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Application of Fuzzy Interference Systems for Prediction of the Total Organic Carbon

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EXTENDED ABSTRACT

Abstract

Characterization and accurate estimation of the hydrocarbon reserve in unconventional reservoirs is important because of the high cost associated with developing these resources. This study is aimed to evaluate the applicability of using different fuzzy interference systems in predicting the total organic carbon (TOC) which is an important factor for evaluating unconventional resources. More than 500 data points of gamma-ray, formation resistivity, formation bulk density, sonic transit time, and their corresponding TOC were used to train Takagi-Sugeno-Kang fuzzy interference system (TSK-FIS) and Mamdani fuzzy interference system (M-FIS) for TOC estimation, the training data were collected from Barnett shale. The optimized fuzzy systems were tested and validated on data from Barnett and Devonian shale, respectively. The accuracy of the developed fuzzy systems was compared with other recently developed correlations. The results confirmed the high accuracy of the developed fuzzy systems in predicting the TOC in both Barnett and Devonian formations, even when compared with available correlations, M-FIS model outperformed TSK-FIS model in predicting the TOC for testing and validation data.

1. Introduction

Total organic carbon (TOC) is a critical parameter required for estimation of the hydrocarbon reserve of unconventional resources, TOC is affected by several parameters such as the maturity, carbon content, and gas adsorption; which affects the organic porosity of the reservoir, the wettability and pore structure of the reservoir rock also affect the TOC content of the reservoir (Ross and Bustin, 2007). Therefore, an accurate method for TOC estimation is required to accurately predict the reserve of the unconventional reservoir.

TOC is currently evaluated either through conducting extensive laboratory experiments that predict the TOC accurately, but they are costly, time-consuming, as well as it is very difficult to obtain a continuous profile of the TOC along the drilled hole by conducting this extensive laboratory work. Other researchers developed regression-based empirical correlations to evaluate the TOC on specific formation (Schmoker, 1979; Passey et al., 1990; Wang et al., 2019a; Zhu et al., 2019a). These correlations require modifications to make it possible to be applied in formations different than the one used to develop it.

By assuming that TOC is directly related to the formation density, and the change in the bulk formation density is only affected by the change in the TOC while assuming the density of the other formation components is constant, Schmoker (1979) came up with the first empirical correlation for TOC prediction in Devonian shale. The weight percent of the TOC could be calculated based on the volumetric percentage calculated using the Schmocker correlation in Eq. (1), more detail about TOC conversion from volumetric to weight percentage is available in Schmoker (1979).

$$TOC(vol.\%) = \frac{(\rho_B - \rho)}{1.378} \tag{1}$$

where ρ_B represents the bulk formation density (g/cm^3), and ρ denotes the organic matter free rock density (g/cm^3).

In 1980, Schmoker revised his correlation to make it applicable to the Bakken formation, Schmoker (1980) calculated the TOC as a weight percentage using Eq. (2).

$$TOC(wt.\%) = \frac{[(100\rho_o) - (\rho - 0.9922\rho_{mi} - 0.039)]}{[(R\rho)(\rho_o - 1.135\rho_{mi} - 0.675)]} \tag{2}$$

where ρ_o is the organic matter density (g/cm^3), R is the organic matter to organic carbon weight percentage ratio, ρ_{mi} denotes the grain and formation fluid average density (g/cm^3).

The most commonly used correlation for TOC estimation is called ΔlogR model, summarized in Eq. (3) and Eq. (4), This model was developed by Passey et al. (1990). ΔlogR model is based on properly scaled resistivity and sonic transit time logs. It is important to mention that ΔlogR could be calculated using density log or sonic log.

$$\Delta logR \ = \ log_{10}\left({}^{R}/_{R_{baseline}}\right) + 0.02 \times (\Delta t - \Delta t_{baseline}) \tag{3}$$

$$TOC \ = \ \Delta logR \ \times 10^{(2.297 - 0.1688 \times LOM)} \tag{4}$$

where ΔlogR denotes the separation between the resistivity and sonic transit time logs, R and Δt are the resistivity of the target formation (Ω·m) and the sonic transient time (μs/ft), respectively, $R_{baseline}$ and $\Delta t_{baseline}$ denote the base formation resistivity and sonic transit time both corresponding to an organic lean shale, and LOM is the level of maturity.

