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Models for Estimating Total Organic Carbon from Well Logs

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Abstract. These days unconventional reservoir is more intense to discuss because of its potentially prospective to be produced due to the depletion of conventional hydrocarbon reserves. To find out the potential of hydrocarbons in source rocks it is necessary to analyze the content of total organic carbon (TOC) as one of its parameters. The method used to estimate the value of TOC is using well log data, the most famous and widely used is Passey's TOC model. The use of well log data is more preferred than other methods such as coring and cutting done in the laboratory as it only exists at certain points, requires a long time, and needs expensive cost. The TOC model that is obtained may not be suitable to use in all conditions of formation, therefore a summary of the TOC models are made from the results of direct tests in the fields to make it easier or as a reference for development wells. There are 25 models to predict TOC using well log data from 14 shale formation around the world, those are: Antrim Shale, Bakken Shale, Baong Shale, Brown Shale, Devonian Shales, Duvernay Shale, Goldwyer Shale, Green River Shale, Jiaoshiba Shale, Kimmeridge Formation, Longmaxi Shale, Monterey Formation, Talang Akar Formation, and Woodford Shale. These TOC models are different based on its condition. So, the TOC equation chose must be considered to the characteristics of formation.

Keyword: Unconventional Reservoir, Shale Hydrocarbon, Total Organic Carbon, Well Log

1 Introduction

The world's interest in unconventional reservoirs is very high, many papers discuss starting from determining the potential up to economical production schemes. One of the important parameters in determining this potential is the organic content in the layer, which is also defined as the Total Organic Carbon (TOC). TOC determination is usually carried out in a field scale which unfortunately requires a long time and high cost, and does not represent all depth intervals. Therefore, many methods have emerged to determine TOC based on well logging. The use of well logs was chosen because the results can be quickly available in the field, cheaper cost, utilizing commonly used log tools, and logs can record formations to all desired depths. In line with these matters, this paper contains a summary of the many TOC equations from various shale formations around the world, so that it can make it easier for researchers to learn them.

2 Total Organic Carbon Prediction Models

As it is well known that generally organic-rich mudstones have generated much of the oil and gas that resides in conventional reservoirs around the world, this type of rock is known as "source rocks" (Waliy, et al., 2020). The critical parameters related to whether or not a given rock will be a good source rock is the organic richness (generally recorded as wt% Total Organic Carbon), the current and past maturity level of the formation (generally referenced as Vitrinite Reflectance, Ro), and the organic matter type (whether the primary thermogenic product will be oil, gas, or a mixture) (Passey, et al., 2010).

2.1 Passey's Model (1990)

Passey et al. (1990) generated a model to predict total organic carbon (TOC) in source rock or clay-rich rocks based on ΔlogR separation, a separation of transit-time curve and resistivity curve. In application, the transit-time curve and resistivity curve are scaled such that their relative scaling is –100 µs/ft (–328 µs/m) per two logarithmic resistivity cycles (i.e., a ratio of –50 µs/ft or –164 µs/m to one resistivity cycle) (Passey et al., 1990). The empirical equation is:

$$TOC = \Delta logR \times 10(2.297-0.1688 \times LOM) \quad (1)$$

where TOC is the total organic carbon measured in wt%, ΔlogR is the separation measured in logarithmic resistivity cycles, and LOM is the level of organic maturity. Passey et al. (2010) established a relationship between vitrinite reflectance (Ro) and level of organic maturity (LOM), both parameters further will be used to predict TOC (Waliy, et al., 2020). The principal generation windows for oil-prone kerogen (Type I and Type II) ranges from Ro=0.5 (for early generation) through peak generation Ro=0.8, to overmature Ro>1.1 (Passey et al., 2010). From this Passey's correlation, Waliy et al. (2020) proposed a correlation to simplify the relationship between Ro and LO, as shown below for Ro of 0.2–1.1 (R^2=0.994):

$$LOM = 16.066\ Ro^3 - 48.897\ Ro^2 + 52.7\ Ro - 9.0712 \quad (2)$$

while the second equation for Ro of 1.1 – 5 is (R^2=0.9979):

$$LOM = 0.2276\ Ro^4 - 2.8826\ Ro^3 + 12.295\ Ro^2 - 17.765\ Ro + 19.539 \quad (3)$$

The ΔlogR separation can be calculated from baseline condition and organic-rich intervals with the equation below:

$$\Delta logR = Log10\ R/R_{baseline} + 0.02 \times (\Delta t - \Delta t_{baseline}) \quad (4)$$

