes were converted from SEGY format to ASCII format, to be easier to perform the action. Subsequently, the converted data have been moved to MATLAB software and they have been normalized. And then, the obtained weighting coefficients were applied to the attributes and the Total Organic Carbonwas calculated by the equation 8.

$$\mathrm{TOC}_{\mathrm{ACO(nlin)}} = 1.086 \times \mathrm{Dom.Freq.}^{0.989} + (-0.885) \times \mathrm{Int.Abs.Amp.}^{0.947} + (-0.313) \times \mathrm{Inv.Res.}^{0.356} + 0.357 \times \mathrm{Amp.Env.}^{0.706} + 0.345 \quad (8)$$

Finally, a TOC seismic section was produced for 551 seismic traces using nonlinear ACO. The seismic section of the predicted TOC values using the optimization method of nonlinear ACO is shown in Fig. 9.

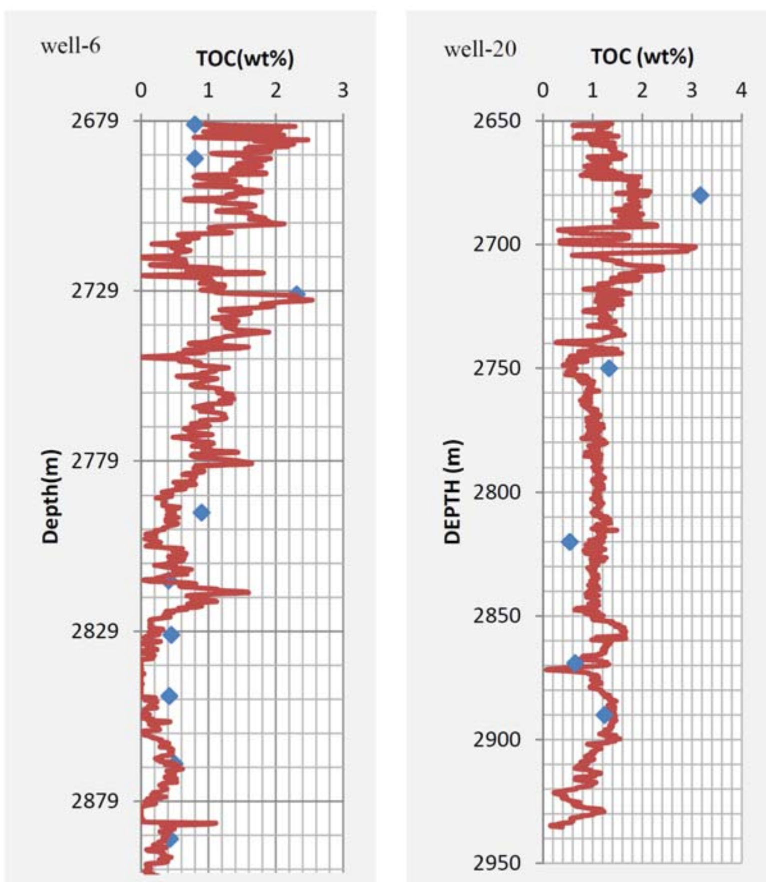

Figure 5. A graphical comparison between measured and estimated TOC from ΔLogRversus depth in wells 6 and 20. The red line marks the estimated TOCfrom ΔLogR .Lozenge shapes are measured TOC.