As indicated in Eq. (3), ΔlogR model considers 1:50 linear relationship between the formation porosity and logarithmic resistivity, because of this assumption ΔlogR model is applicable only on a limited range of data with a specific relationship between the porosity and resistivity. Another drawback of this model is that it was developed assuming constant properties of the formation, this could not be applied to organic-rich shale which is characterized by an extreme variation for different resource plays. The use of LOM in estimating the TOC which was considered by this model is not recommended since it leads to problems in practice.

The predictability of TOC using Schomoker and ΔlogR was evaluated by Charsky and Herron (2013) on data collected from four wells. The results showed that the TOC was estimated with a high average absolute difference of 1.6 wt% for Schomoker and 1.7 wt% for ΔlogR model. To improve the accuracy of predicting the TOC for Devonian shale, Wang et al. (2016) suggested a revised ΔlogR model which uses gamma-ray (GR) log in addition to resistivity and sonic or density logs as inputs. Eq. (5) and Eq. (6) could be used to calculate

ΔlogR based on sonic or density logs, respectively, and TOC could be estimated using Eq. (7).

The main advantage of Wang's models is that he did not use the approximation of the linear relationship between sonic and resistivity logs. Another positive point about this model is that LOM replaced T_{max} or R_o as shown in Eq. (7).

$$\Delta logR = log_{10}\left(\frac{R}{R_{baseline}}\right) + \frac{1}{ln10}\frac{m}{(\Delta t - \Delta t_m)} \times (\Delta t - \Delta t_{baseline}) \quad (5)$$

$$\Delta logR = log_{10}\left(\frac{R}{R_{baseline}}\right) + \frac{1}{ln10}\frac{m}{(\rho_m - \rho)} \times (\rho - \rho_{baseline}) \quad (6)$$

$$TOC = [\alpha \Delta logR + \beta(GR - GR_{baseline})] \times 10^{(\delta - \eta T_{max})} \quad (7)$$

where m is the cementation exponent, Δt_m and ρ_m denote the matrix sonic transit time and density in (μs/ft) and (g/cm^3), respectively, $\rho_{baseline}$ represents the baseline density corresponding to $R_{baseline}$ (g/cm^3), α, β, δand η are formation constants which must be determined, the maturity indicator T_{max} is in °C, $GR_{baseline}$ is the baseline gamma-ray value of shale (API).

After comparing the original and revised ΔlogR models in Devonian shale, the results showed that the revised models accurately predicted the TOC with a coefficient of determination (R^2) greater than 0.92 while R^2 for the between the actual TOC and that predicted using the original ΔlogR model was 0.82 (Wang et al., 2016).

Recently with advances in the fourth industrial revolution, artificial intelligence tools were extensively applied in different applications related to the petroleum industry. Artificial intelligence tools were susseccfully implemented for estimation of the formation pore and fracture pressure (Ahmed et al., 2019a; 2019b), real-time prediction of the changes in drilling fluid properties (Elkatatny, 2017; Abdelgawad et al., 2019), optimization of drilling hydraulics (Wang and Salehi, 2015), prediction of the TOC (Mahmoud et al., 2017a; 2020a; Zhu et al., 2018; 2019b; Wang et al., 2019b; Siddig et al., 2021), prediction of the recovery factor (Mahmoud et al., 2017c; 2019d), estimation of rock mechanical parameters (Mahmoud et al., 2019c; 2020b; 2022a; 2022b), characterization of the heterogeneous hydrocarbon reservoirs (Mohaghegh et al., 1994), prediction of the formation porosity (Gamal et al., 2021), evaluation of the integrity of wellbore casing (Salehi et al., 2009; Al-Shehri, 2019), optimization of rate of penetration (Al-AbdulJabbar et al., 2018; Osman et al., 2021; Gamal et al., 2022), prediction of the formation tops (Elkatatny et al., 2021; Mahmoud et al., 2021), and others.

