[PS]TOC Prediction Analysis of Utica-Point Pleasant Formations in the Appalachian Basin*

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Abstract

Total organic carbon (TOC) content is one of the most important parameters in shale gas and oil exploration and development. Core and cutting test data, well logs, and seismic data all can provide certain information of TOC content. However, the most feasible method to analyze the vertical and lateral distribution of TOC is to calibrate well log interpretation with core analysis data. The TOC prediction from well log data is not a trivial task. Uranium from spectral gamma ray log or normal gamma ray (GR) log has been used as an important proxy of TOC content in many shale plays, for instance the Marcellus Shale in the Appalachian Basin. However, as we move to the Utica-Point Pleasant formations in the same basin, Uranium and GR log lose their power. A potential reason could be that organic-rich shale in Utica-Point Pleasant formations was deposited in a relatively shallow (<100ft), well oxygenated water body with possible seasonal anoxia. As a result, most uranium was dissolved in the water and did not deposit into the rock with organic matters Therefore, we should utilize other logs such as density. There are some problems with using density for TOC interpretation. First, it is hard to determine the density of shale matrix: density varies in different minerals from 2.5 to 3.0 g/cm^3. This problem becomes more serious when pyrite, siderite, and barite exist in shale. The physical density of organic matter varies also from 0.95 to 1.6 g/cm^3 with different thermal maturity, burial depth, and organic matter type. Given that different types of fluids in the pores with a range of densities from 0.3 to 1.1 g/cm^3, TOC content can look like porosity in the density log. Thus, for TOC prediction, we should combine density log with other types of logs such as GR, neutron and PE curve to evaluate the mineral composition for matrix density and porosity in shale. For example, we grouped all the minerals in shale to silica minerals, clay minerals, carbonate minerals, and trace heavy minerals (e.g., pyrite) to estimate the matrix density using density, PE, and GR logs. Thermal maturity serves as an indicator of organic matter density and hydrogen types in the pores. With careful evaluation of matrix density, organic matter, and fluids, the TOC prediction from density logs becomes more reliable.

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Introduction

Total organic carbon (TOC) content is one of the most important parameters in shale gas and oil exploration and development. Core and cutting test data, well logs, and seismic data all are able to provide certain amount of information about TOC content. However, as tending to analyze the vertical and lateral distribution of TOC, well logs that are calibrated with core analysis data are the most reliable. TOC prediction from well log data is not a trivial task.

Even though there are multiple logs that can be used for predicting TOC content, each of them has its own problems. Uranium from spectral gamma ray log or normal gamma ray (GR) log has been used as an important proxy of TOC content in many shale plays, such as the Marcellus Shale in the Appalachian Basin. However, for the Utica-Point Pleasant formations in the same basin, Uranium and GR log lose their power. We think this might be as a result of depositional environment. Due to the difference of mineral and kerogen density, density log is another broadly used proxy of TOC content. Nonetheless, there are some issues with using density log for TOC interpretation. Two main issues are: (1) it is difficult to determine the shale matrix density, and (2) it is hard to differentiate the TOC content and porosity in shale. These difficulties cause a complex, non-linear relationship between density log and TOC content. ΔLogR method utilizing resistivity log and acoustic log is another potential and popular technique. However for the Utica-Point Pleasant formations, the absence of acoustic log and the stability of resistivity log have limited the utilization of this method. In this research, these three methods were estimated using 740 data points in five wells with systematic sampling (constant interval: 0.5 ft).

Besides establishing an explicit relationship between TOC content and well logs, the advanced mathematical methods neural network and support vector machine could combine the multiple well logs together to predict the TOC content. In this way, it will build a black box between well logs and TOC content: an implicit relationship. This method could overcome the problems existed in the three methods mentioned above.

Geological Background

The Utica-Point Pleasant formations, covering most of the Appalachian basin, were deposited above the Trenton Platform, during Early-Middle Ordovician. The burial depth in Ohio is relatively shallower and becomes deeper in the eastern Appalachian basin.