ΔlogR is the curve separation measured in logarithmic resistivity cycles where exists at depth of 6000 ft and deeper, R is the resistivity measured in ohm.m, Δt is the transit-time measured in µs/ft, Rbaseline and Δtbaseline are the resistivity and transit-time baselined. Baseline condition can be obtained from the overlay of resistivity and transit-time curve, the directly overlay presents as the non-source rock. If a suitable transit-time curve is not available, the density or neutron curve can be subtituted (Passey et al., 1990). The determination of baseline condition for density or neutron curve is the same way to the baseline of transit-time curve. The ΔlogR separation from density and neutron curve are:

$$\Delta logR = Log10\ R/R_{baseline} + 4 \times (\Phi N - \Phi N_{baseline}) \quad (5)$$

$$\Delta \log R = \text{Log10 } R/R_{baseline} - 2.5 \text{ x } (\rho - \rho_{baseline}) \quad (6)$$

The log-derived TOC is then compared with measured TOC values from sidewall cores, conventional cores, or cutting samples obtained from six wells. For these six wells, the standard deviation of difference between calculated and measured TOC value is ± 1.4 wt. % or better (Passey et al., 1990). But some anomalous for using ΔlogR technique can be attributed to (1) conventional hydrocarbon reservoir intervals, (2) poor borehole conditions, (3) uncompacted sediments, (4) low-porosity (tight) intervals, (5) igneous rocks, (6) evaporites, or (7) overpressured zones. After all, in most cases the match is very good and has given us confidence to apply the technique in wells for which no samples are available (Passey et al., 1990).

2.2 Schmoker's Model (1981)

Schmoker (1981) established a model to determine the organic-matter content (TOC). Disseminated organic matter is the source of the large quantities of natural gas present in the Devonian Shale in the western part of the Appalachian basin (Schmoker, 1981). The facies of Devonian Shale consist high-organic matter content or black shale rather than grey shale. The shale itself mostly contains potassium-40 and constituent in the uranium and thorium decay series.
The organic content from Devonian Shale of the Appalachian basin can be calculated using gamma-ray wire-line logs. Gamma ray log is assessed has advantage of economy or less costly, available sources of data and continuos sampling of verticallly heterogenous shale section over density log. Furthermore, the gamma-ray data used are from uncased well and corrected to empty-hole condition using service-company data. So the equation is:

$$\Phi o = \frac{(\gamma_B - \gamma)}{1.378\, A} \quad (7)$$

where, Φo is the fractional volume of organic matter (TOC), γ_B is constant gamma-ray intensity assumed at a given location, γ is gamma-ray intensity, and A is the slope of the crossplot of gamma-ray intensity and formation density. The relation between natural gamma-ray intensity and organic-matter content is examined as a function of location in the Appalachian basin (Schmoker, 1981).
The test intervals range in thickness from 20 to 160 ft and average about 80 ft from 12 wells. Eventually, this method can be utilized in almost entire western part of the Appalachian basin, though outside the region that already mentioned gamma-ray intensity is not dependable indicator of organic-matter content. Unless the Cleveland member of Ohio Shale and the lower part of the Olentangy Shale, distribution of differences between volume percent of organic matter content and calculated gamma-ray log has a mean 0.44% and a standard deviation of 1.98%.

2.3 Schmoker & Hester's Model (1983)

Schmoker and Hester (1983) had investigated the organic carbon content of the upper and lower members of the Bakken Formation of The Williston basin. Organic-carbon data are calculated from compensated formation-density logs using a method resembling that applied by Schmoker (1979, 1980) to Devonian shales of the western Appalachian basin, but which is broader in concept and may prove applicable to other black shales similar to those of the Bakken Formation (Schmoker & Hester, 1983). Characteristics of this formation are high gamma-ray intensity and high density-log porosity. So, it called black shale which is rich of organic matter. And also in this formation there is pyrite, whose the amount does not available. The data of Strahl, et al (1955) and Brown (1956), and analyses from Appalachian basin well cored by U.S. Department of Energy (Morgantown Energy Technology Center), suggest a linear increase of pyrite with organic matter (Schmoker & Hester, 1983).

In an approach analogous to that used for Appalachian Devonian shales (Schmoker, 1979), the upper and lower members of the Bakken Formation are treated as a fourcomponent system consisting of rock matrix, interstitial pores, pyrite, and organic matter (Schmoker & Hester, 1983). Some of assumptions used toward the equation are the porosity in the upper and lower formation assumed to be low and does not vary enough to alter formation density significantly, the distinction density between pore-fluid types can be neglected at low porosities, furthermore pyrite content is linear increase with organic matter, and the calculation are permitted for shale that thicker than 4 ft. Therefore obtained the formula for calculating organic content from formation density:

$$\mathrm{TOC} = \frac{154.497}{\rho} - 57.261 \tag{8}$$

Value 154.497 and 57.261 are constants specifically calculated for a particular formation, member, or area. Fifty-nine data of laboratory organic-carbon of Bakken shales from 39 wells in North Dakota, with organic-carbon contents ranging roughly from 6 to 20%, provide a reasonably representative data set for comparison to calculated organic-carbon values. The average of the absolute values of the differences between organic-carbon content determined from core samples and that calculated from density logs is 1.1 % (Schmoker & Hester, 1983). For upper members of Bakken Formation show average 12.1 wt. % organic carbon content with total samples are 159, and for lower members has 11.5 wt. % with total samples are 107. So, for each member have standard deviation 3.1 wt. % and 2.3 wt. %.