Recently, one of the most accurate correlations for estimation of the TOC was suggested by Mahmoud et al. (2017b). This correlation was based on the weights and biases of the optimized artificial neural networks (ANN) and it predicts the TOC from the GR, deep resistivity (DR), sonic transit time (DT), and formation bulk density (RHOB). When applied to evaluate TOC on Devonian shale, Mahmoud correlation outperformed Wang correlations.

One year later, Elkatatny (2019) optimized the ANN model for TOC estimation using the self-adaptive differential evolution algorithm, Elkatatny's model outperformed Mahmoud's model in TOC estimation for Devonian formation.

The use of the Mamdani fuzzy interference system for estimating the TOC in Barnett formations was evaluated by Mahmoud et al. (2019a). Well-log data of GR, DR, DT, and RHOB were used by the authors. The results showed that the fuzzy logic technique was able to accurately estimate the TOC.

This study aims to evaluate the predictability of two fuzzy interference systems (FIS) namely the Takagi-Sugeno-Kang fuzzy interference system (TSK-FIS) and Mamdani fuzzy interference system (M-FIS) on predicting the TOC as a function of conventional well log data of GR, DR, DT, and RHOB. The predictability of TOC using these FIS models was also compared with two of the recently developed linear-regression-based correlation.

2. Methodology

2.1. Core Samples Collection

The core samples collected for this study are from Barnett (USA) and Devonian (Canada) shale. The samples were analyzed using Rock-Eval 6 to measure the TOC, more details about the sample's preparation are reported by Mahmoud et al. (2019b).

2.2. Proposed TSK-FIS and M-FIS-Based Methodology

The two FIS considered in this study (i.e. TSK-FIS and M-FIS) were trained to predict the core-derived TOC from the GR, DR, DT, and RHOB. The FIS models were optimized using the data obtained from Barnett shale, the well logs used to learn the FIS models are shown in Figure 1, these data were introduced to the FIS and then the optimization process was started to select the optimum combination of the model's design parameters that improve TOC predictability. Both FIS were trained using part of the Barnett shale data; which was randomly selected during the optimization process, the optimized models were then tested on the remaining data of Barnett shale, and after that, they were validated on another unseen data from Devonian shale.