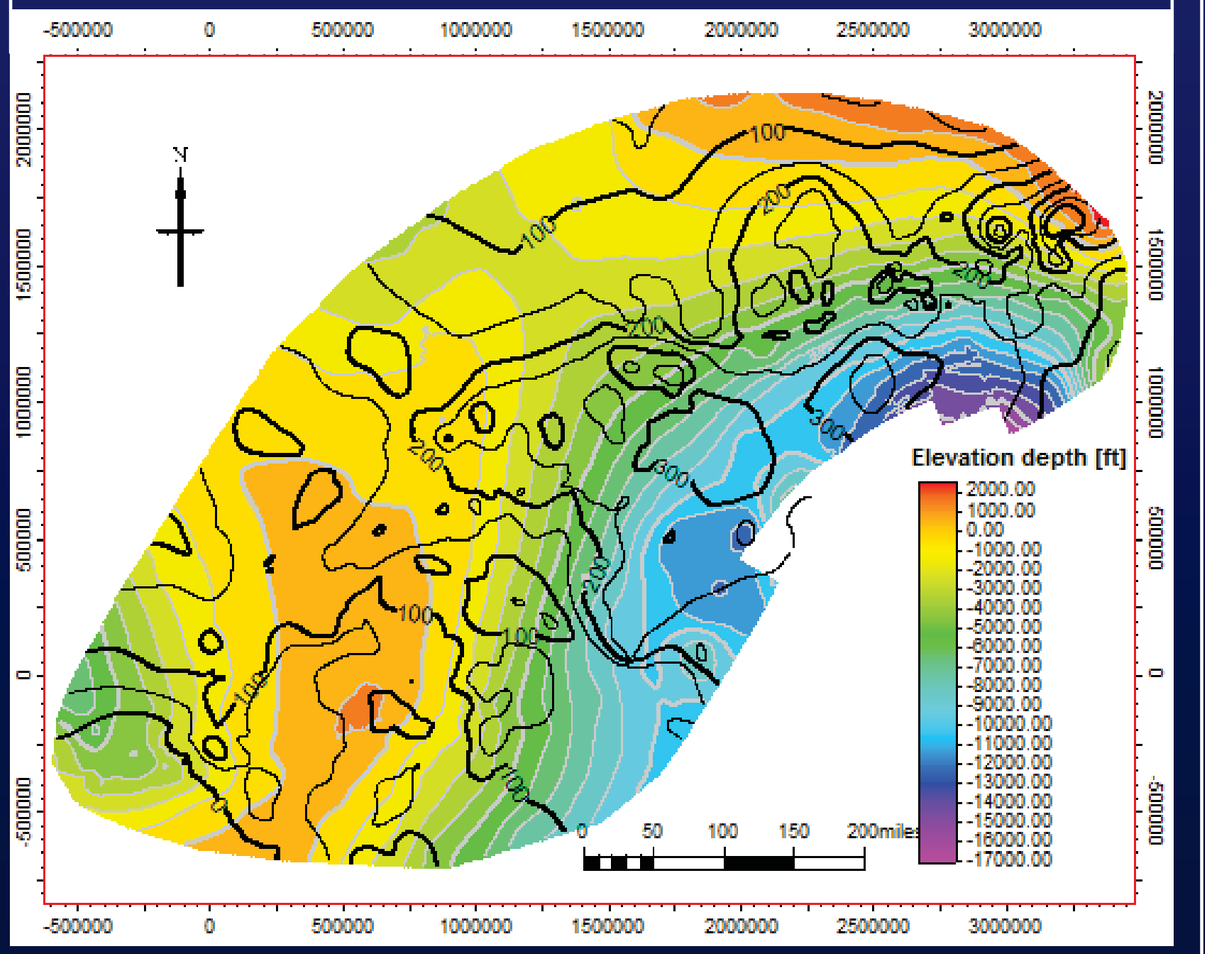

Figure: Structural contour map and isopach map of Utica-Point Pleasant formations.

TOC wt% or vl%?

TOC content is measured using unit of weight percentage (wt%). However, the contribution of different minerals and organic matter to the log response is summed on the basis of volume percentage (vl%). For example, the bulk density is

$$\rho_{rock} = \sum_{i=1}^{N}(\rho_{Mi} \times vl\%_{Mi}) + \rho_{kero} \times vl\%_{TOC} + \rho_{pore} \times vl\%_{pore}$$

where, ρ_{Mi} and $vl\%_{Mi}$ are the density and volume percentage of mineral ***i*** (1~*N*), respectively.