2.4 Mendelson & Toksoz's Model (1985)

Meyer and Nederlof (1984) describe an approach using discriminant analysis to differentiate barren and organic-rich facies based on sonic, density, and resistivity logs (Mendelson & Toksoz, 1985). Then, Mendelson and Toksoz (1985) proposed a paper with three main objectives: supply a physical model to determine log responses relative to source rock properties, recognize high source rock potential from the logs, and determine if there are quantitative relationships between log responses and source rock properties, such as total organic carbon, measured in the laboratory.

They proposed new method a standardized multivariate least squares regression equation that permit the assessment of the importance of each log in this combined analysis, if there exist two or more independent variables which are well correlated to the dependent variable, but are uncorrelated themselves. Similarities and differences in the multivariate equations demonstrate the strengths and weaknesses inherent in using these equations as predictors (Mendelson & Toksoz, 1985).

The regression is based on combination of individual log data such as sonic, neutron-porosity, density, gamma-ray. Data that used in this case derived from the Kimmeridge Formation in The North Sea and the

Monterey Formation in California. There four wells from Kimmeridge Formation (Well A to D) and a well from Monterey Formation (Well E) that were used to generate the correlation. These correlations are:

From Well A, TOC = 0.327 DT + 0.931 NPHI – 0.18 RHOB – 0.645 GR (9)

From Well B, TOC = 0.494 DT – 0.344 NPHI – 0.077 RHOB + 0.85 GR (10)

From Well C, TOC = – 0.363 DT + 0.452 NPHI + 0.172 RHOB + 0.904 GR (11)

From Well D, TOC = 0.479 DT + 0.295 NPHI – 0.072 RHOB + 0.281 GR (12)

From Well E, TOC = 0.249 DT – 0.299 NPHI – 0.247 RHOB + 0.665 GR (13)

Standardized regression equations are more meaningful when one compares the regression equations from different wells, standard variables have a mean of zero and a standard deviation of one (Mendelson & Toksoz, 1985). After standardization, there is no obvious similarity among the five regression correlations. The log which is best correlated with TOC has the greatest weight in the regression correlation.

Well A and D is quite similar, because they have containing less water, lower matrix density, and lower matrix time travel. These are indicated there are organic matter, faster but less dense. And also Well B and C fairly similar inverse from Well A and D that indicates kerogen already change to bitumen, oil and gas. Looking for similarities like above called bivariate regression analysis. After that, get the linier multivariate regression from least square and standardized the equation. In all the result, multivariate regression has ability to predict TOC. Even though has weakness, there is no clear similarity of multivariate equation, hence the success may be rarely happened.

2.5 Hester & Schmoker's Model (1987)

For the further step Hester and Schmoker (1987) reached out the Woodford shale of Anadarko basin to estimate the quantity of organic matter. The Woodford shale itself contains black shale that extremely rich of organic matter that is probably a major source of oil and gas in the Anadarko basin. In this case to estimate the organic matter Hester and Schmoker (1987) using formation-density log. Beside using density-log, Hester & Schmoker (1987) also compare with laboratory analysis.

The "Density-log" method has several advantages over laboratory analyses: 1) the density log provides continuous measurement of the formation, reducing the statistical uncertainties of limited (and possibly non-random) spot sampling; 2) density logs are more common and more readily available than core or cuttings; 3) working with density logs is simpler and less costly than laboratory procedures (Hester & Schmoker, 1987). Equation that used for the Woodford shale is:

$$\text{TOC} = \frac{151.012}{\rho} - 55.97 \quad (14)$$

Value 151.012 and 55.97 are constants specifically calculated for a particular formation, member, or area. The density-log method is based on the straight-forward concept that the major cause of changes in the formation density of organic-rich, well-compacted shales, is variation in organic-matter content. Based on comparisons to laboratory measurements, we conclude that this concept is applicable to the Woodford shale of the Anadarko basin (Hester & Schmoker, 1987).

Based on data cumulative frequency, the differences between laboratory analysis dan density-log, shows that 68% of the differences (one standard deviation) are less than 1.4 wt.% TOC and 90% of the differences are less than 1.6 wt.% TOC. An error must be occurred because maturity, type organic matter, compaction or burial, but the density log assed adequately accurate for application to Woodford shale. This level of accuracy is sufficient for regional source-rock studies, but may not suffice for some localized geologic applications (Hester & Schmoker, 1987).