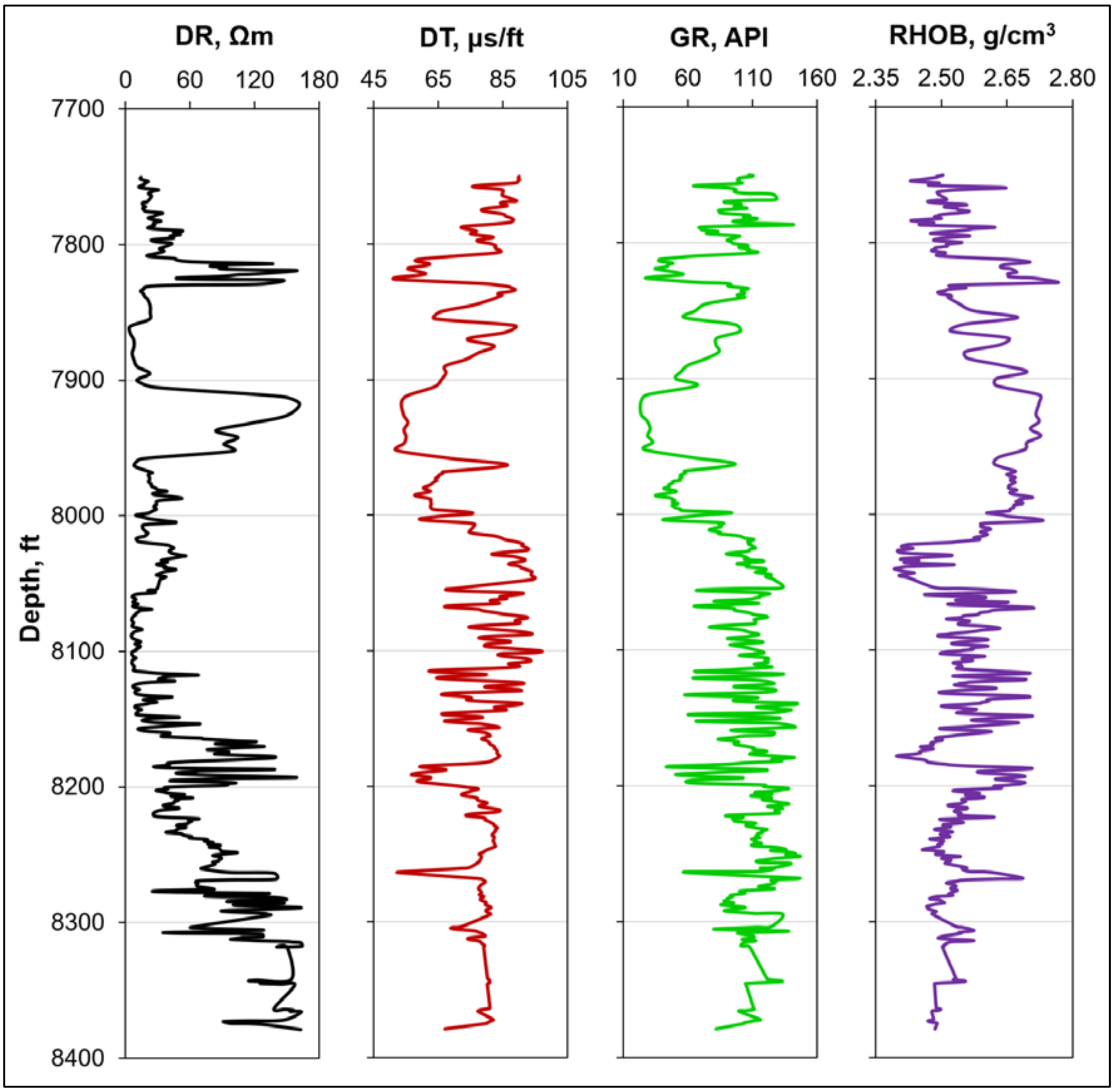

Figure 1. Well logs collected to develop the TSK-FIS and M-FIS models, this data (838 datasets) was collected from Barnett shale.

2.3. Data Description and Preprocessing

Before training the fuzzy logic models, the conventional well-log data of the GR, DR, DT, and RHOB and their corresponding core-derived TOC data were preprocessed to remove the outliers and unrealistic values. 838 datasets of the well log and core-derived TOC data collected from Barnett shale passed the preprocessing step and are considered valid to optimize the FIS models. 545 datasets were considered to train the FIS models, and the number of training datasets was selected based on the results of the optimization process. It should be noted that the training datasets (545 datasets) considered for training the TSK-FIS and M-FIS models are not the same, and the datasets that optimize the predictability of every FIS system were selected based on the optimization process.

The statistical parameters of the data used to learn and optimize both FIS models are summarized in Table 1. When new data is used to predict the TOC using the FIS models optimized in this work, it is important to ensure that this new data is within the range of the Table 1 data to ensure accurate prediction of the TOC.

Table 1. Statistical parameters of training datasets considered for TSK-FIS and M-FIS models.

Takagi-Sugeno-Kang Fuzzy Inference System					
Data points = 545	DR, Ωm	DT, µs/ft	GR, API	RHOB, g/cm^3	TOC, wt%
Minimum	4.97	50.95	23.73	2.39	0.75
Maximum	163.3	97.1	146.9	2.7	5.1
Range	158.3	46.1	123.2	0.3	4.4
Standard Deviation	40.86	9.27	24.91	0.07	1.03
Sample Variance	1670	86	621	0.0055	1.061
Mamdani Fuzzy Inference System					
Data points = 545	DR, Ωm	DT, µs/ft	GR, API	RHOB, g/cm^3	TOC, wt%
Minimum	4.97	53.78	28.07	2.39	0.76
Maximum	163.3	95.0	146.9	2.7	5.0
Range	158.3	41.2	118.9	0.3	4.2
Standard Deviation	38.95	8.24	22.31	0.07	0.98
Sample Variance	1517	68	498	0.0053	0.953

