



VIETNAM OIL AND GAS GROUP

**VIETNAM PETROLEUM INSTITUTE**

# ESTIMATION OF TOTAL ORGANIC CARBON USING ARTIFICIAL INTELLIGENCE TECHNIQUES

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# INTRODUCTION

- In term of source rock, sedimentary rocks may become or have been able to generate petroleum are source rocks
- Total Organic Carbon (TOC) is one of the most important parameters that measured the quantity but not the quality of organic carbon in sedimentary rocks.
- Total organic carbon or kerogen content is an indicator of potential hydrocarbon source rocks.
- Total organic carbon is needed for calculating original organic carbon (TOC<sub>o</sub>) that supported for petroleum system modeling

Therefore, TOC parameter needs to be measured or estimated for source rock evaluation





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# APPLICATION OF TOC IN SOURCE ROCK EVALUATION



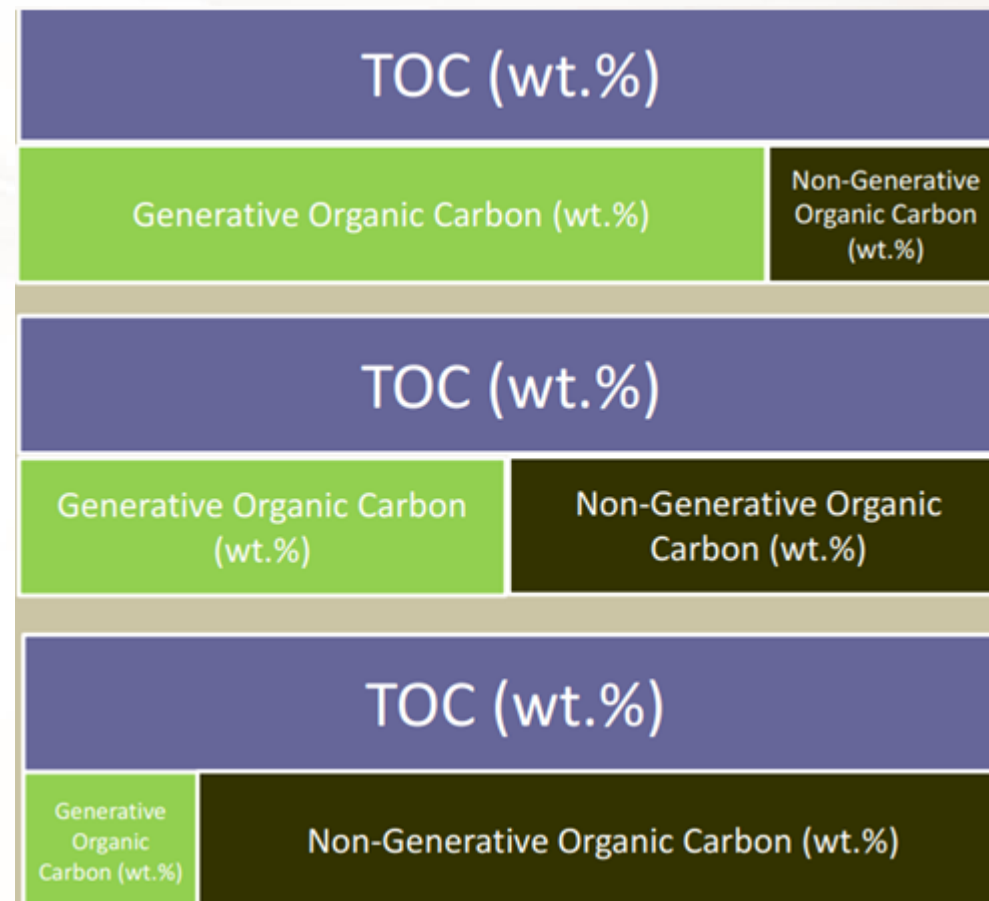
# TOTAL ORGANIC CARBON (TOC)

## 1. Total Organic Carbon (TOC)

TOC refers to the amount of organic carbon in sedimentary rocks, soils or in a geological formation, particularly the source rock for a petroleum play.

### *TOC parameter is:*

- A measure of present-day organic carbon content as received in the laboratory
- It is reported in weight percent but can be converted to volume percent
- It can be restored to original values with knowledge of original kerogen composition
- It will be affected by the presence of organic additives and other conditions



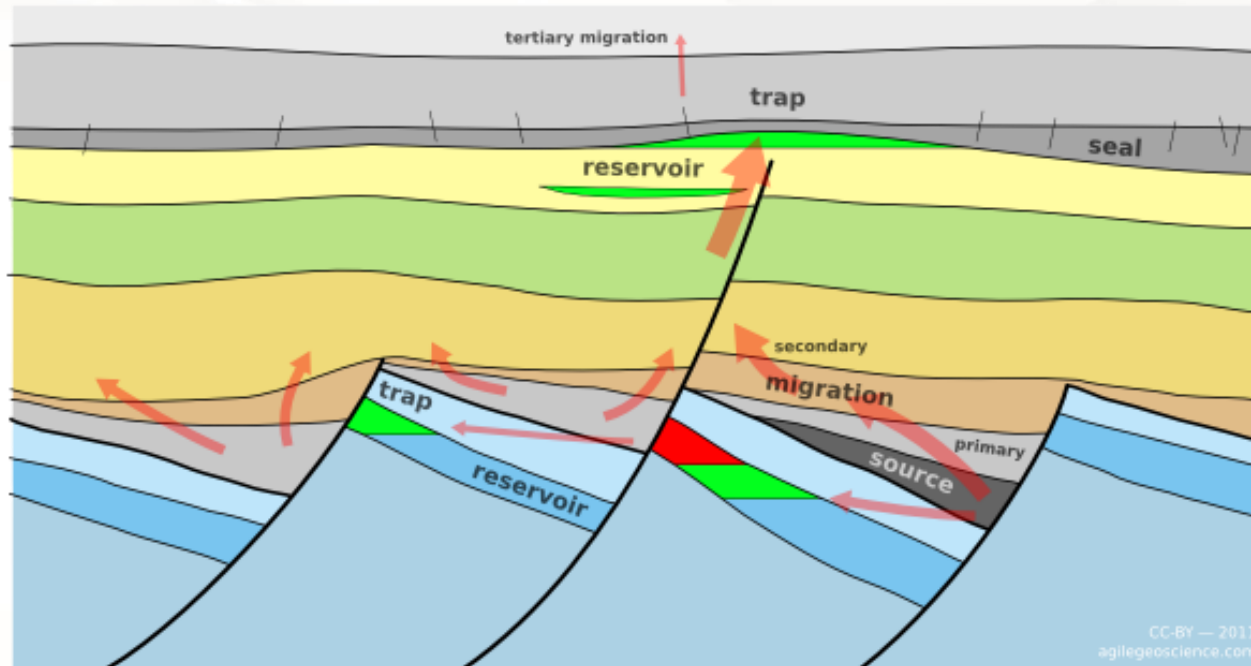
# TOTAL ORGANIC CARBON (TOC)

## 2. Source rock (SR)

### *In conventional petroleum system*

- a rock unit containing sufficient organic matter of suitable chemical composition to generate and expel petroleum;
- the SR must be thermally mature;
- expulsion of hydrocarbons must occur from that SR;
- a trap for these hydrocarbons must exist somewhere;
- the expelled hydrocarbons must migrate from the source to the trap