2.6 Decker, Hill & Wicks' Model (1993)

Advanced Resources International (ARI), working under contract to the Gas Research Institute (GRI), has developed a cost-effective method to determine gas content in the Antrim Shale from logs (Decker, Hill, & Wicks, 1993). Natural gas in the Antrim Shale of Michigan Basin caused by three primary processes: adsorbed on organic matter and clays, dissolved in bitumen, and as free gas in the pore volume. The reservoir and production characteristics similar to coalbed methane reservoir because covered by bitumen. Because of it, conventional reservoir engineering based cannot be used to measure the gas content, but using coal bed methane technique. Based on the stratigraphy, Antrim Shale has two classification of shale, they are black and grey shale. The high intensity of gamma ray in black shale showing organic richness within high uranium.

Decker, Hill & Wicks' Model (1993) proposed and tested the hypothesis that relationships exist between gas content and total organic carbon (TOC), and between TOC and bulk density. They assumed that the Antrim is equally gas saturated in all study wells (5 wells in their study), though not necessarily fully gas saturated, and that gas content only varies as a function of organic matter. The correlations are limited to depths of 1300 – 2100 ft and shale maturities ranging from 0.45 – 0.55 of Ro. The TOC/gas content and the TOC/bulk density relationships are:

$$\text{Gas Content} = 5 + 7.2\,(\text{TOC}) \tag{15}$$

$$\text{TOC} = \frac{2.6 - RHOB}{0.03} \tag{16}$$

where gas content in scf/ton, TOC in wt.%, and bulk density in gr/cc.

The results of the TOC/gas content relationship shows a correlation coefficient of 94%, and the TOC/bulk density relationship shows a correlation coefficient of 91% from 54 samples. Using linkage gas content and density log is possible for the first time locate and indicate gas bearing. To measure gas content using open-hole log that potentially accurate and less cost rather than core analysis. There is correlation between shale bulk density and TOC. So the elucidation is gas content will increase if TOC increases, TOC increases when shale density decreases.

2.7 Herron's Model (2011)

Herron, et al (2011) proposed a model to estimate the total organic carbon (TOC) that was applied to Green River shale of Piceance Creek basin. Lots of the Green River formation in the western United State contains immature kerogen. The formation characterized by fine-grained, low permeability, organic-rich mudstone, referred to oil shale (Allix, et al., 2010). The typical oil shale of the Green River formation are well bedded and display microlaminations (0.1 mm thick) that have been attributed by many workers to seasonal variation in amount of organic and inorganic matter settling on the bottom of the lake (Bradley, 1929).

A new model by combining magnetic resonance log with density log will provide an independent method to estimate the TOC of oil shale formations. The typical density of inorganic minerals in the Green River formation is ρ_{ma}= 2.7 g/cm^3, whereas the density of fresh water is 1.0 g/cm^3, and the density of kerogen is assumed to be 1.07 g/cm^3 (Herron, et al., 2011). So the TOC is determined as:

$$\mathrm{TOC} = 0.812\,\frac{\rho_{\mathrm{k}}}{\rho_{\mathrm{b}}}\left[\left(\frac{\rho_{\mathrm{ma}}\text{-}\rho_{\mathrm{b}}}{\rho_{\mathrm{ma}}\text{-}\rho_{\mathrm{p}}}\right)\text{-}\Phi_{\mathrm{MR}}\right] \tag{17}$$

where TOC is in g/g, ρ_k is density of kerogen in g/cm^3, ρ_b is bulk density in g/cm^3, ρ_{ma} is density of matrix (inorganic minerals) in g/cm^3, and Φ_{MR} is MR porosity.

Herron, et al (2011) said, borehole magnetic resonance logging tools are sensitive to protons, but only those in rapid molecular motion. Thus the MR logging tool is sensitive to pore water and clay bound water, but insensitive to protons in minerals. They noted that the accuracy of the density-magnetic resonance method can be compromised by: 1) lack of accurate knowledge of inorganic mineral density; 2) the presence of gas, which affects both the pore fluid density and the NMR estimate of fluid-filled porosity; and 3) a failure of the NMR porosity to include all clay bound water. The study showed that it is possible to determine the amount of organic matter by various logging techniques including nuclear magnetic resonance.

2.8 Renchun's Model (2015)

Renchun, et al (2015) generated a model for estimating TOC using bulk density. Decker, et al. (1993) proved that there was a linear relationship between TOC and bulk density, then established the relationship between TOC and bulk density for the Antrim shale, and reached the conclusion that shale rock density decreases with the decrease of TOC (Renchun, et al., 2015). The field that had been taken as the object of the experiment is Jiaoshiba shale. Jiaoshiba shale gas field located upon Sichuan basin. The shale is rich in grapolite, radiolarian, and other fossils, also have thin layers of pyrite, and a lot of scattering pyrite grains.