The training inputs were selected based on the results of the previous studies as well as because of their relative importance on the actual TOC. Figure 2 compares the relative importance of the GR, DR, DT, and RHOB data used to train FIS models on the actual TOC. As shown in Figure 2, TOC is strongly affected by the RHOB, while it has a moderate dependence on the DR, DT, and GR.

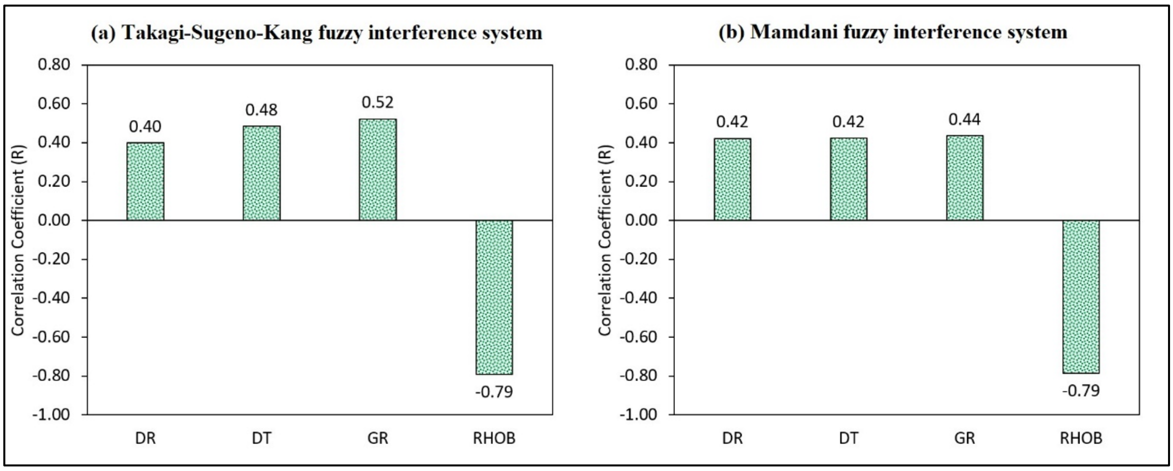

Figure 2. The relative importance of the training data for (a) TSK-FIS and (b) M-FIS models.

2.4. TSK-FIS and M-FIS Models Optimization

The TSK-FIS and M-FIS models were optimized to predict the TOC based on GR, DR, DT, and RHOB. As discussed earlier the input well logs were selected based on their relative importance on TOC. However, the selection conforms to their reported relation with TOC. The TSK-FIS and M-FIS were trained on the data collected from Barnett shale, the models were optimized using inserted *for* loops built in MATLAB software to consider all combinations of the possible values of different design parameters and the ratios of the training-to-testing data. As a result of the optimization process (sensitivity analysis), the parameters listed in Table 2 are found to optimize TOC predictability for the TSK-FIS and M-FIS models.

Table 2. Optimum design parameters of the TSK-FIS and M-FIS models.

Takagi-Sugeno-Kang Fuzzy Inference System	
Training/Testing Data Ratio	65/35
Number of Membership Functions	2
Input Membership Function	Gaussian Membership Function
Output Membership Function	Linear Function
Mamdani Fuzzy Inference System	
Training/Testing Data Ratio	65/35
Cluster Radius	0.35
Number of Iterations	300