Thus, it would be better to use vl% than wt% for the petrophysical analysis of TOC content. To convert the wt% to vl% for TOC, assume the total weight of rock is W,

$$vl\%_{TOC} = \left(\frac{W \times wt\%_{TOC}}{\rho_{kero}}\right) / \left(\frac{W}{\rho_{rock}}\right) = \frac{\rho_{rock} \times wt\%_{TOC}}{\rho_{kero}}$$

If the density of kerogen ρ_{kero} is a constant and the relationship between $vl\%_{TOC}$ and wireline log is $vl\%_{TOC} = f(log)$

$$wt\%_{TOC} = \frac{\rho_{kero} \times vl\%_{TOC}}{\rho_{rock}} = \frac{\rho_{kero}}{\rho_{rock}} f(log)$$

For example, a linear relationship between $vl\%_{TOC}$ and Uranium concentration becomes

$$wt\%_{TOC} = \frac{\rho_{kero}}{\rho_{rock}}(mUran + n) = M\frac{Uran}{\rho_{rock}} + N\frac{1}{\rho_{rock}}$$

Or $wt\%_{TOC} \times \rho_{rock} = M \times Uran + N$

where M (constant) is from $m \times \rho_{kero}$, and N from $n \times \rho_{kero}$. Volume percentage were used for uranium and density analysis.

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Uranium Loses Its Power?

In most organic-rich mudrocks (e.g., Marcellus Shale, Barnett Shale), uranium concentration is a good indicator of TOC content (Boyce and Carr, 2010; Wang and Carr, 2012), which is related to the depositional environment and process. Consequently, it is widely used to predict TOC content of shale gas/oil reservoirs. However, in Utica-Point Pleasant formations, the relationship between uranium concentration and TOC content is not clear (Figures below). This has caused confusion, especially the fact that in the same basin Marcellus Shale shows good relationship between uranium and TOC content.

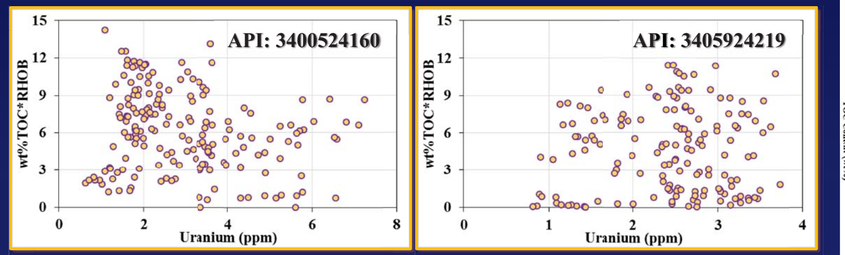

Figure: The relationship between uranium concentration and TOC content of Utica-Point Pleasant formation in two wells.

We think about three reasons for this behavior: (i) the amount of dissolved uranium in water body is relatively lower for Utica-Point Pleasant formation than Marcellus Shale; (ii) the Utica-Point Pleasant formations was deposited in a relatively shallow (<100ft), well oxygenated water body with possible seasonal anoxia; consequently, most uranium was dissolved in water and did not deposit into the rock with organics; (iii) clay minerals contribute significantly to the uranium concentration (area A in figure blow), and the increase of uranium concentration due to organic matters is blurred by clay minerals (area B in figure below), especially the low TOC content in Utica-Point Pleasant formations.

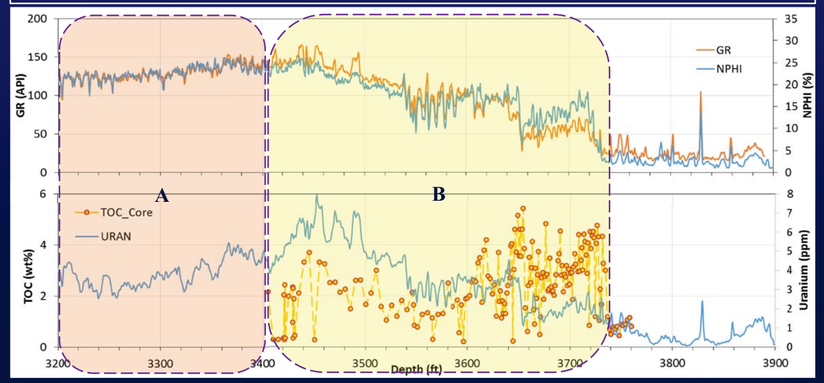

Figure: The effects of organic matters and clay minerals on uranium concentration in Utica-Point Pleasant formations

TOC Prediction by Density Log

Generally, kerogen, or organic matter, has density of 0.95~1.6 g/cm^3, which is much smaller than the primary density range (2.5~2.8 g/cm^3) of minerals in mudrock. Therefore, the increase of TOC content decreases the bulk density of mudrock. Thus, high bulk density from wireline logs indicates lower TOC content. This trend is clear in Utica-Point Pleasant formations as shown in the left figure below.