Basically, Renchun, et al. (2015) proposed some models to estimate TOC with different well logging responses include: the natural gamma spectroscopy model, the gamma intensity model, the bulk density model, and the ΔlogR model. But the result showed that the bulk density model has the most suitable method for this case. As it shown below:

$$\mathrm{TOC} = -15.491\,\rho + 42.708 \tag{18}$$

where the value –15.491 and 42.708 are constant number representative the location. The equation based on experiment data of 173 core samples in Well Y1 and least-square fitting. The result of TOC interpretation of major wells in Jiaoshiba gas field, and core analysis data were used to perform precision analysis. The results show that the correlation coefficient is 0.905, this model is much easier to use and wider in application, because less well logging curves are involved in this method (Renchun, et al., 2015).

2.9 Wang's Model (2016)

Wang, et al (2016) proposed revised models based on Passey's ΔlogR model (1990). They divided the Passey's model into two model, there are revised sonic-based ΔlogR and revised density-based ΔlogR. A discussion of the revision of the ΔlogR method is followed by application examples from the Devonian Duvernay shale in the Western Canada sedimentary basin to illustrate TOC estimations using the revised ΔlogR method in shale gas evaluation (Wang, et al., 2016). Recent studies in the Western Canada sedimentary basin and elsewhere suggest mineral compositions and rock texture of organic-rich shale vary considerably among different shale plays (Rokosh et al., 2010; Boak, 2012). Based on fixed parameters of mineral compositions, compaction and rock texture, the original Passey's ΔlogR model may result in biased estimates to the target shale.
Another limitation of Passey's model is, the restricted ranges of resistivity and sonic transit time due to an assumed linear approximation of the relationship between logarithmic resistivity and porosity logs, the so called 1:50 relationship (Passey, et al., 1990). The use of LOM, a much less commonly used measure of thermal alteration of organic matter, is an additional weakness of the method (Wang, et al., 2016). Passey's model is popular in conventional source rock evaluation and has been applied to unconventional resource play evaluation by many practitioners, this condition may give some biased in result estimation as the assumption in unconventional resource is much different with the conventional source rock. Hence, Wang, et al (2016) was giving revisions to ΔlogR model through equations below, revised sonic-based ΔlogR model:

$$\Delta \log R = \text{Log10} \frac{R}{10} + 0.181\ e^{(-0.026 \text{ x } \Delta t)} \text{ x } (\Delta t - 51) \quad (19)$$

For the revised density-based ΔlogR as shown below:

$$\Delta \log R = \text{Log10} \frac{R}{10} - 0.0056\ e^{(2.34 \times \rho)} \text{ x } (\rho - 2.23) \quad (20)$$

And the revised TOC estimate models could be expressed as following:

$$TOC = [1.381\ \Delta \log R + 8.593\ (GR - 15)] \text{ x } 10^{(2.81 - 0.012 \text{ x } Tmax)} \quad (21)$$

$$TOC = [5.362\ \Delta \log R + 4.532\ (GR - 15)] \text{ x } 10^{(2.52 - 0.01 \text{ x } Tmax)} \quad (22)$$

where R is the resistivity measured in ohm.m, Δt is the transit-time measured in μs/ft, ρ is density log measured in in g/cm^3, GR is gamma ray measured in API, and Tmax is the maturity indictor in ^oC. These equations showed the revision from conventional ΔlogR model which combination from sonic-resistivity to revised sonic-resistivity and density-resistivity. The major revisions include: 1) redefining ΔlogR with estimated slopes related to target shale play to remove the assumed linear approximation; 2) introducing GR as an optional term for improving TOC prediction; 3) replacing the LOM with a more commonly used thermal maturity indictor Tmax or Ro% (Wang, et al., 2016).
Several adjustments that explained such as replacing LOM with thermal maturity indicator such as Tmax. Because actually LOM is rarely used to measure of thermal alteration. Another matter is, the ΔlogR based on linear approximately, this is restricted zone with sonic transit time range. This weakness is changed into petrophysical property. And the last is put in GR as rock type indicator could cut the impact from TOC lean high resistivity "non-source rock" on TOC estimation.

Three datasets were collected in the study: 1) a Rock-Eval dataset with over 70 available data of the Duvernay Shale were generated using Rock-Eval VI at the Geological Survey of Canada, depth of which were corrected by log curves, 2) a well log data set with total of 670 log curves from over 180 wells, 3) a test data consisting of GR, resistivity, density and sonic logs and TOC measurements (Wang, et al., 2016). The correlation coefficients of the determined TOC from revised sonic-based and density-based ΔlogR model and measured ones are having result 0.92 and 0.93 respectively. The conclusion is the revised ΔlogR models is having higher correlation coefficient than the conventional ΔlogR model.