3. Results and Discussion

3.1. Training the TSK-FIS and M-FIS Models

The TSK-FIS and M-FIS models were trained and optimized for their design parameters and the ratios of the training-to-testing data using the datasets collected from Barnett Shale. As mentioned earlier, 545 datasets which represent 65% of the total data collected from Barnett shale for training purpose was found to optimize the TSK-FIS and M-FIS predictability for the TOC. It should be noted that the training datasets (545 datasets) considered for training the TSK-FIS and M-FIS models are not the same, and the datasets that optimize the predictability of every FIS system were selected based on the sensitivity analysis. The optimum design parameters of the FIS models are reported in Table 2. As shown in Figure 3, the optimized TSK-FIS model was able to estimate the TOC with AAPE of 7.12% and R of 0.968, while the M-FIS model predicted the TOC with AAPE and R of 7.48% and 0.962, respectively. Visual comparison of the actual and estimated TOC also confirms the high accuracy of both FIS models in predicting the TOC for the training data (Figure 3).

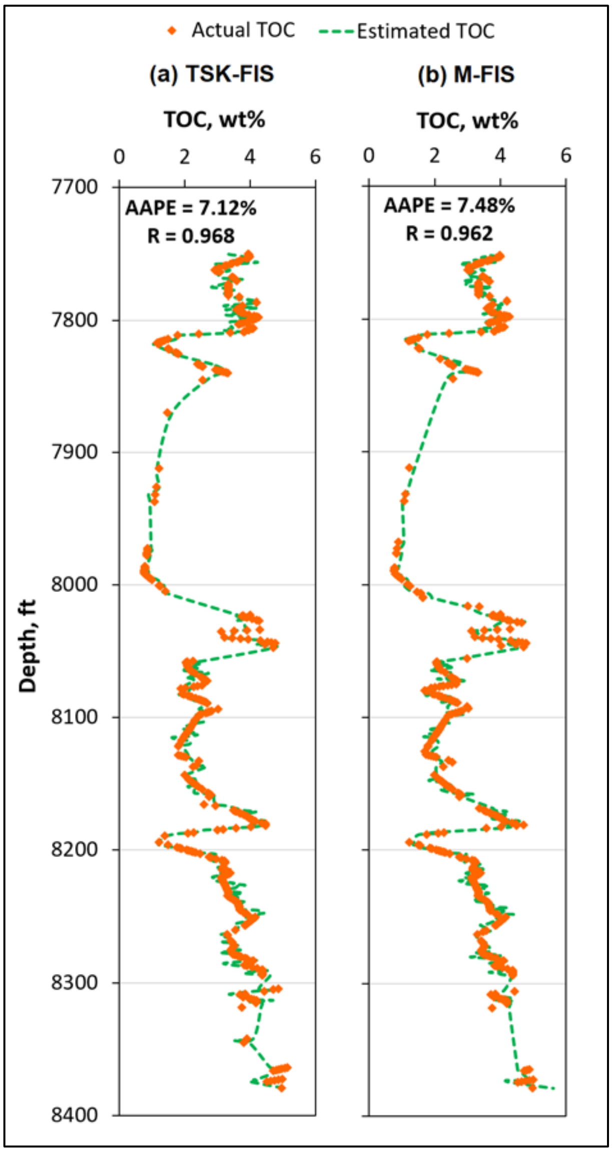

Figure 3. Comparison of actual and predicted TOC using the optimized (a) TSK-FIS and (b) M-FIS models for the training data.

3.2. Testing the TSK-FIS and M-FIS Models

The remaining 35% of datasets collected from Barnett shale were then used to test the predictability of the trained and optimized FIS models. As shown in Figure 4, both FIS models estimated the TOC for the testing data with high accuracy. The AAPE's for the TOC predicted with TSK-FIS and M-FIS models are 11.20% and 11.10%, while the R's are 0.918 and 0.933, respectively. Visual comparison of the actual and estimated TOC also confirms the high accuracy of the TSK-FIS and M-FIS models in predicting the TOC for the testing

data
(Figure 4).