Conventional petroleum system



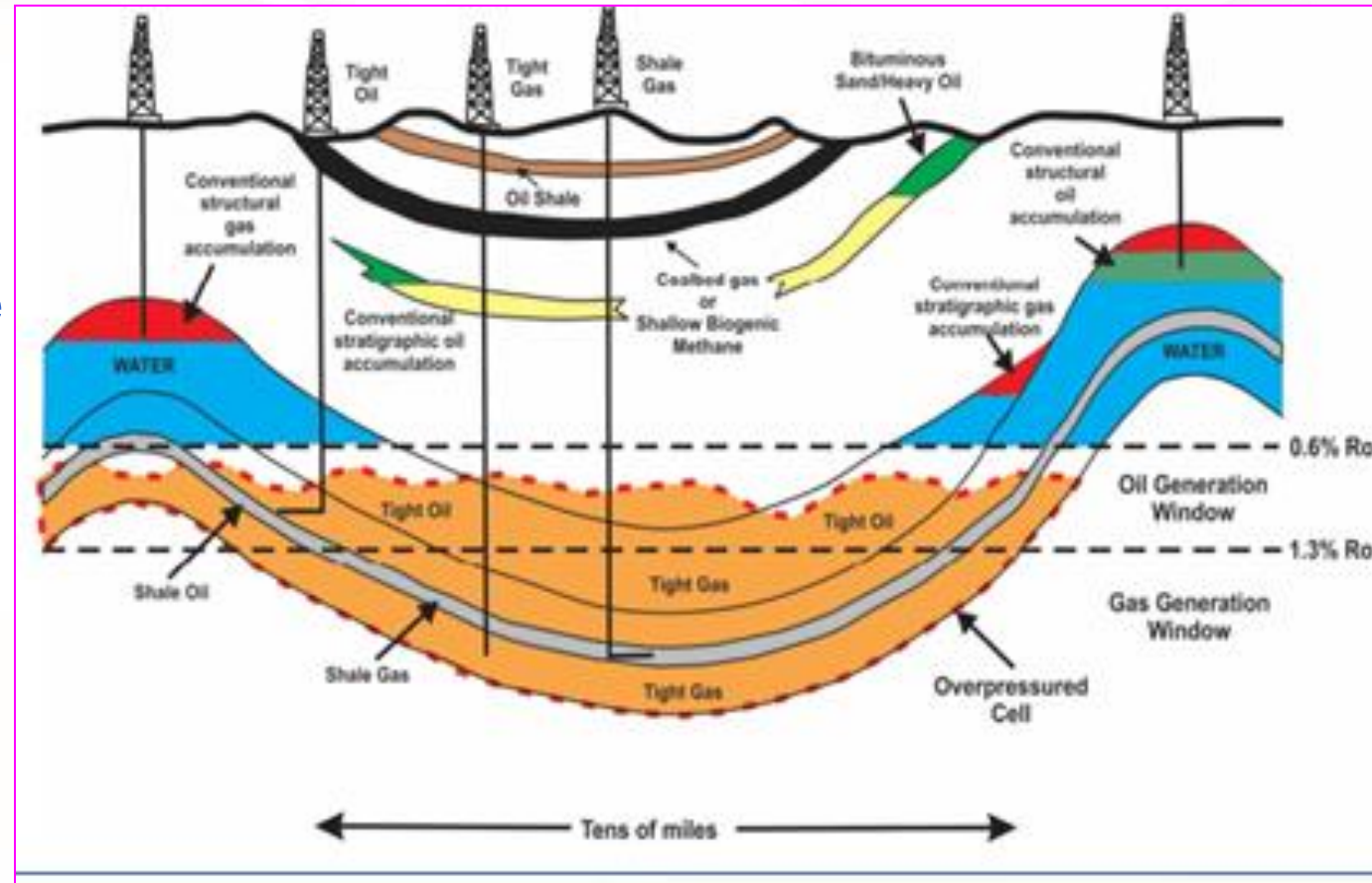


# TOTAL ORGANIC CARBON (TOC)

## *In Tight petroleum system /unconventional reservoir*

- Shale SR is recognized as a potential reservoir for hydrocarbons with very low permeability and high content of OM
- In a shale reservoir, gas typically occurs in two modes: adsorbed on OM within the shale bed
- The low permeability of shale reservoirs specifically hydraulic fracturing

**Unconventional reservoirs:** Coal bed methane (CBM), Shale oil and shale gas, Tight gas sands, Fractured reservoirs, Gas hydrate





# TOTAL ORGANIC CARBON (TOC)

## 3. Application of TOC in source rock evaluation

- Defining current quantity of organic matter;
- Defining original TOC for input data in petroleum system modeling;
- A key factor in determining the prospectivity of any shale play;
- It significantly influences hydrocarbon production

## 4. Screening source rock evaluation

Source rock assessment is based on parameters, i.e., **TOC**, S1, S2, S3, HI, PI, Tmax, Ro that are traditionally measured on Rock-Eval machine in laboratory from cores, SWCs and cuttings

However, this analysis provides non-continuous measurements of the source rock section

as it has limited samples and is usually associated with higher costs and longer measurement time



To overcome these limitations, **Artificial Intelligence** techniques are applied for estimation TOC







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# LAB ANALYSIS TECHNIQUES



**TOC is determined by analyses:**

## 1. LECO

- Defining TOC
- Often used for sedimentary rocks with high carbonate content

## 2. ROCK-EVAL

- The pyrolytic analysis is performed on Rock-Eval I/II/6 that is widely used for sedimentary rocks
- Providing TOC and pyrolytic parameters: S1, S2, S3, HI, PI, Tmax





**04**

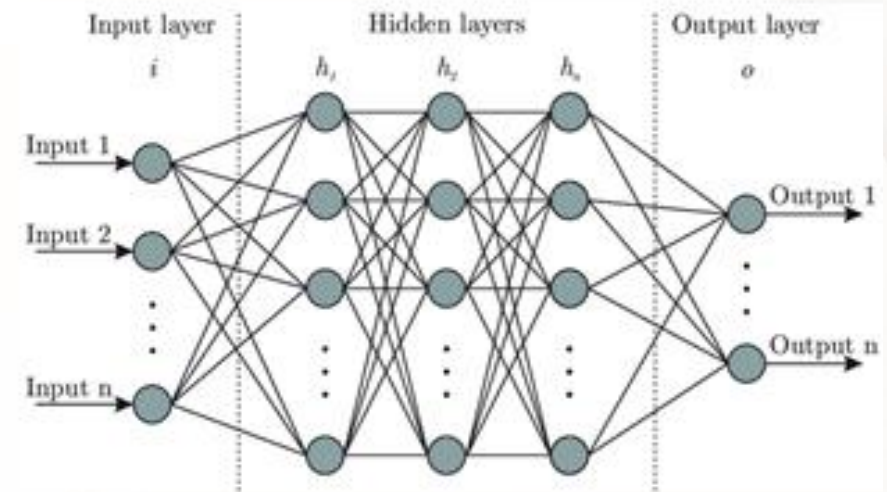
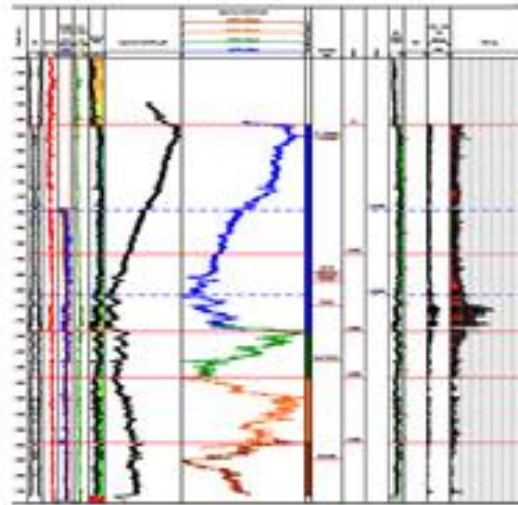
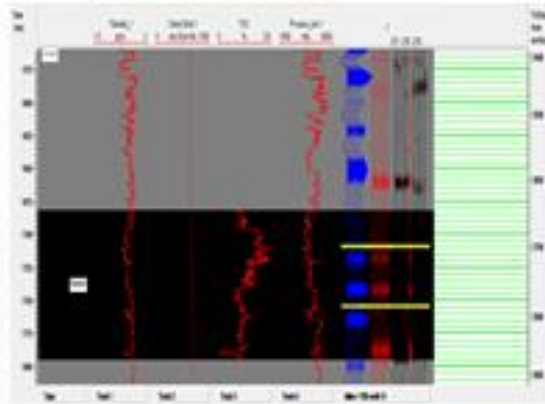
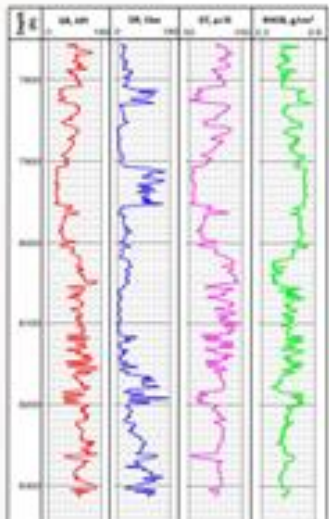
# **CALCULATION TECHNIQUES**



# CALCULATION TECHNIQUES

Some techniques are applied for TOC calculation as follows:

- Well logging data
- Seismic section combining with well logs
- Softwares based on well logs: Cyclolog, Interactive Petrophysics, Techlog, etc.
- Artificial Intelligence (AI) models



# CALCULATION TECHNIQUES

## ❖ **Calculating TOC from well logs**

- Well logging methodology in geochemical evaluation is an important technique not only for its usefulness as a quick scan of potential source rock, but also in its ability to identify the organic richness (TOC, wt.%) of these rocks
- Wireline logs can be used to identify source rock intervals in the primary stage of well drilling
- Consequently, the logs used for source rock evaluations and calculation of Total Organic Carbon (TOC) most commonly include density, sonic, gamma ray, neutron and resistivity using several methods

In this study, a suite of geophysical logs and measured TOC were applied for determining TOC and compare them together



# CALCULATION TECHNIQUES

## ❖ Calculating TOC from well logs

- The presence of Organic matter (OM) generally associated with: higher GR, lower Density, higher Resistivity, slower Sonic
- TOC can be calculated by overlaying log curves: Resistivity-Sonic, Resistivity-Neutron, Resistivity-Density (Passey et al., 1990)

$$\Delta \log R = \log_{10}(R/R_b) + 0.02 * (\Delta t - \Delta t_b)$$

$$\text{Est. TOC} = (\Delta \log R) * 10^{(2.297 - 0.1688 * \text{LOM})}$$

where:  $\Delta \log R$  = Log overlay separation

$R$  = deep resistivity

$R_b$ : baseline resistivity

$\Delta t$  = sonic curve transit time value

$\Delta t_b$  = sonic curve transit time baseline value

LOM = Level of organic maturity



## Workflow of calculating TOC

Workflow overview

Method settings

TOC computation

save and display

Inputs	Zonation	Schmoker	DeltaLogR	Modified Schmoker	NMR	Uranium	Kerogen Volume	FINAL									
Group	Well	Dataset	Zone	Top	Bottom	Vitrinite_Reflectance	Vitrinite_Reflectance Unit	Resistivity_Baseline	Resistivity_Baseline Unit	DT_Baseline	DT_Baseline Unit	RHOB_Baseline	RHOB_Baseline Unit	NPHI_Baseline	NPHI_Baseline Unit	DeltaLogR_Model	TOC_Type
1	SH-1X		1	620	1340	0.56	%	- 2	ohm.m	- 95	us/ft	- 2.45	g/cc	- 0.25	v/v	- Sonic	II
2			1340.1	2440	0.56	%	- 2.2	ohm.m	- 91	us/ft	- 2.38	g/cc	- 0.24	v/v	- Sonic	II	
3			2440.1	3437	0.56	%	- 2	ohm.m	- 95	us/ft	- 2.45	g/cc	- 0.25	v/v	- Sonic	II	
4			3437.1	4150	0.56	%	- 2	ohm.m	- 95	us/ft	- 2.45	g/cc	- 0.25	v/v	- Sonic	II	

