A novel workflow for predicting TOC in a Utica play

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Summary

Utica is one of the major source rocks in Ohio and extends across much of Pennsylvania, West Virginia and into Quebec, Canada. The Utica is a stacked play that consists of the Utica formation and the underlying Point Pleasant formation. The geologic characteristics of these two formations such as thickness, maturation, depth, organic richness, etc., are favorable for the accumulation and production of hydrocarbons. Considering its importance, a 3D seismic dataset was acquired in order to characterize the Utica play in eastern Ohio. Identification of sweet spots, which represent the most favorable drilling targets, is the main goal for any shale resource characterization. Generally, such sweet spots can be picked up as those pockets in the target formation that exhibit high total organic carbon (TOC) content, high porosity as well as high brittleness. This can also be achieved using well log data or core analysis. However, such analyses are only possible at well locations, which are sparse and random. But, our goal is to characterize the Utica play, not vertically but laterally, so that sweet spots over different pockets can be detected, and thus we turn to seismic data. Any approach adopted for providing information about TOC, porosity and brittleness using seismic data could be useful for the delineation of sweet spots in a lateral sense. As density is an important attribute in the prediction of TOC and porosity in the Utica shale, its estimation is desired so as to identify the porous and organic rich zones. Additionally, density plays an important role in predicting brittleness when Young's modulus is considered to be an indicator.

The present study is limited to the TOC computation and consists of an innovative methodology adopted for predicting it when limited seismic as well as well-log data are available.

Introduction

The Utica play is believed to be the source rock that holds over 300 million barrels of oil and 3 trillion cubic feet of gas reserves from overlying Clinton sandstones and deeper Cambrian-Ordovician age Knox carbonates and sandstones in Eastern Ohio. The Utica play extends over close to 60,000 mi^2 (155,400 km^2) across Ohio, West Virginia, Pennsylvania, and New York. The Utica shale is about 2000 ft (610 m) deeper than Marcellus Shale, but with more or less the same general distribution (Patchen and Carter, 2012). The geological factors such as formation thickness, depth, organic richness, porosity, fracability, thermal maturation, reservoir pressure etc. are favorable for the accumulation and production of hydrocarbons. As per the US EIA, production of hydrocarbons from the Utica shale play has increased several fold in the last little while, as since 2011, more than 1700 wells were drilled till Jan 2016.

Considering the importance of the Utica play, TGS acquired a 3D seismic data in the eastern Ohio with the goal of characterizing the Utica and Point Pleasant formations in terms of sweet spots. In fact, the primary target zone in the Utica play includes the basal Utica, an organic calcareous shale, the Point Pleasant, an organic rich carbonate interbedded with calcareous shale that underlies the Utica, and the upper Trenton of the Black River group, an organic rich carbonate that underlies the Point Pleasant. The three zones represent a transgressive system tract where the shallow shelf-carbonates of the Trenton were cyclically flooded by rising seas. For the present study, the Point-Pleasant interval has been considered as the zone of interest. The interval in the target formation that exhibit high total organic carbon (TOC) content, high porosity as well as high brittleness is believed to be the most favorable drilling zone. These conclusions are based on the facts that the higher the TOC and porosity in a formation, the better is its potential for hydrocarbon generation, and the higher the brittleness, the better is its fracability. Therefore, any approach of providing information about TOC, porosity and brittleness using seismic data could be useful for the delineation of sweet spots in a lateral sense. Petrophysical modeling carried out in the target formation regionally using well log data as well as core samples reveals a strong relationship of bulk density with TOC and porosity (Patchen and Carter, 2012). Thus, organic rich and porous zones can be identified if somehow density is estimated from the seismic data. Such pockets can then be transformed into sweet spots once brittleness information is available. Attempts have been made to identify the brittle zone based on the Young's modulus and Poisson's ratio. The computation of the former requires the availability of density. Consequently, the estimation of density from seismic data is required for mapping the sweet spots laterally in the Utica play.