2.10 Alshakhs & Rezaee's Model (2017)

Alshakhs and Rezaee (2017) saw an increasing interest in the Goldwyer shale of the Canning basin as a potentially prospective shale play. This Ordovician shaly formation is one of the most prominent source rocks in the Canning Basin, but the limited well distribution in the large area of the Canning Basin makes a basin-wide study not warranted at this stage, a focused look into the Barbwire Terrace was carried out instead (Alshakhs & Rezaee, 2017). The Canning basin had deposited in early Ordovician and took place under different marine settings. Two primary halite form a regional seal over the Ordovician deposits. The middle Ordovician Goldwyer shale is the most prominent source rock in the section. The formation consists of two primary black shale section. The depth of the Goldwyer shale is about 1330 m and thickness is about 350 m.
Alshakhs and Rezaee (2017) delivered some new model for estimating TOC after the pre-defined models like Schmoker's model (1981) and Passey's ΔlogR model are not suitable to this area, because the result between ΔlogR model and Rock Eval shows misfit. After being analyzed maturity data from this formation tend to be ignored and frequent manipulation. Hence, this area using multivariate regression from available data in the Barbwire Terrace utilizing adjustment Schmoker's model. The model below generated by density log and received correlation coefficient of 0.5067. And the properties from this model derived from density log the Lacustrine Shale.

$$TOC = 57.65 - 21.65\ RHOB \tag{23}$$

Continue model gamma ray-density-sonic tested in Canning Basin, this model derived from gamma ray-density lacustrine shale with correlation coefficient of 0.6246. Moreover, the next model is still from lacustrine shale from density-sonic model with correlation coefficient of 0.6912. The model that firstly tested in Goldwyre shale eventually works in outside the region, it is Lacustrine shale which is has different type shale of Goldwyre shale. These models shown below:

$$TOC = 32.13 + 0.0208\ GR - 12.45\ RHOB \tag{24}$$

$$TOC = 13.88 + 0.1257\ DT - 8.37\ RHOB \tag{25}$$

Both of these models below are following the global application from Goldwyer shale model. Derived from lacustrine shale based on gamma ray-density-neutron and gamma ray-density-sonic. The first model below has correlation coefficient of 0.7036. the next model has the highest correlation coefficient of 0.7941. These models shown below:

$$TOC = 44 + 0.01618\ GR - 17.02\ RHOB - 0.0009\ NPHI \tag{26}$$

$$TOC = -8.24 + 0.01946\ GR + 0.1206\ DT - 0.3\ RHOB \tag{27}$$

However, based on logs available in the Barbwire Terrace wells, deriving TOC from gamma ray and density provided sufficiently well-validated solution of TOC. For future implementation outside the region combination gamma-ray, density, and sonic will be excellent for estimating TOC. Gamma ray and density are on behalf lithology and adding sonic for compaction property. Hence, the equation can be used even globally outside Golwyre Formation.

2.11 Manaf's Model (2017)

Manaf's model (2017) was used to analyze total organic carbon (TOC) in Talang Akar Formation (TAF), South Sumatra basin. South Sumatra basin is one of the largest resources in Indonesia with 56.11 TCF volume of gas in place. Total organic carbon was calculated by analyzing petrophysical and geochemical of shale formation and predicted by data of well log. In the study, they used well log data over the field and two of available wells contain cutting data, which is important for assessing mineral content assessment. Some of well logging data are used such as gamma ray, sonic, density, neutrons, and resistivity. The model below was derived an equation from multi-linear regression as the function of gamma ray (GR), density (RHOB), neutron porosity (NPHI), P-wave velocity (DT) (Manaf, et al., 2017):

$$TOC = -1.74 + 0.00038\ GR + 0.0062\ DT + 1.023\ RHOB - 0.00582\ NPHI \tag{28}$$

A cutting sample of Well-1 from selected depth of 2182-2396 m, which is classified as TAF, have been analyzed to obtain organic geochemical data and pyrolysis values (Manaf, et al., 2017). Using well log data to validate the result from petrophysical analysis by geochemical laboratory which is less representative of entire depth. The result from the model above showed a good match with the laboratory data as it indicated with high correlation coefficient of 0.92.

2.12 Haris's Model (2017)

The integrated analysis including geochemical, rock mechanic, and geophysics reported in paper of Haris et al (2017) aimed to characterize and map the unconventional reservoir shale hydrocarbon in term of potential source rock, and thermal maturity of the rock succession in Baong shale, North Sumatera basin. The availability of data consists of 2D seismic data and 3 wells will be used to characterize and map shale hydrocarbon, which is guided by AI, TOC, and rock strength. Geochemical analysis on the core data were carried out to determine TOC. While for petrophysical analysis, they performed multi-linear regression of log data to estimate TOC relationship with the seismic attribute.

TOC collected from geochemical analysis at certain depth while TOC data is needed for entire depth, therefore TOC data is derived from empirical relationship to gain TOC as a function of depth (in the range of shale formation) by using multilinear regression method (Haris, et al., 2017). The empirical relationship of TOC data will be the function of gamma ray, density, neutron porosity, sonic, and resistivity is given follow:

$$TOC = 1.8994 – 0.06\ GR + 1.0176\ RHOB + 20.893\ NPHI – 0.0488\ DT + 0.321\ R \quad (29)$$

Where the TOC lab and the calculated TOC using multilinear regression show good correlation. It is recommended to apply in Baong shale of North Sumatera basin patch the lack of the data.