Workflow overview

TOC computation

save and display

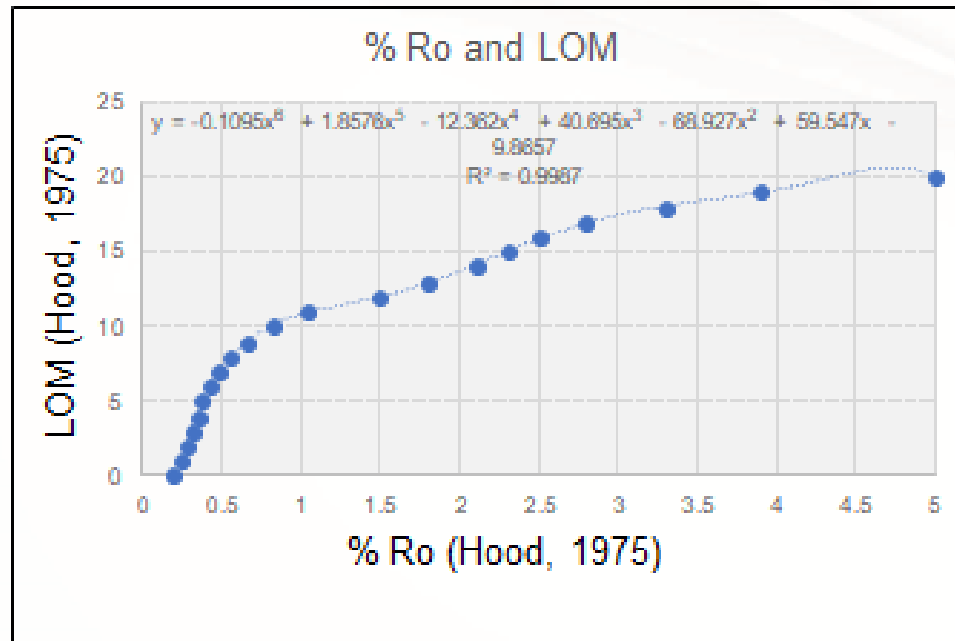
Inputs	Zonation	Schmoker	DeltaLogR	Modified Schmoker	NMR	Uranium	Kerogen Volume	FINAL
Group	Well	Dataset	Zone	Top	Bottom	TOC_Method		
1	SH-1X		1	620	1340	DeltaLogR		
2			1340.1	2440	DeltaLogR			
3			2440.1	3437	DeltaLogR			
4			3437.1	4150	DeltaLogR			



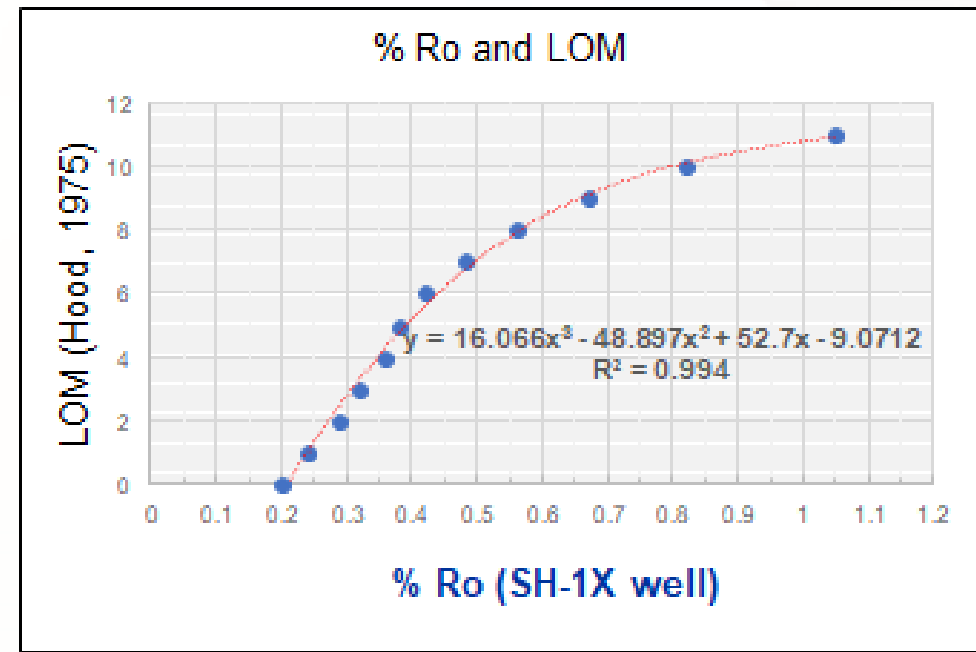
# A CASE STUDY: CALCULATING TOC FOR SH-1X WELL, SONG HONG BASIN

Respective maturity in LOM unit Metamorphism

LOM	Ro
0	0.2
1	0.24
2	0.29
3	0.32
4	0.36
5	0.38
6	0.42
7	0.48
8	0.56
9	0.67
10	0.82
11	1.05
12	1.5
13	1.8
14	2.1
15	2.3
16	2.5
17	2.8
18	3.3
19	3.9
20	5