Methodology

There are usually two conventional ways of estimating density from seismic data. One way is to use vertical component seismic data that contains noise-free long-offset data. It can also be determined from the recorded multicomponent seismic data. However, the unavailability of either datasets in the present area of study lead us to explore other alternative methods of computing density from available seismic data. Multiattribute regression analysis and probabilistic neural network approach could be alternative ways for the purpose. But, the accuracy of this approach depends on how uniformly a sufficient number of wells are distributed on the 3D seismic data being used for reservoir characterization. While, a sufficient number of wells with density curve were found to be distributed uniformly on the 3D seismic data at hand, sonic curves were missing for most of them. The absence of the sonic curve at different wells restrains us from using them in the neural network analysis, as the time-depth relationship is a prerequisite for executing any approach on the seismic data that are recorded in the time domain. In such a scenario, sonic curves can be predicted from available density curves using Gardner's equation or an equivalent equation calibrated locally. For doing so, a crossplot of measured density and velocity available for 6 wells is generated as shown in Figure 1. A poor correlation (15%) between the attributes plotted suggests that an alternative method is required. Multiattribute analysis, in which multilinear transformation is used to predict a target log from the combinations of other logs, could have been followed if consistency had existed in terms of available measured well-logs for all the considered wells. As Gamma Ray (GR) and density curves were consistent for all the wells, P-velocity was crossplotted with GR sonic curves as shown in Figure2a. The cluster of points on the crossplot show a correlation coefficient of 0.68, which is better than obtained between P-velocity and density. However, while the linear relationship is indicated for a majority of points, for those points enclosed in the ellipse and which are coming from our zone of interest, the linear relationship would overestimate the P-velocity. In Figure 2c (left-track), we illustrate the overestimated sonic curve in red compared with the measured curve in blue in a well where the data was available in the zone of interest. Similarly, when synthetic seismograms are generated using overpredicted sonic curves and compared with the real seismic data, a mismatch is noted in the zone of interest. Examination of the points enclosed in the ellipse and which are coming from our zone of interest in Figure 2a suggests that these points exhibit low values of GR. This seems contradictory to what is generally observed, i.e. high GR response being related with organic richness. Another interesting observation from the regional analysis over the Utica play is that the organic richness is correlated more with the carbonate content (Patchen and Carter, 2012). As porosity and organic richness both affect the sonic and density curves in a similar manner, a positive relationship must exist between them in our zone of interest. A second look at Figure 1, especially for points in the ellipse does indeed show a low velocity, low density and low GR. It should therefore be possible to correct the overprediction of sonic curves by considering the density curves.

Correction for over prediction of P-velocity

In our attempt to correct for the overprediction of P-velocity, especially in the zone of interest, we first compute the difference between the measured and predicted P-velocity values and overlay them on the flipped density curve. With a bit of scaling applied to the curves it is observed that the two curves overlay each other. A similar observation is made for all the other wells. A crossplot of density versus delta V_P, shows the difference between the measured and predicted P-velocity, shown in Figure 2b exhibits a linear relationship. This relationship was then used to predict delta V_P from the available density curves, which are far more than the sonic curves. In Figure 2c, we see a very good match between the predicted and measured sonic curves on the right track. Thus when the overestimated sonic curve is predicted using the GR curve, a correction is made by considering the density log curve.

Furthermore, not relying just on the visual examination, when the predicted and measured sonic log curves are crosscorrelated, a large correlation coefficient is seen, which adds confidence in the predictions made by the workflow. This workflow is found useful in the present analysis as the GR and density curves are available in a large number of wells over the 3D volume, and are also uniformly distributed. These are then used to predict reliable sonic log curves, which in turn are used to obtain the depth-time relationships for well ties, where a high correlation coefficient is observed. With the availability of sonic and density curves at uniformly distributed wells over the 3D seismic volume, it is now possible to make use of multiattribute regression and neural network workflows for determination of density as discussed below.