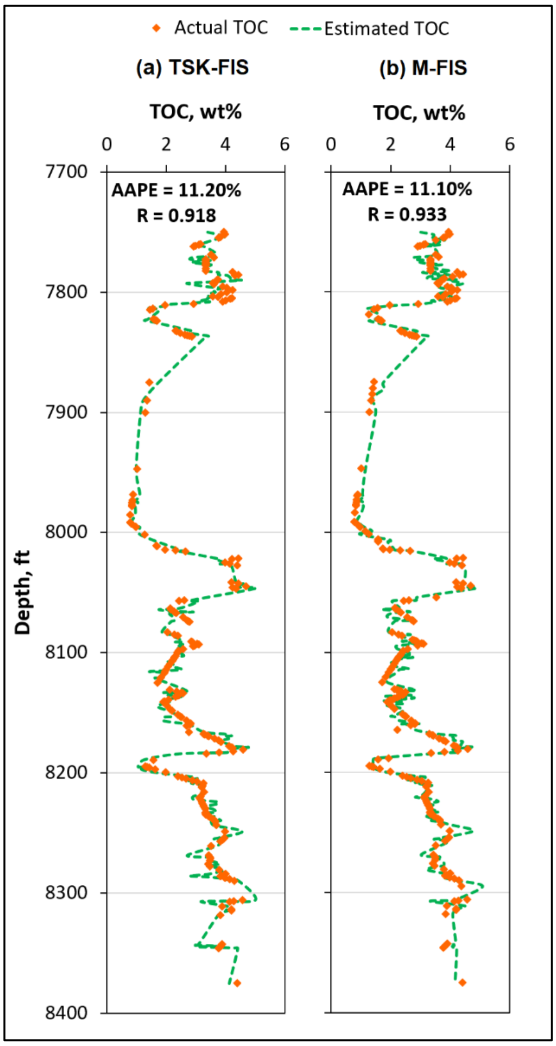

Figure 4. Comparison of actual and predicted TOC using the optimized (a) TSK-FIS and (b) M-FIS models for the testing data.

3.3. Validating the TSK-FIS and M-FIS Models

Unseen data collected from Devonian shale which is different than the formation used to train and test the TSK-FIS and M-FIS models were used to validate the optimized models. 22 core-derived TOC values and their corresponding well logs were collected from Devonian shale, 20 and 19 of these datasets were found to fit within the ranges of the data used to train the TSK-FIS and M-FIS models (Table 1). The predictability of the FIS models was also compared to WDC and WSC which were originally developed to evaluate the TOC for Devonian formation (Wang et al., 2016).

Figure 5 compares the TOC predictability of TSK-FIS, M-FIS, WDC, and WSC for the validation dataset. As indicated in this figure, both FIS models outperformed Wang's correlations in estimating the TOC for the validation dataset. TSK-FIS predicted the TOC with AAPE and R of 15.62% and 0.832, respectively. M-FIS outperformed TSK-FIS and predicted the TOC for the validation data with AAPE of 13.18% and R of 0.875. Although WDC and WSC were developed based on data collected from Devonian shale, they showed the lowest accuracy compared to both FIS models, the AAPE and R for the TOC estimated by WDC are 34.6% and 0.606, while WSC predicted the TOC with AAPE of 34.58% and R of 0.806, respectively. Visual comparison of the actual and estimated TOC for the validation data shown in Figure 5 also confirms the good matching for the data predicted with the FIS models compared to that predicted with WDC and WSC.