2.13 Haris's Model (2017)

Haris et al. (2017) did the integrated approach for analyzing organic-rich shale reservoirs involves calibration of core and well log data to characterize the TOC data. Some of selected samples of the Pematang Formation have been analyzed to obtain organic geochemical data and pyrolysis values on the assessment to potential Brown shale, Central Sumatra basin of wells Afaf-1 and Fahed-2. The TOC content of the selected samples of Brown shale ranges from 0.5 to 1 wt. %, which means the quantity of shale into the medium category (fair) (Haris, et al., 2017). This condition is because of the well location of Fahed-2 is on the edge of the sub-basin, the TOC value will be higher due to the central basin sedimentation rate is slower and gives rich organic material (Haris, et al., 2017).
Since the limitation of samples as they will not cover for the whole depth, Haris et al. (2017) established a model to estimate TOC as function depth by applying multilinier regression in order to patch the lack of the data. The derived equation is from multilinear regression as function of well logging data, such as gamma ray, density, neutron porosity, sonic, and resistivity:

$$TOC = -14.8534 - 0.0168\ GR + 3.9498\ RHOB + 4.7925\ NPHI + 0.0751\ DT + 0.0651\ R \quad (30)$$

As the TOC result was calibrated with the TOC lab data from geochemical analysis, it showed a good match. The multilinier regression model of well logging data is recommended to apply in Brown shale of Central Sumatra basin.

2.14 Zhu's Model (2018)

There are three main models for calculating TOC using conventional well logging: 1) based on the good-single correlation between the conventional well logging curves and the TOC, 2) based on the combination of conventional logging acoustic wave and electrical resistivity, such as ΔlogR method, 3) by taking advantage of multi curve features. Zhu, et al. (2017) claimed that existing calculation TOC enable to be upgraded. They proposed an Intergrated Hybrid Neural Network (IHNN) algorithm on the basis of original BP Neural Network (BPNN) to identify total organic carbon.
In order to compare the models conveniently, the measurement of TOC was carried out for 132 rock samples from Longmaxi shale gas reservoir of Jiaoshiba area in Sichuan Basin (the first large shale gas field in China) (Zhu, et al., 2018). Algorithm inside IHNN was compared with ΔlogR for well A and well B. This first equestion derived from density log, as the ΔlogR method is not suitable when level of maturity is over, as shown below:

$$TOC = -15.567\ RHOB + 43.258 \quad (31)$$

This is continuity equation from IHNN model Longmaxi shale gas field. This equation below derived from sonic log and resistivity log:

$$\mathrm{TOC} = 2.139\ \left[log\left(\frac{R}{Rbaseline}\right) + \frac{(DT - Dtbaseline)}{100}\right] + 1.952 \tag{32}$$

According to the modeling results, the IHNN model had the best precision and generalization ability when the number of hidden neurons was set to 2, the number of serial networks was set to 100, the number of parallel networks was set to 100 (Zhu, et al., 2018). It can be known that the accuracy of the proposed IHNN model was much higher than that of other prediction models, the mean square error for the sample which did not be joined to establish model is reduced from 0.586 to 0.442 (Zhu, et al., 2018).

2.15 Jamaluddin's Model (2018)

Jamaluddin, et al., (2018) proposed a model to estimate total organic carbon (TOC) by multilinear regression with well log data approach. Multilinear regression is a method which used for predict the data that will serve as target based on several variables input (Jamaluddin, et al., 2018). This research located in Talang Akar Formation. This equation below integrated by well logging such as gamma ray, sonic, resistivity, density, and neutron-porosity:

$$\mathrm{TOC} = -3.5 + 0.00215\ \mathrm{GR} + 0.006\ \mathrm{DT} + 0.0005\ \mathrm{R} + 1.2849\ \mathrm{RHOB} + 3.7705\ \mathrm{NPHI} \tag{33}$$

Beside using multilinear regression, TOC measurement also use pyrolysis or rock eval analysis to calibrate the TOC estimation from multilinear regression. Determination of the potential source rock based on the value of organic carbon content shows that only two shales from a depth of 2280−2885 m (17 samples) are classified as good as source rock. Furthermore, a crossplot is carried out between the measured TOC and the TOC model or the result of the estimation, in the end the result showed regression coefficient of 0.1432.

3 Result and Discussion

Total organic carbon (TOC) is one of the parameters in determining the potential of an uncoventional reservoir which must be considerated. TOC is obtained from geochemical analysis which exist at certain depth, require a long time, and need expensive cost. The use of TOC from well log data is more preferred as it can patch the lack of data and gain TOC as a function of depth. The most famous and widely used is Passey's TOC model, but it may not be suitable to use in all conditions of formation. Therefore a summary of the TOC models are made from the results of direct tests in the fields to make it easier or as a reference for development wells.