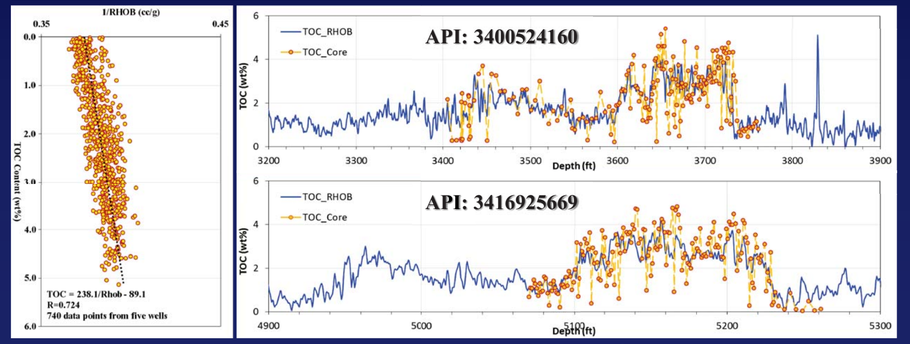

Figure: (left) the cross plot of bulk density from wireline log and the measured TOC content from core samples in five wells; (right): the comparison between the predicted TOC by density log and the measured TOC in two wells.

The variation in the mineral composition of mudrock (figure below) could alter the matrix density significantly. For instance, the presence of pyrite, a common mineral in organic-rich mudrock with the density of 4.99 g/cm^3, can escalate the matrix density. As a result, the samples with same TOC content might have different bulk density (figure above). In many local areas, the errors between the core-measured TOC values from core and the density-predicted TOC are large. Meanwhile, it is hard to differentiate the effect of porosity and kerogen on bulk density. Depending on the fluid types filled in pores, the density of pores varies from 0.3 to 1.1 g/cm^3.

Even though problems exist, density log is still a good candidate to predict TOC content in Utica-Point Pleasant formations, since that density log is available in most wells, is good at showing the trend of TOC change vertically, is easy to use, and usually doesn't require normalization among wells which is another entangling issue for the other logs, like neutron.

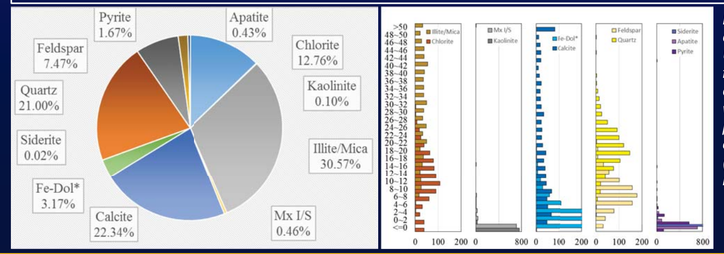

Figure: mineral composition features of Utica-Point Pleasant formation on the basis of core and cutting samples with total of 849 data points. (left): the average of mineral concentration; (right): histogram of minerals.

TOC Prediction by ΔLogR Method

ΔLogR method was proposed by Passey et al. in 1990, which used the overlaying of deep resistivity log and acoustic log to predict TOC content.

$\Delta LogR = \log(RT/RT_{base}) + 0.02(DT - DT_{base})$ & $TOC = \Delta LogR \times 10^{(2.297-0.1688\times LOM)}$

To use this method, the baselines of resistivity log and acoustic log (or neutron log or density log) should be determined. And, LOM (Level of Organic Maturity) should be set on the basis of thermal maturity. In addition, if acoustic log is not available, which happens commonly, neutron log or density log can be used instead. Therefore, ΔLogR method is affected by many factors, which limits its application for TOC prediction.