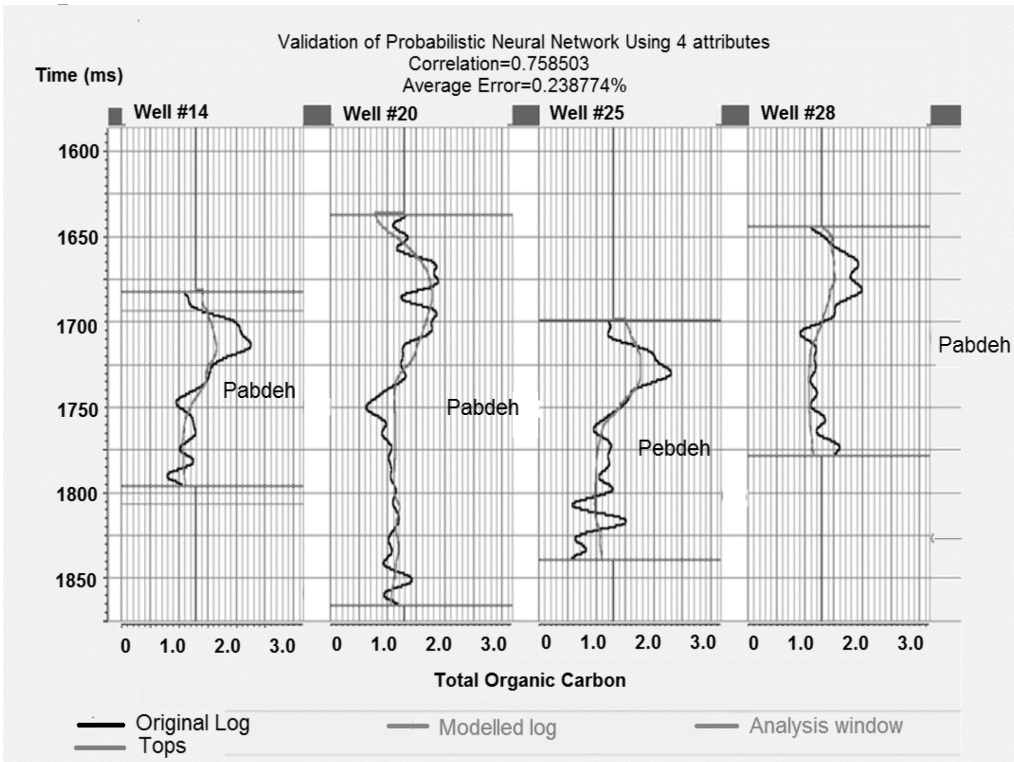

Figure 6. Graphical comparisons between measured and simulated TOC logs for validation data by using Probabilistic Neural Network model. The correlation coefficient is 75%.