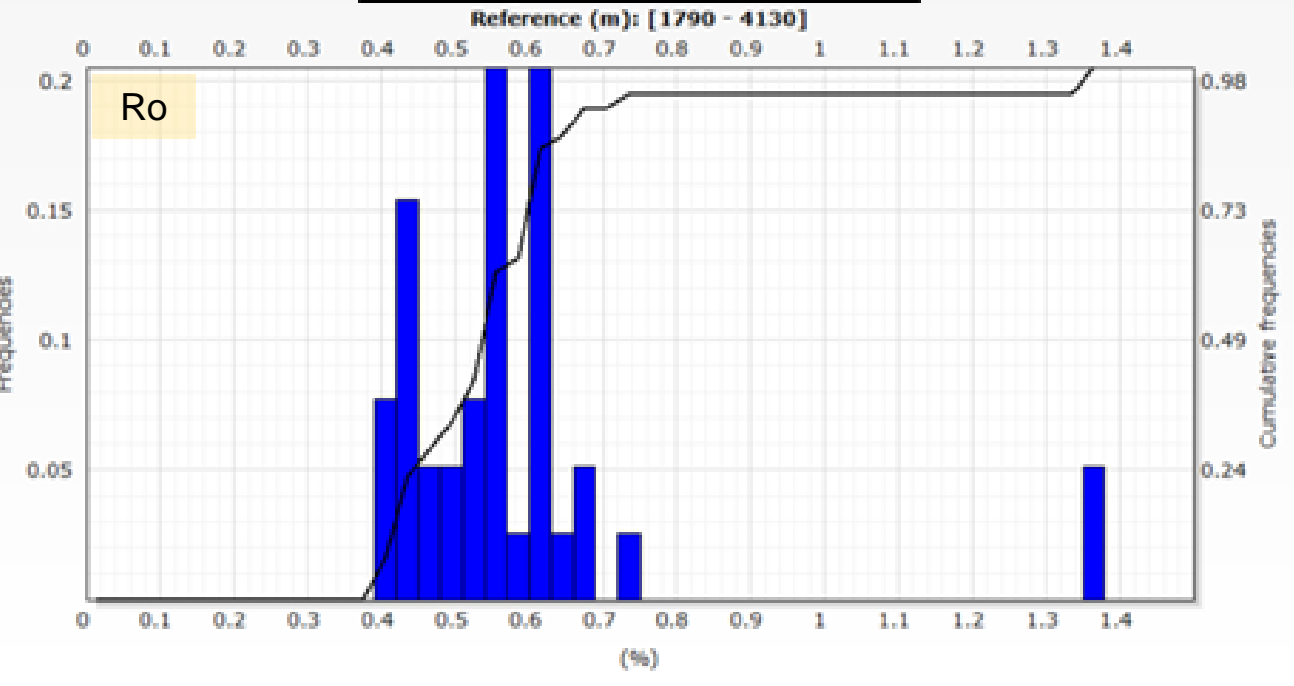
Ro < 1 % in most samples in SH-1X well





# A CASE STUDY: CALCULATING TOC FOR SH-1X WELL, SONG HONG BASIN

**Histogram\_SH-1X well**

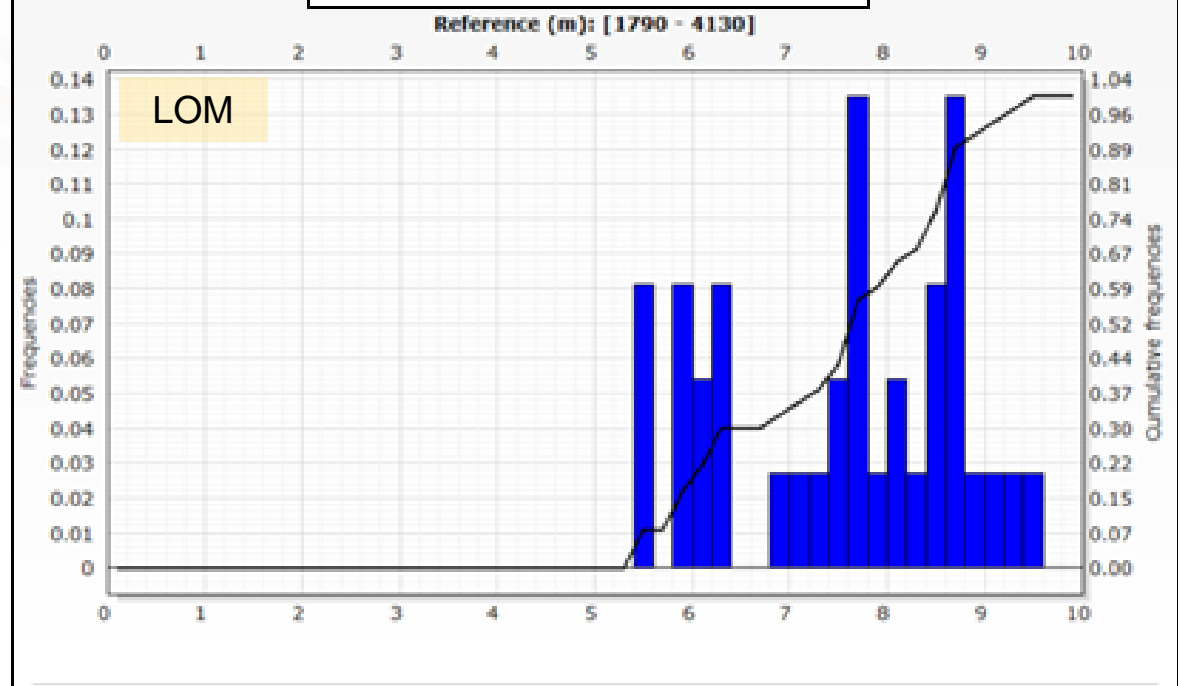


**Variables:**  
 Ro: [1790 - 4130]

**Statistics:**

Mode: 0.5525	Median: 0.55
Arithmetic mean: 0.583077	Possible values: 81
Average deviation: 0.113531	Standard deviation: 0.202239
Number of missing values: 42	Variance: 0.0409008
Minimum value: 0.41	Maximum value: 1.38
Skewness: 2.85694	Kurtosis: 8.58672

**Histogram\_SH-1X well**



**Variables:**  
 LOM: [1790 - 4130]

**Statistics:**

Mode: 7.68571	Median: 7.79544
Arithmetic mean: 7.76883	Possible values: 81
Average deviation: 1.19361	Standard deviation: 1.64707
Number of missing values: 42	Variance: 2.71285
Minimum value: 5.4235	Maximum value: 12.758
Skewness: 0.945988	Kurtosis: 1.54579

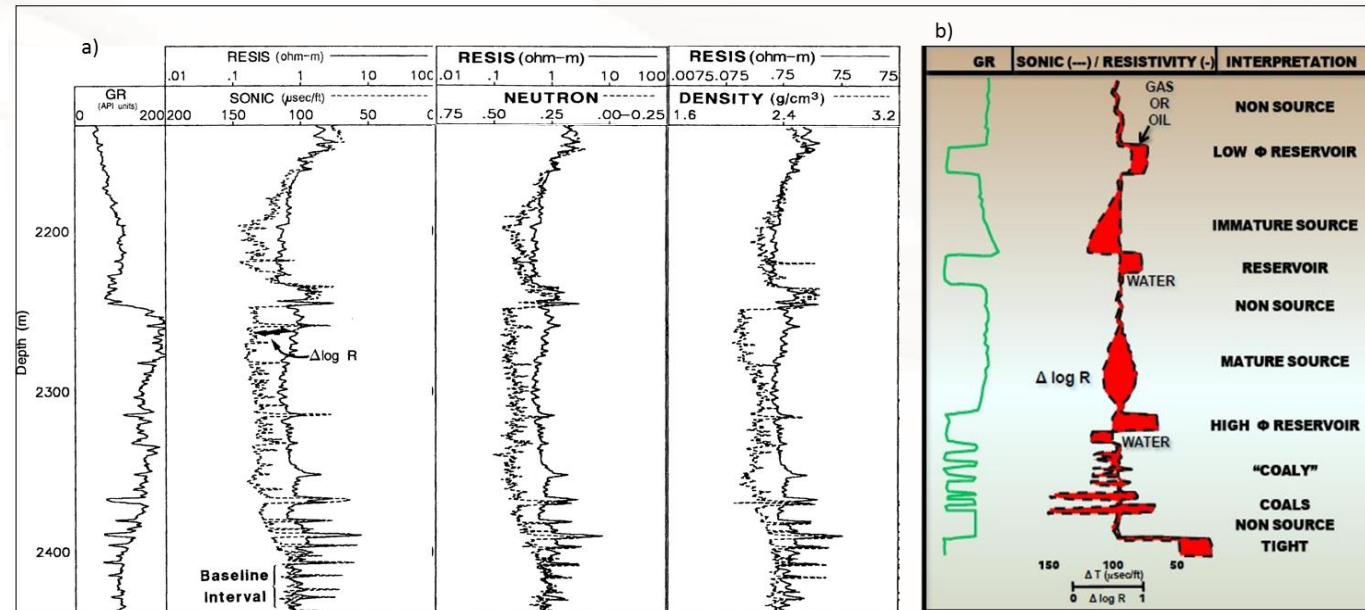
# A CASE STUDY: CALCULATING TOC FOR SH-1X WELL, SONG HONG BASIN

$$\Delta \log R = \log_{10} (R / R_{\text{baseline}}) + 0.02 * (\Delta t - \Delta t_{\text{baseline}})$$

$$\Delta \log R_{\text{neu}} = \log_{10} (R / R_{\text{baseline}}) + 4 * (\Phi N - \Phi N_{\text{baseline}})$$

$$\Delta \log R_{\text{Den}} = \log_{10} (R / R_{\text{baseline}}) + 2.5 * (\rho_b - \rho_{\text{baseline}})$$

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

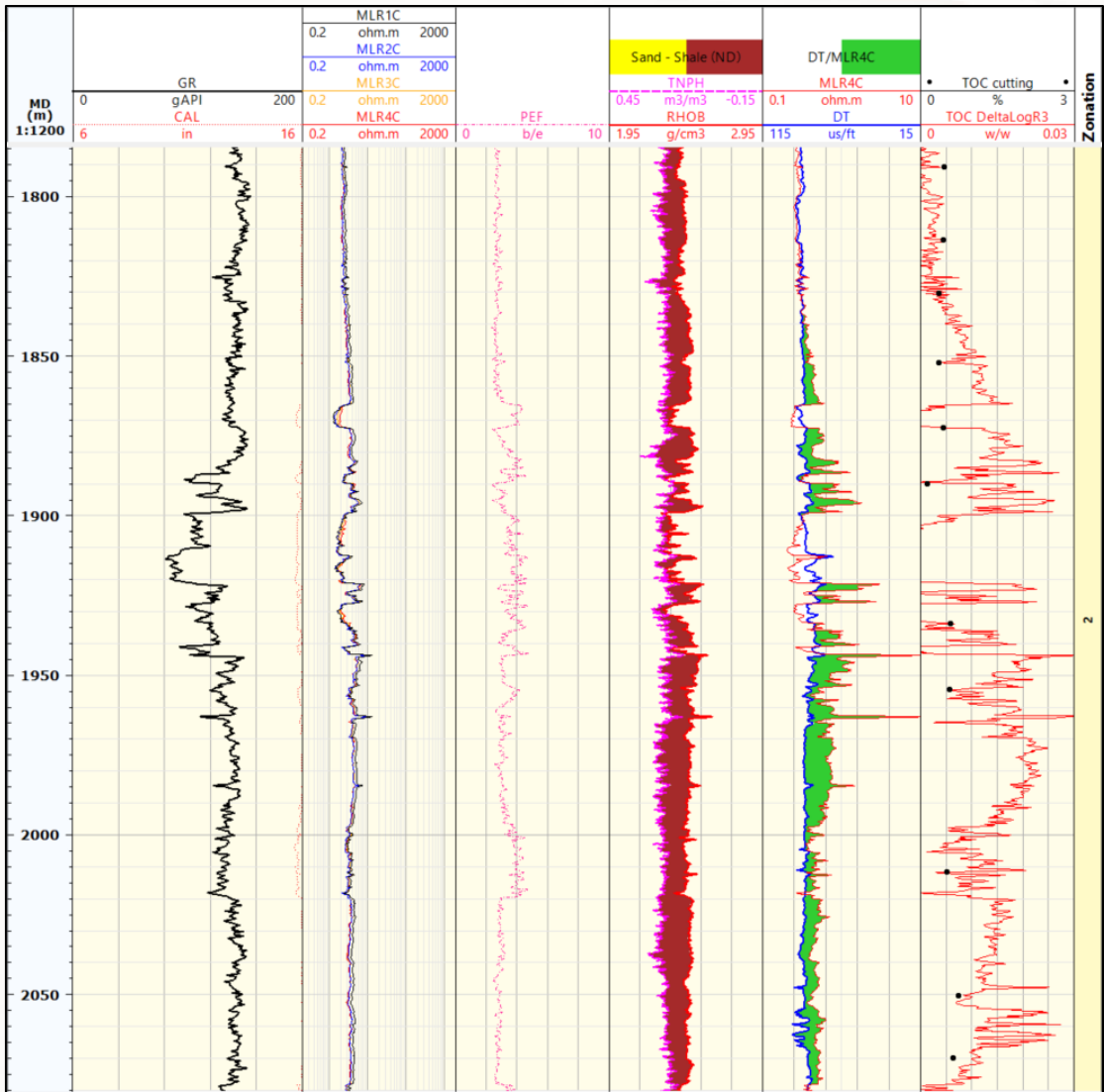


Delta log R method of Passey et al. (1990):