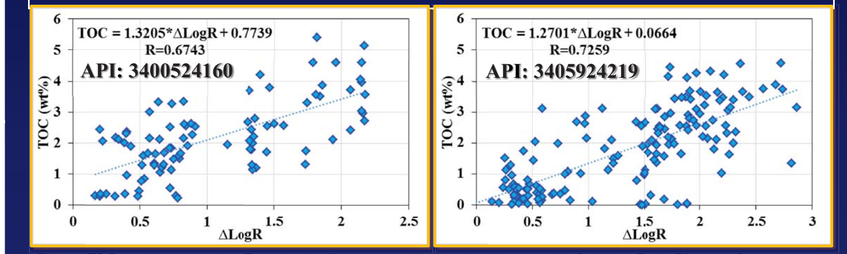

Figure: TOC prediction by ΔLogR using the linear regression method in two wells for Utica-Point Pleasant formation.

Among the five wells with systematic sampling, two wells have acoustic log and resistivity log (Figure above). The baseline for resistivity log in the two wells is 10 and 60 ohmm, respectively. The baseline for acoustic log is 78 and 66 μsec/ft, respectively. Due to the difficulty of determining LOM, the linear regression method is used to predict TOC content by ΔLogR. Figure below shows the comparison among, core-measured TOC, and the predicted TOC by density and Passey method.

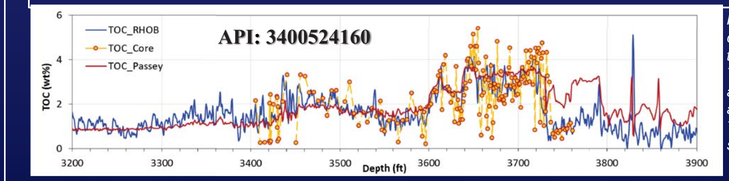

Figure: the comparison of the predicted TOC by ΔLogR and density and measured TOC by core samples.

Neural Network and Support Vector Regression for TOC Prediction

Petroleum geologists and engineers prefer to establish the explicit formula with physical meanings for logging analysis. TOC prediction is one example. However, due to the complex relationship among different parameters, finding a linear formula that includes all the complexities is not possible. For instance, the change of mineral composition, porosity, and fluid causes a complex relationship between density log and TOC content.

Artificial neural network (ANN) and support vector regression (SVR) are good at solving non-linear complex problems. Therefore, we investigate the effectiveness of ANN and SVR for TOC prediction by multiple wireline logs.

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ANN Architecture and Results

We tried different combinations to find the best ANN design for TOC prediction. First, we selected the logs that are sensitive to TOC prediction and are available in a large number of wells Density log (Rhob), deep resistivity log (RT), neutron log (NPHI), photo-electron log (PE), and gamma ray log (GR) were assigned as the inputs. Instead of directly using these logs, we derived five parameters for the inputs: Rhob ($= Rhob$), LogRT ($= Log(RT)$), Umaa ($= PE * Rhob$), Vclay_NPHI ($= (NPHI_{log} - NPHI_{base1})/(NPHI_{base2} - NPHI_{base1})$) and Vclay_GR ($= (GR_{log} - GR_{base1})/(GR_{base2} - GR_{base1})$).

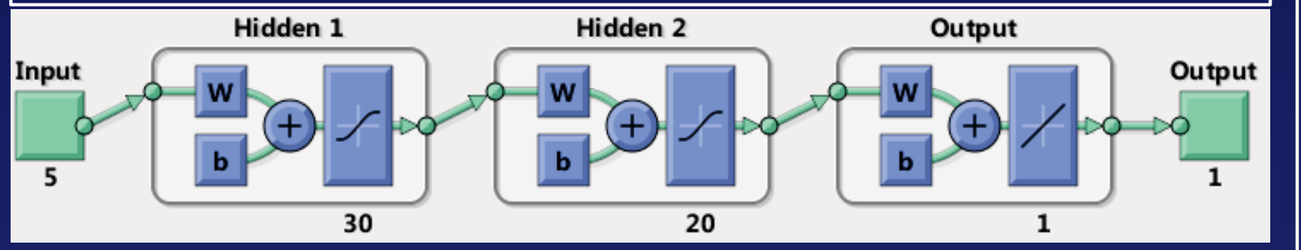


Figure: Artificial Neural Network architecture with layers of input, hidden, and output

Another important issue is the determination of the number of the hidden nodes and layers. Therefore, we tested 18 ANN architectures with 1~2 hidden layers and 10~60 hidden nodes. For each architecture, we run three training processes. As shown below, the ANN architecture with 30 nodes in the 1st layer and 20 nodes in the 2nd layer works best, with training and testing R value up to 0.81 and 0.81, respectively. The TOC prediction has been improved by using ANN and five inputs. Meanwhile, this results indicate that the generalization of this ANN model is very well.