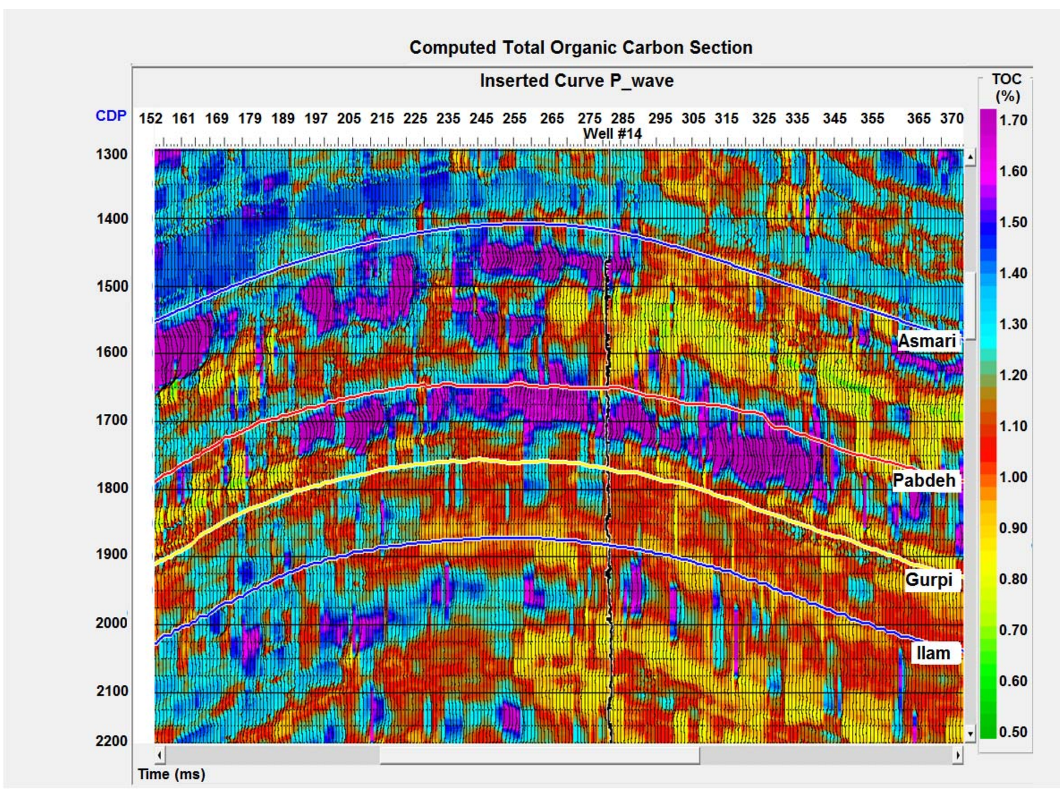

Figure 7. Seismic section showing predicted TOC values using PNN model in well 14. The dark and light scale on the right shows TOC in percent.

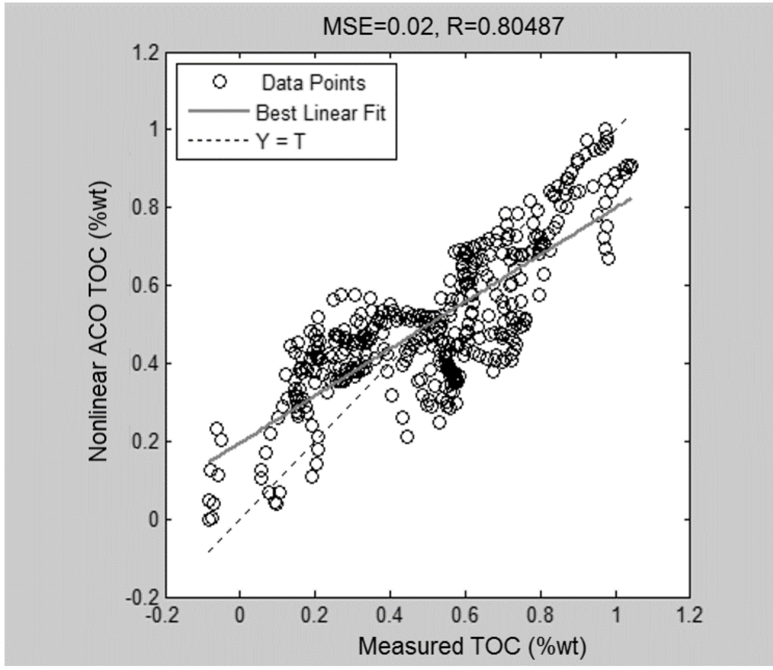

Figure 8. Cross plot showing relationships between predicted and measured TOC from ACO model. The correlation coefficient is 80%.