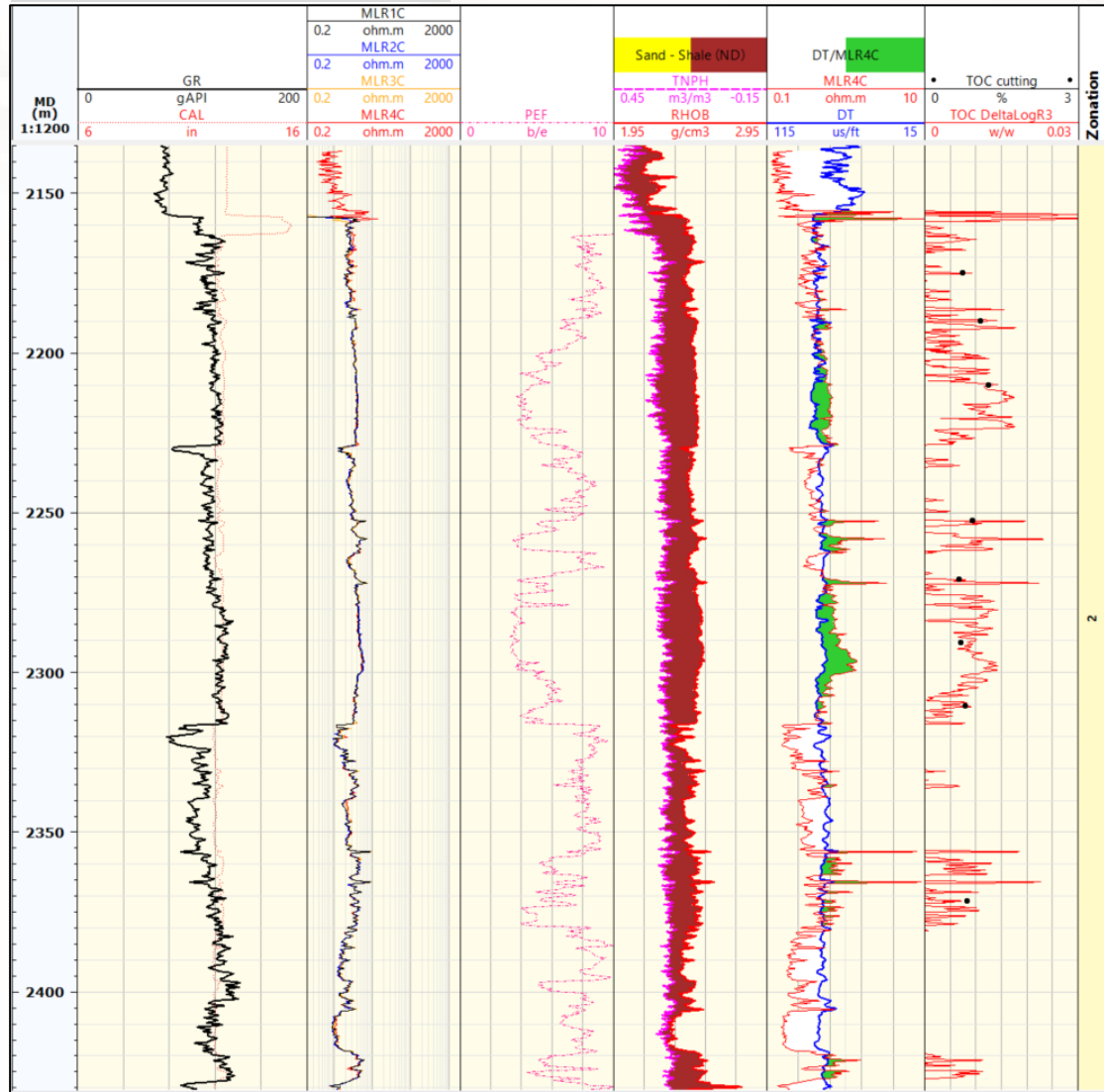
- (i) Sonic/resistivity overlay showing Delta log R separation in the organic-rich interval;
- (ii) Schematic log showing sonic/resistivity overlay in a variety of situations