Passey's ΔlogR model (1990) is a combination of LOM and Ro (vitrinite reflectance) use, therefore it is necessary to calculate LOM before calculating TOC using Passey (1990) model. Schmoker's model (1981) was used in the Devonian shale which contains a lot of potassium-40 and is constituent in the uranium and thorium decay series, therefore the calculation of TOC uses gamma-ray. In the model owned by Schmoker and Hester (1983) used in the Bakken Formation using a density log which is based on the high density of the formation and the difference in density between the formations is quite small so that it can be ignored. Starting with Mendelson & Toksoz's (1985) model, the multivariate least square regression method was introduced which was applied to the Kimmeridge & Monterey Formation. In this model there are five models that represent each well.

In 1987, Hester & Schmoker calculated the TOC at Woodford Shale using the same tool, namely the density log. Decker, Hill, & Wicks (1993) calculated the TOC of gas reservoirs in the Antrim shale, Michigan Basin using density logs as the medium. Accompanied by their assumption that all wells contain saturated gas. Herron's model (2011) calculates TOC in a Green River Shale which contains a lot of immature kerogen. Herron's model uses a combination of log density and nuclear magnetic resonance. Renchun (2015) performed the TOC calculation with his model in the Jiaoshiba Shale using density logs because they were considered the most suitable, easier, and widely applicable. Wang (2016) model provides a revision of the Passey Model (1990), which then produces two new TOC models even though it is based on Passey's ΔlogR model.

Alshakhs & Rezaee (2017) used their model to calculate TOC on Goldwyer shale, which then turned out to be successful in calculating TOC outside its region. So that we get five equations from Alshakhs & Rezaee (2017). Manaf's model (2017) is used in Talang Akar Formation which comes from multi-linear regression with a combination of logs including GR, RHOB, NPHI, DT. Then Haris's (2017) model which uses Baong shale also uses multi-linear regression logs to calculate its TOC because the data is not completely available, as well as when Haris's model is used in Brown shale. Zhu's model (2018) introduces the IHNN algorithm in calculating TOC in his paper.Zhu said that the IHNN accuracy is higher than other models. Apart from Manaf (2017), Jamaluddin (2018) also again calculates the Talang Akar Formation by using multi-linear regression with the addition of a log combination, namely resistivity.

Table 1 shows a summary of the models for determining TOC based on the location of the sides and well logging such as gamma ray, sonic, density, neutrons, and resistivity.

Table 1. Models for Estimating TOC

TOC Model	Shale Formation	Well Logging	Equation
Passey (1990)	-	R/DT, R/RHOB, R/NPHI	Eq. 1
Schmoker (1981)	Devonian shale	GR	Eq. 7
Schmoker & Hester (1983)	Bakken form.	RHOB	Eq. 8
Mendelson & Toksoz (1985)	Kimmeridge & Monterey form.	GR, DT, RHOB, NPHI	Eq. 9-13
Hester & Schmoker (1987)	Woodford shale	RHOB	Eq. 14
Decker, Hill & Wicks (1993)	Antrim shale	RHOB	Eq. 16
Herron (2011)	Green River shale	RHOB, NMR	Eq. 17
Renchun (2015)	Jiaoshiba shale	RHOB	Eq. 18
Wang (2016)	Duvernay shale	GR/R/DT, GR/R/RHOB	Eq. 21-22
Alshakhs & Rezaee (2017)	Goldwyer shale	RHOB, GR/RHOB, DT/RHOB, GR/RHOB/NPHI, GR/DT/RHOB	Eq. 23-27
Manaf (2017)	Talang Akar form.	GR, DT, RHOB, NPHI	Eq. 28
Haris (2017)	Baong shale	GR, DT, R, RHOB, NPHI	Eq. 29
Haris (2017)	Brown shale	GR, DT, R, RHOB, NPHI	Eq. 30

Zhu (2018)	Longmaxi shale	RHOB, R/DT	Eq. 31-32
Jamaluddin (2018)	Talang Akar form.	GR, DT, R, RHOB, NPHI	Eq. 33

4 Conclusion

The use of well log data is more preferred than other methods such as coring and cutting done in the laboratory as it only exists at certain points, requires a long time, and needs expensive cost. The TOC model that is obtained may not be suitable to use in all conditions of formation. There are 25 models to predict TOC using well log data from 14 shale formation around the world, those are: Antrim Shale, Bakken Shale, Baong Shale, Brown Shale, Devonian Shales, Duvernay Shale, Goldwyer Shale, Green River Shale, Jiaoshiba Shale, Kimmeridge Formation, Longmaxi Shale, Monterey Formation, Talang Akar Formation, and Woodford Shale. These TOC models are different based on its condition. So, the TOC equation chose must be considered to the characteristics of formation.

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