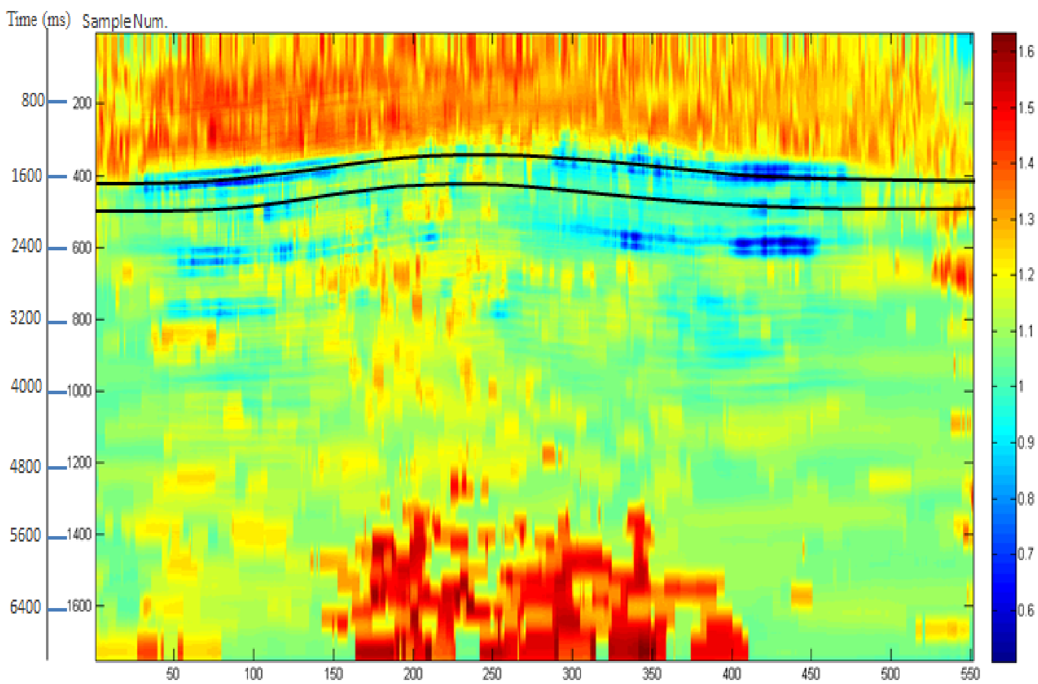

Figure 9. Seismic section showing predicted TOC values using ACO model. The color scale on the right shows TOC in percent. The black curves mark the predicted TOC window extent for Pabdeh formation.

The results of this study indicated that the TOC can be mapped form seismic data with an acceptable accuracy. A part from reducing exploration risks and costs, it cangenerated a quick volume of organic richness distribution throughout the Mansuri oil field. Moreover, it is beneficial for alleviating the time consuming and expensive methods of preparing and analyzing drilling samples in laboratory. Overall, ACO method can be applied as a robust, quick and easy method to estimate and evaluate TOC. It is expected that the methodology described in this study will aid in the most successful implementation of geochemical and exploration projects.

Conclusions

In this paper, the nonlinear ACO and PNN approaches were developed to predict the TOC from seismic attributes in the Mansuri oil field. Fourteen cutting samples have been analyzed using Rock-Eval pyrolysis. The analysis shows TOC between 0.41 to 3.17 wt%.Using the ΔLogR method, the TOC of the studied source rock was calculated. These calculated values were then used as the multi-attribute analysis input. In this study, the physical relationship between seismic attributes and TOC investigated through multi-regression analysis. The optimal multi attributes selected based on the trend obtained regression analysis and utilized in the construction of PNN model. 4 attributes, including Dominate Frequency, Integrated Absolute Amplitude, Inversion Result and Amplitude Envelope, are considered to be the optimal inputs for predicting TOC. According to the results of PNN method, the correlation coefficient and the mean error of validation between the measured and predicted values are 0.75 and 0.23, respectively. Moreover, the nonlinear ant colony algorithm created to estimate TOC from the attributes of Dominant Frequency, Integrated Absolute Amplitude, Inversion Result and Amplitude Envelope. The correlation coefficient and MSE between the input and output data were 0.804 and 0.02 respectively. The results from the PNN and ACO methods were compared to each other. The results revealed that the accuracy of ACO model is higher than the PNN model. Based on the nonlinear ACO model, the weighting values for $\alpha 1$, $\beta 1$, $\alpha 2$, $\beta 2$, $\alpha 3$, $\beta 3$, $\alpha 4$, $\beta 4$ and $\alpha 5$ are (1.086), (0.989), (-0.885), (0.947), (-0.313), (0.356), (0.357), (0.357), (0.706) and (0.345) respectively. Finally, a TOC seismic section was produced for 551 seismic traces using the weighting coefficients resulting from a nonlinear ant colony.

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