# A CASE STUDY: CALCULATING TOC FOR SH-1X WELL, SONG HONG BASIN

Interval: 1785-2080m



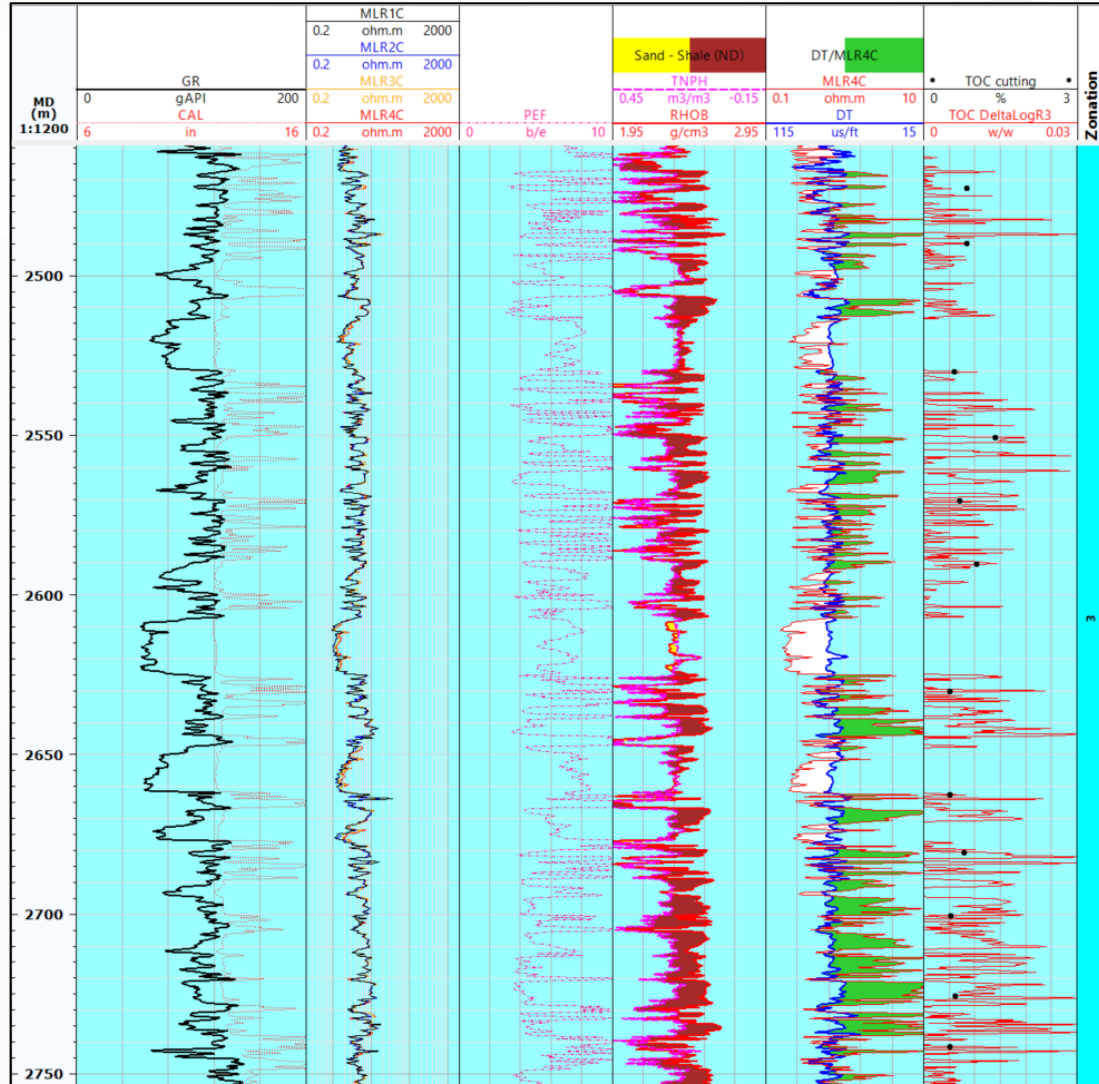
Interval: 2140-2430m



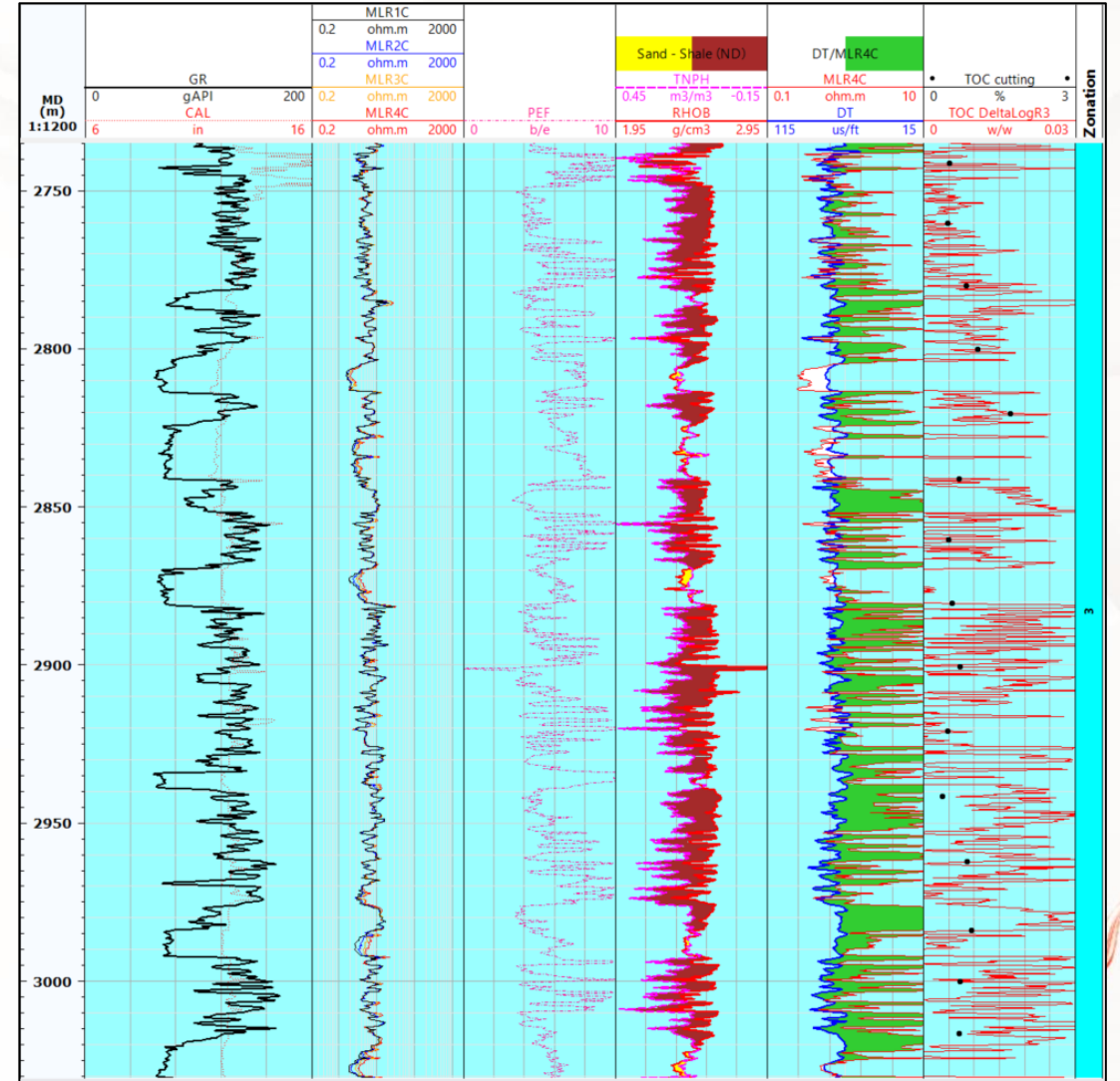


# A CASE STUDY: CALCULATING TOC FOR SH-1X WELL, SONG HONG BASIN

Interval: 2430-2750m

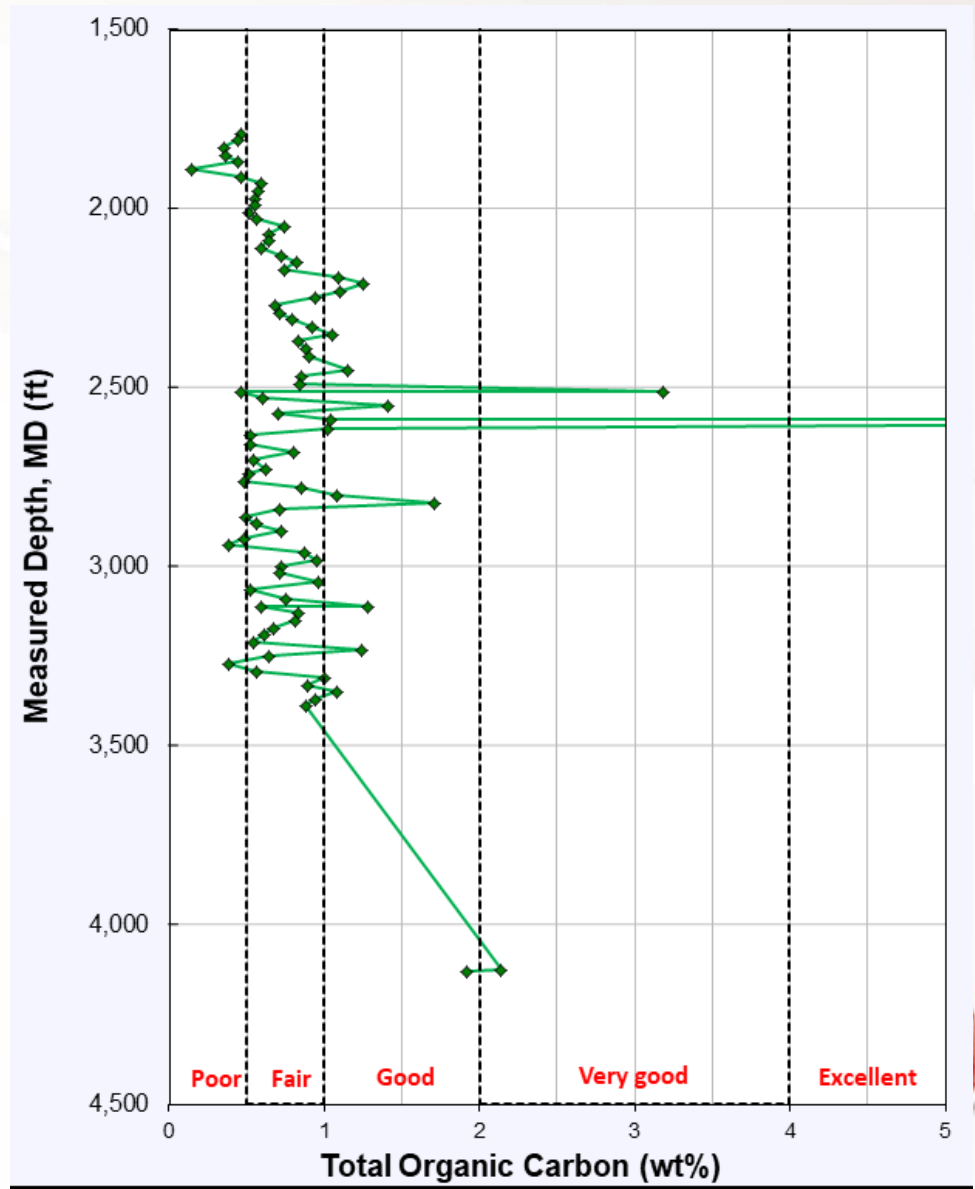
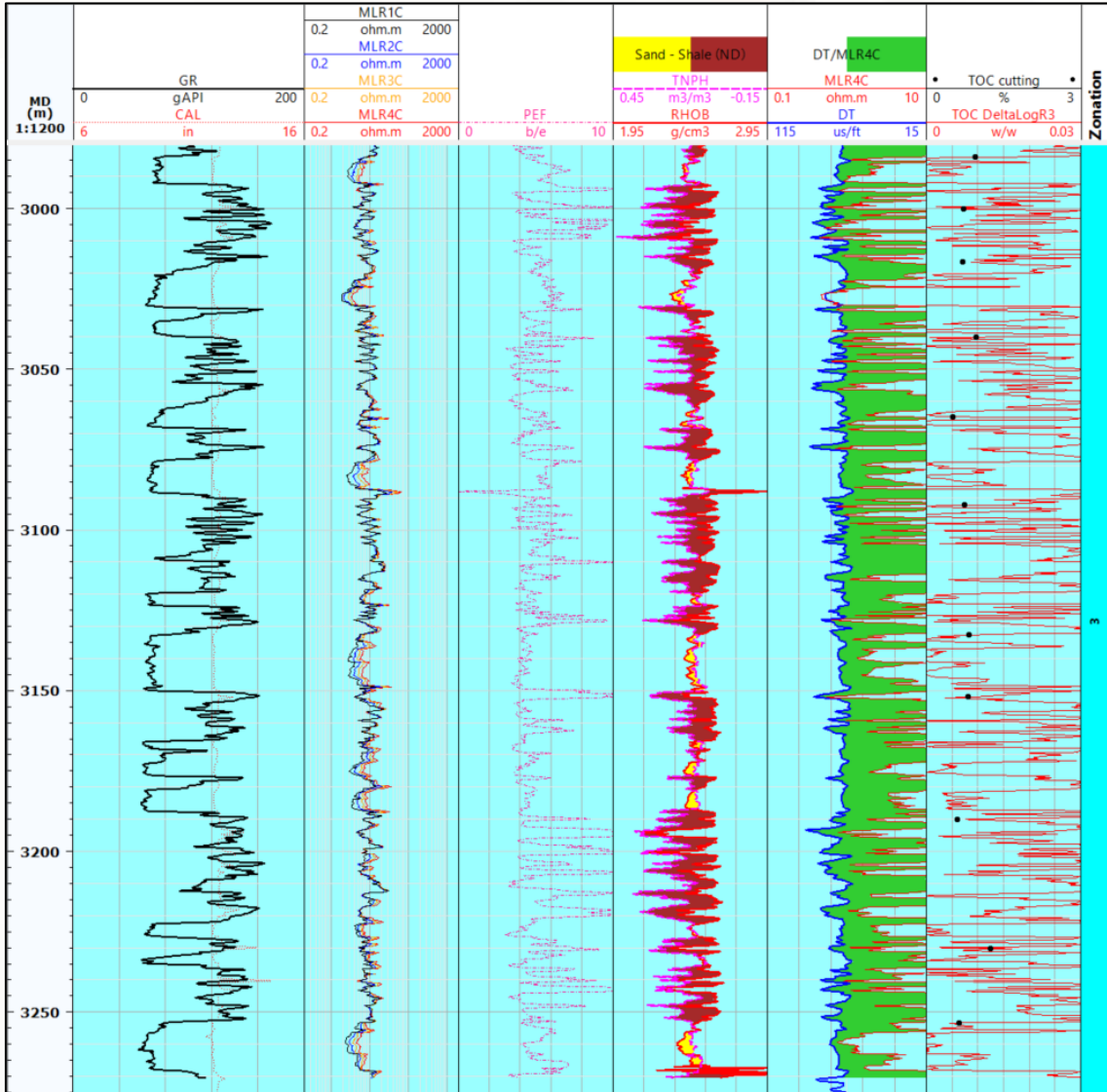