Density prediction using neural network approach

The probabilistic neural network (PNN) implementations have been applied to a variety of geophysical problems (Leiphart and Hart, 2001; Hampson et al., 2001). In such an approach, a nonlinear relationship is determined between seismic data as well as its various attributes and petrophysical properties. The determined relationship is then used to predict the desired properties away from the well control. For the present study, a multiattribute linear regression and PNN are implemented to predict the density volume for estimating the TOC volume. We first derive the relevant attributes for our study by applying a prestack simultaneous inversion to conditioned gathers using partial-angle stacks, a reliable low-frequency model and angle-dependent wavelets. The attributes derived from the simultaneous inversion are P-impedance, S-impedance, Lambda-rho, Mu-rho, E-rho, and Poisson's ratio volumes. A combination of these different attributes are input to the multiattribute regression and PNN process to predict density. An important aspect of this method is the selection of seismic attributes to be considered in the neural network training. To that effect, a multiattribute stepwise linear regression analysis (Hampson et al., 2001) is performed using available uniformly distributed wells. An optimal number of attributes and the operator length are selected using the crossvalidation criteria (Hampson et al., 2001) where one well at a time is excluded from the training data set and the prediction error is calculated at the excluded well location. The analysis is repeated for all the wells, each time excluding a different well. An operator length of 9 samples exhibited the minimum validation error with 6 attributes. The attributes are Poisson's ratio, E-rho, relative impedance, absolute P-impedance, S-impedance and a filtered version of the input seismic data. Using these attributes, the PNN was trained. A correlation of 98.12% is noted between predicted and measured densities at the well locations. After training, a validation process was followed, which showed a correlation of 93.59% at the well locations. A representative section from the predicted density volume along an arbitrary line that passes through different wells is shown in Figure 3. The measured density curve is inserted as a variable color log on this section. A very good match between the inserted curve and predicted density is seen. Such a match enhances the confidence in the analysis of predicting density. A variation of density values within the zone of interest is also noted as we go from the northern to the southern side of the 3D survey.

Density/ TOC transformation

Kerogen or organic matter exhibits low density compared with the primary density range of minerals in mudrocks. Hence, density decreases as TOC content increases. A similar observation is found to exist in the Utica-Point Pleasant formations. The density and TOC measurement made on the core samples in the zone of interest are crossploted by Wang et al. (2016) as shown in Figure 4(a). Five representative wells from the Appalachian basin and close to the area of our interest are used to generate this crossplot. A strong linear relationship is seen between density and TOC as expected. Furthermore, this relationship is calibrated with the available core data for the present area of study. Figure 4(b) shows the match between predicted TOC and measured from the core samples for the area of study after proper calibration. A reasonable match between them endorses the relationship which is then used to transform the predicted density volume into a TOC volume. To map the variation of TOC content laterally, a horizon slice from its volume over a 10 ms window in the zone of interest is generated as shown in Figure 5, low TOC zones are indicted by yellowish and bluish colors, whereas black and grey colors represent high TOC zones. Note that the northern part of the survey exhibits a higher TOC content than the southern zone which is consistent with the prior information available regionally and matches the available production data (green circles).

Conclusions

In order to identify the organic rich zones for the Utica play, an innovative workflow has been demonstrated which makes use of a probabilistic neural network approach to predict density and core data analysis to transform it into a TOC volume. Examination of the TOC volume shows that the upper part of the Point-Pleasant interval exhibits a higher TOC content than the lower. A reasonable match of available production data with the organic rich zones has added confidence in the analysis of TOC prediction.

Acknowledgement

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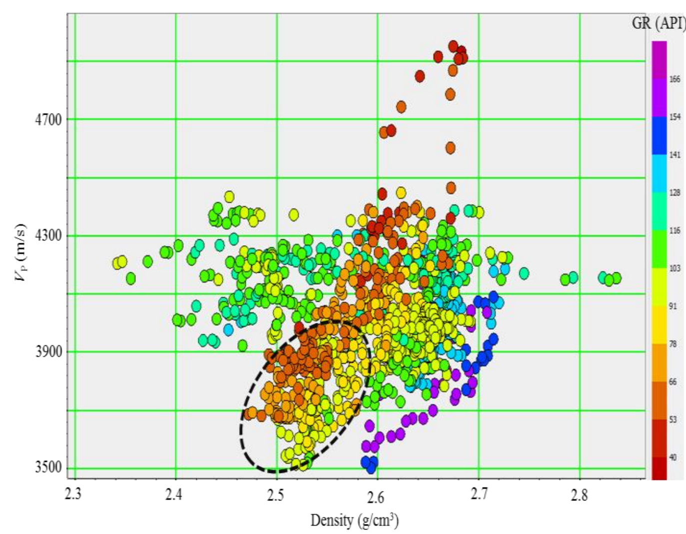