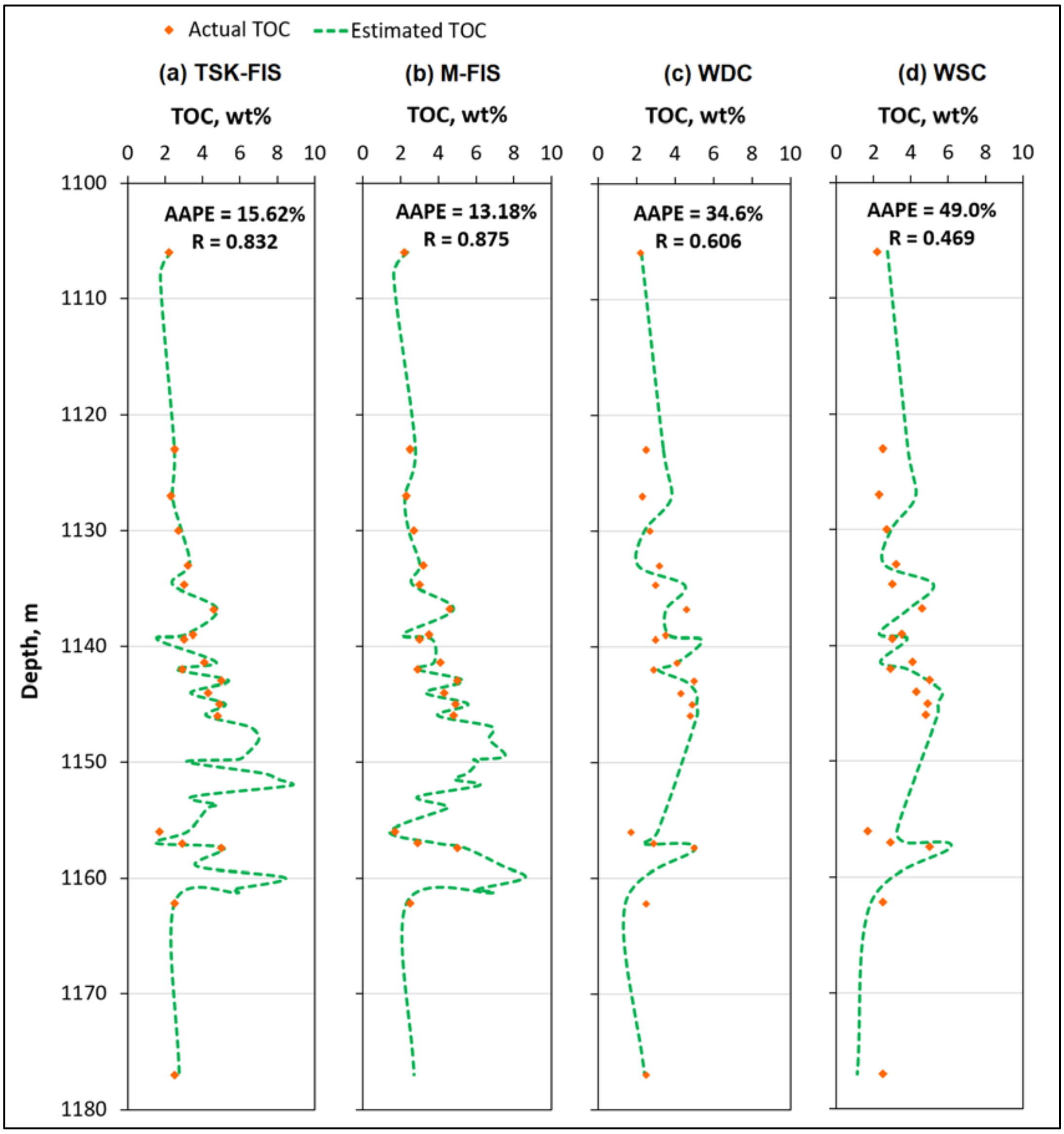

Figure 5. Comparison of actual and predicted TOC using the optimized (a) TSK-FIS and (b) M-FIS models, (c) WDC, and (d) WSC for the validation data.

4. Conclusions

In this study, four conventional well logs of gamma-ray, deep resistivity, sonic transit time, and formation bulk density and their corresponding core-derived TOC for samples collected from Barnett shale were used to optimize the TSK-FIS and M-FIS for TOC estimation. A dataset of 587 and 671 records of the four well logs and measured TOC were used to train the models, which were then tested on the same formation and validated on other data from the Devonian formation. The following are concluded out of this study:

- Both TSK-FIS and M-FIS models predicted the TOC accurately in Barnett and Devonian shale.

- M-FIS outperformed the other models in predicting the TOC for the validation data with an AAPE and R of 13.18% and 0.875, respectively.
- The optimized fuzzy logic models outperformed two recently developed correlations (WDC and WSC) in estimating the TOC in Devonian shale which is the formation used to develop these correlations.

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