Interval: 2750-3030m

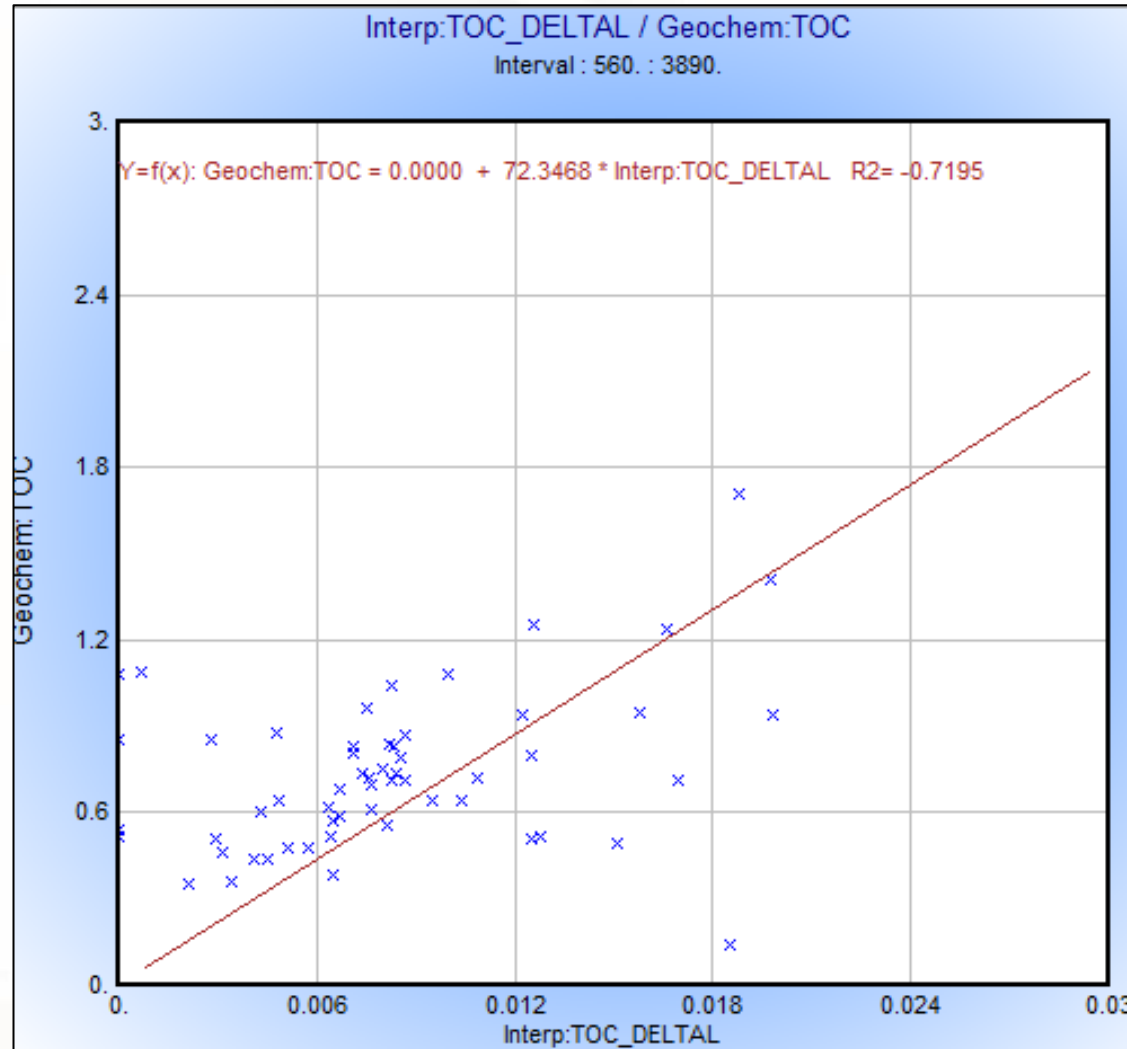


# A CASE STUDY: CALCULATING TOC FOR SH-1X WELL, SONG HONG BASIN

Interval: 3030-3270m



Cross plot of Delta LogR TOC vs the measured TOC from cutting





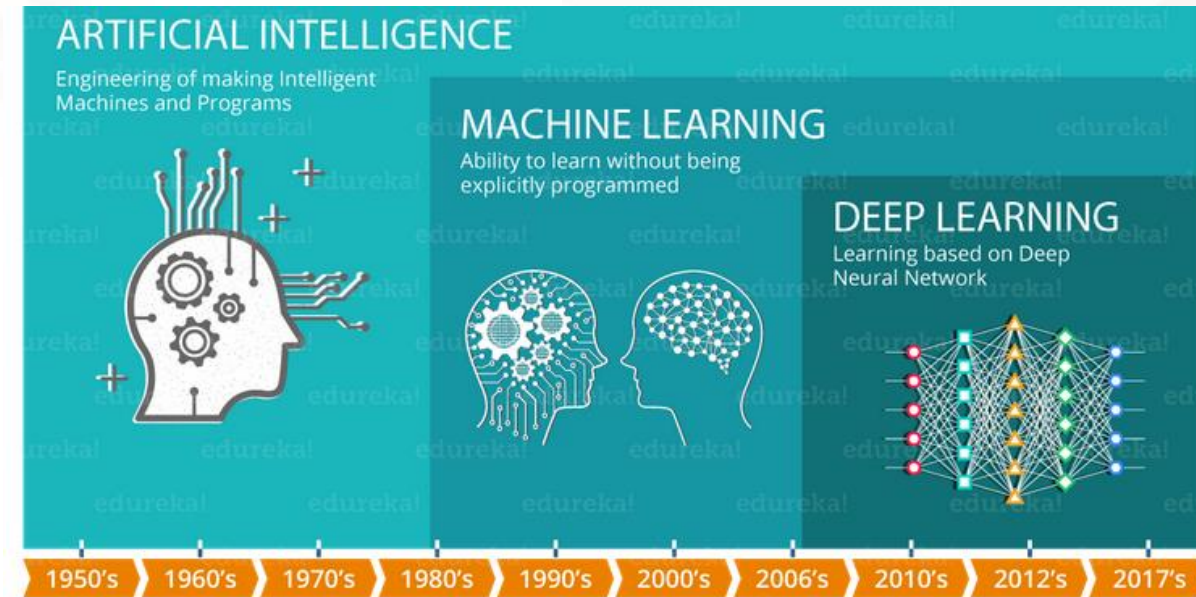
# ESTIMATION OF TOC USING ARTIFICIAL INTELLIGENCE TECHNIQUES



## 1. Artificial Intelligence (AI)

Artificial intelligence (AI) is wide-ranging branch of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence. AI is an interdisciplinary science with multiple approaches, but advancements in machine learning and deep learning

**AI** is an interdisciplinary science with multiple approaches, but advancements in **machine learning** and **deep learning** are creating a paradigm shift in virtually every sector of the tech industry.