Figure 1: Crossplot of V_p versus density for available wells that have measured curves, color-coded with Gamma Ray values. A poor correlation (15%) suggests that this empirical method cannot be used. Points enclosed by ellipse exhibit low values in all the measured logs used in this crossplot. (Data courtesy: TGS, Houston)

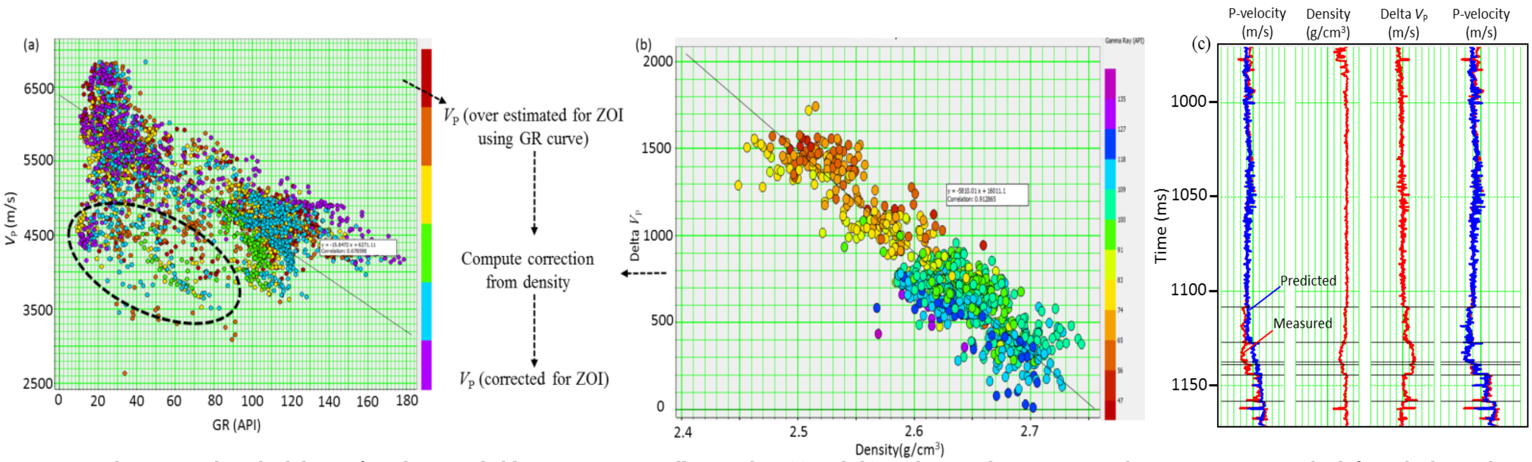


Figure 2: The proposed methodology of predicting reliable sonic curves is illustrated in (a) and (b), and its implementation is shown in Figure 2c. The left track shows the over-predicted sonic curve compared with the measured one. The right track shows a similar comparison when proposed methodology is used to predict the sonic curve. A very good match between the predicted and measured sonic curves enhances our confidence in using the approach. (Data courtesy: TGS, Houston)