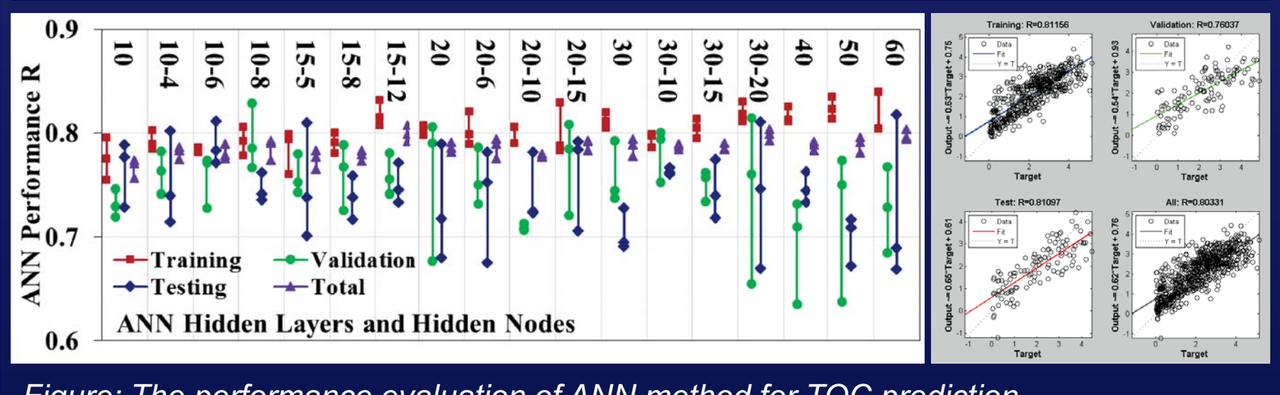


Figure: The performance evaluation of ANN method for TOC prediction.

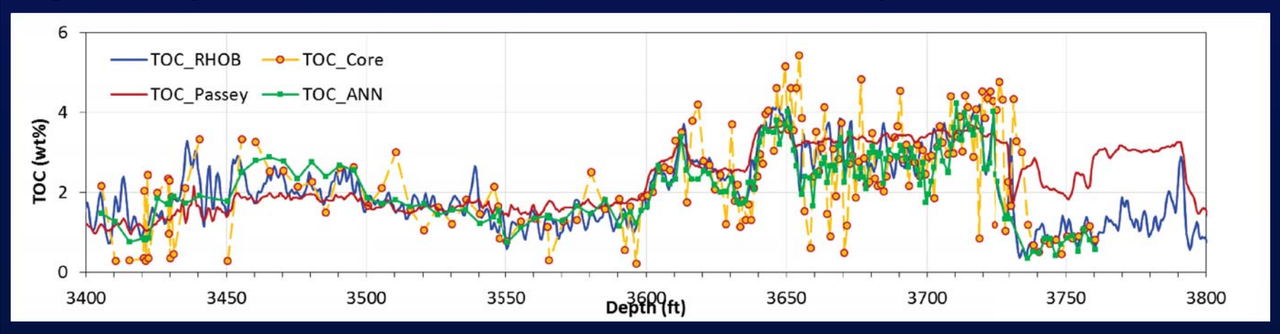
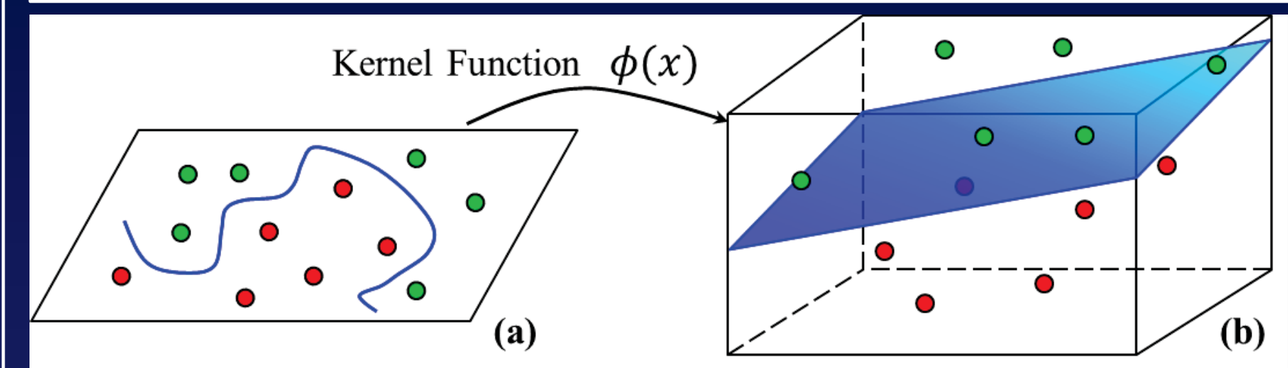