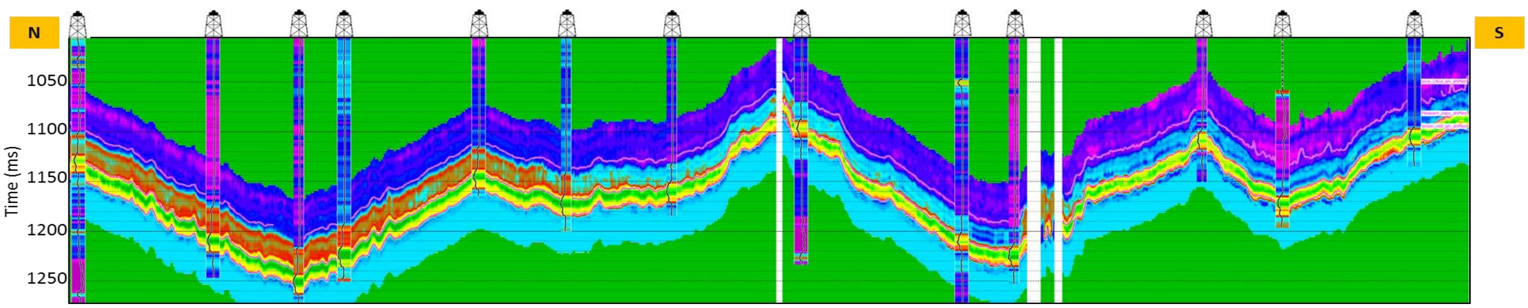
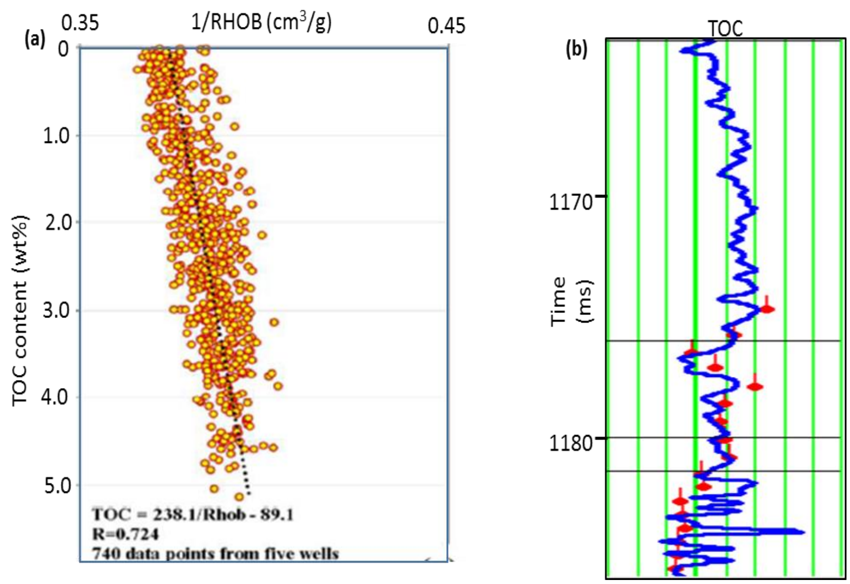


Figure 3: Predicted density section using the neural network approach along an arbitrary line that passes through different wells. Measured density logs have been inserted as variable color strip log. A variation of density can be seen vertically as we go from the Utica to Trenton intervals. Additionally, lateral variation of density can be noticed within the individual intervals. (Data courtesy: TGS, Houston)

Figure 4: (a) Crossplot of measured bulk density versus TOC content from core samples in five wells from Appalachian basin and close to the area of study. A linear relationship exists between them. (b) Comparison of predicted TOC (blue) and TOC measured from the core samples (red-dots) for the area of study when equation shown in Figure 4a was used to predicted TOC after being calibrated properly. A reasonable match between them endorses the used equation for the transformation. *(Modified from Wang et al., 2016)* (Data courtesy : TGS, Houston)



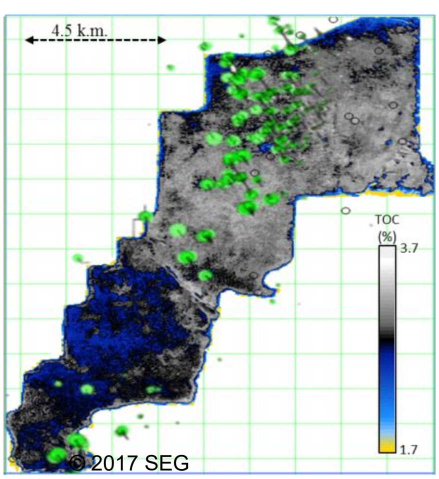


Figure 5: Horizon slice from the predicted TOC volume over a 10 ms window in the zone of interest. Low TOC zones are indicated by yellow and blue colors, whereas black and grey colors represent high TOC zones. Notice that northern zone exhibits the higher TOC content than of southern zone, which is consistent with the prior information available regionally and matches with the available production data (green circles). (Data courtesy: TGS, Houston)

EDITED REFERENCES

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