Figure: Comparison of the predicted TOC by ANN with TOC results by other methods.

SVR Architecture and Results

SVR is effective in representing system's complexity. Briefly, SVR transforms the *N* input variables from *N*-dimension to higher dimension by kernel function, possible to represent the system by relatively simple formulas.



To develop the SVR method, kernel function and its related parameters should be determined. Four kernel functions have been developed and widely used: linear kernel, polynomial kernel, radial basis function (RBF) kernel, and sigmoid kernel. In addition, mixture of polynomial and RBF kernel functions have become a new kernel function, called mix kernel function (MKF). Gridding search was to find the related parameters for each kernel.

The performance was majorly evaluated by the R values of training dataset and testing dataset (table below). Compared with the other kernel functions, MKF performs the best, with R values up to 0.92 and 0.78 for training and testing, respectively. Even the training R value by SVR is better than that of ANN, although the testing R by ANN is better. This shows over-fitting in the SVR model. As testing R is more important than training R, ANN works better than SVR in the TOC prediction.

Table: The performance evaluation of SVR method for TOC prediction. MKF: mixed kernel; RBF: radial base function.

Kernel Function	Training				Testing				Total			
	R Value	MSE	Ave. Err	Max. Err	R Value	MSE	Ave. Err	Max. Err	R Value	MSE	Ave. Err	Max. Err
Linear	0.754	0.823	0.647	2.264	0.765	0.794	0.620	1.813	0.760	0.814	0.638	2.851
Polynomial	0.735	0.851	0.645	2.468	0.760	0.826	0.672	2.011	0.739	0.843	0.654	2.468
RBF	0.791	0.768	0.551	2.375	0.760	0.813	0.619	2.528	0.783	0.783	0.573	2.528
Sigmoid	0.755	0.822	0.650	2.321	0.770	0.790	0.617	2.455	0.762	0.812	0.639	2.455
MKF	0.919	0.505	0.315	2.041	0.783	0.780	0.603	2.369	0.880	0.607	0.393	2.403

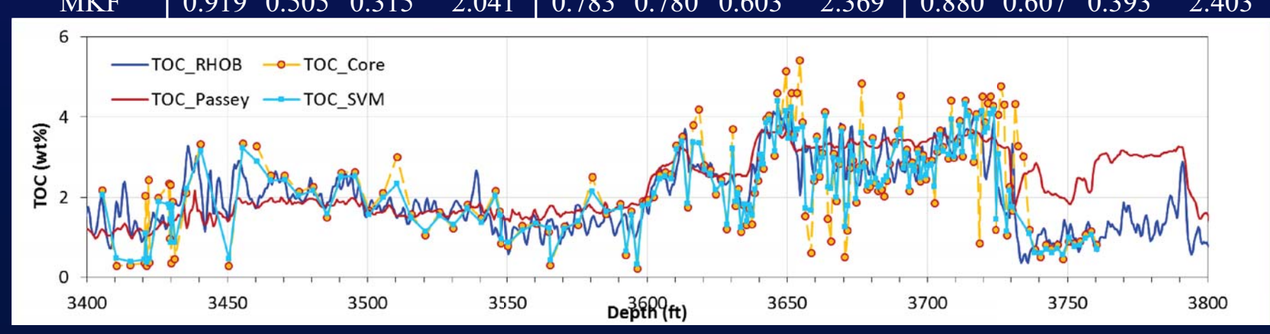


Figure: Comparison of the predicted TOC by SVR with TOC results by other methods.

Conclusion: For TOC prediction of Utica-Point Pleasant formations, density log performs better than uranium; ΔLogR works well, but it is limited due to the availability of acoustic log; ANN using five logs works better than SVR and the petrophysical analysis.