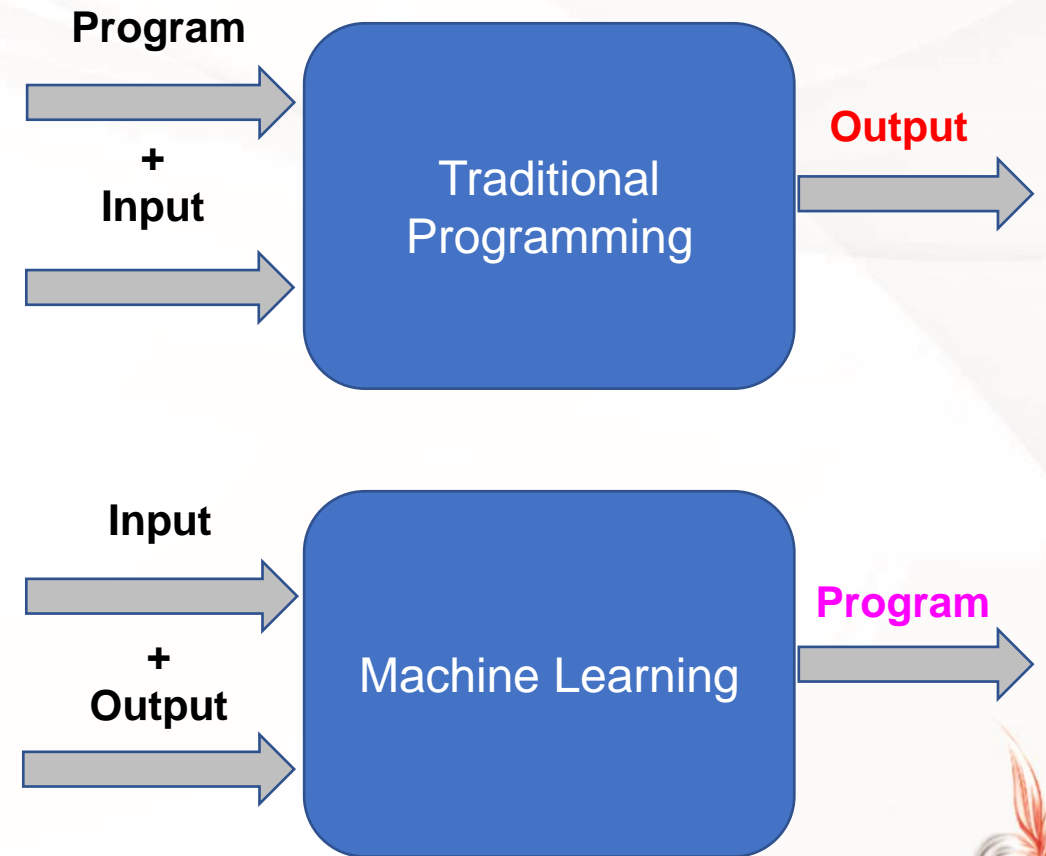
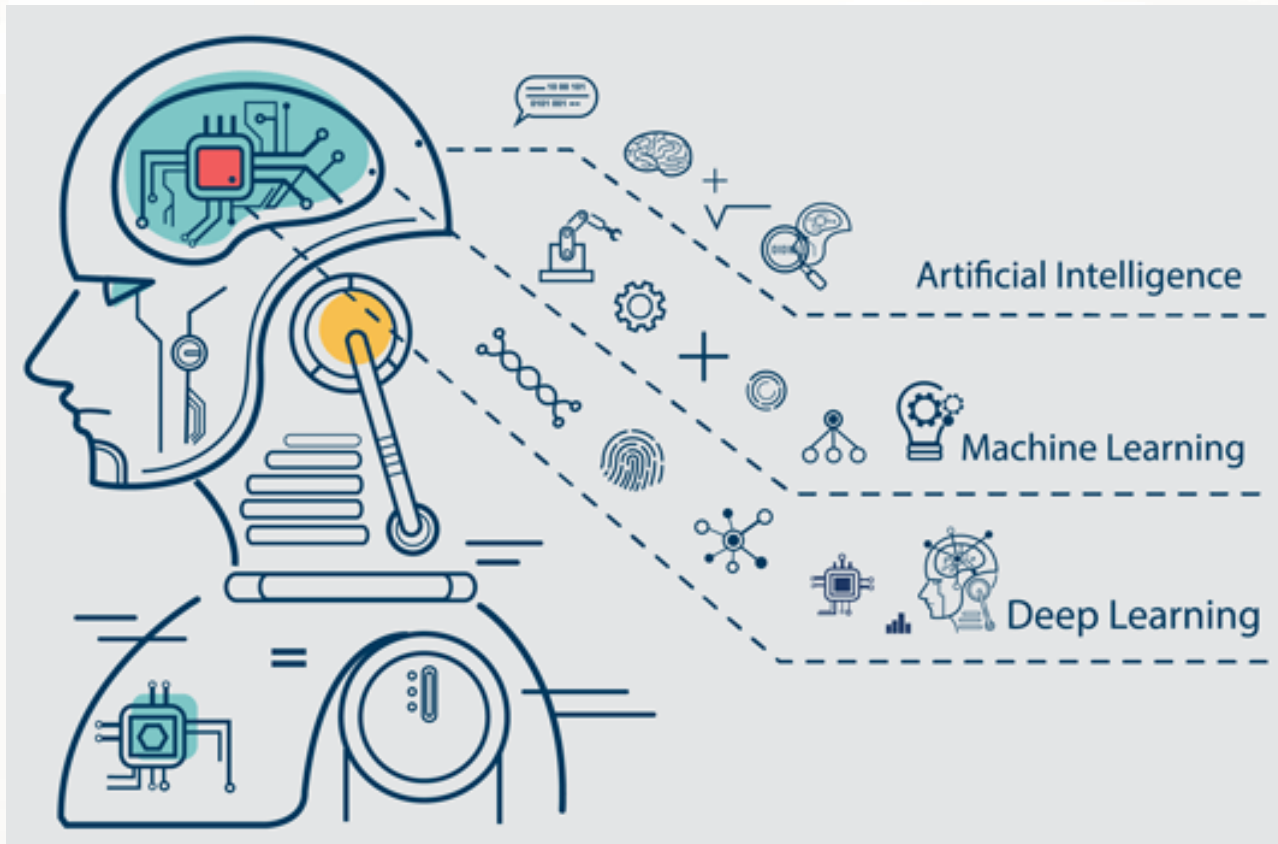


**AI** applies machine learning, deep learning and other techniques to solve actual problems

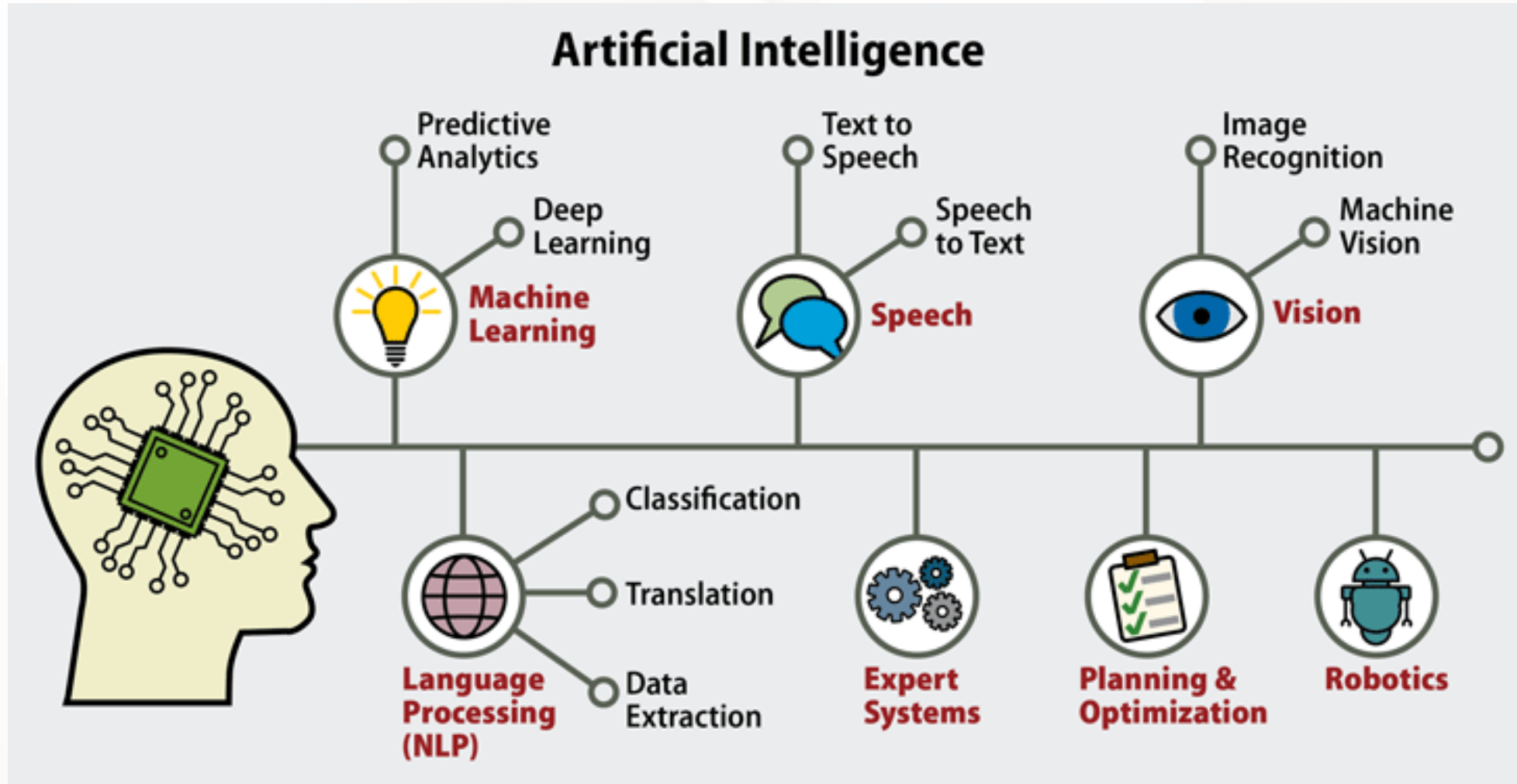




## Comparison between regular programming and AI programming



## 2. Branches of AI



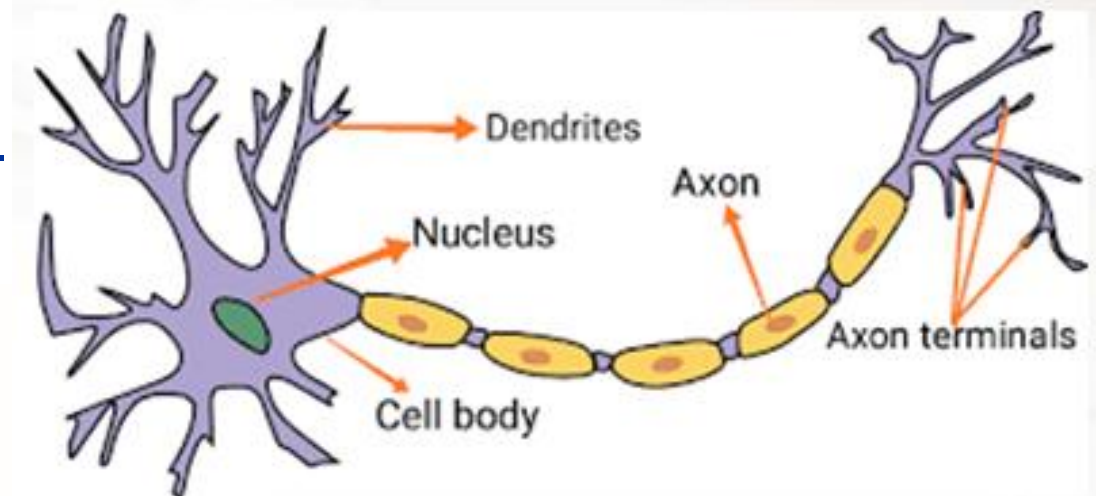
## 3. Some AI Techniques are being used for estimation of TOC

- ANN: Artificial Neural Network
- SVM: Support Vector Machine
- FNN: Functional Neural Network
- M-FIS: Mamdani fuzzy interference system
- TSK-FIS: Takagi-Sugeno-Kang fuzzy
- HNN: Hybrid Neural Network
- ANN-LM: Artificial Neural Network which based on Levenberg-Marquardt logarithm
- ELM: Extreme Learning Machine



## 4. Artificial Neural Network (ANN) for conventional and unconventional reservoirs

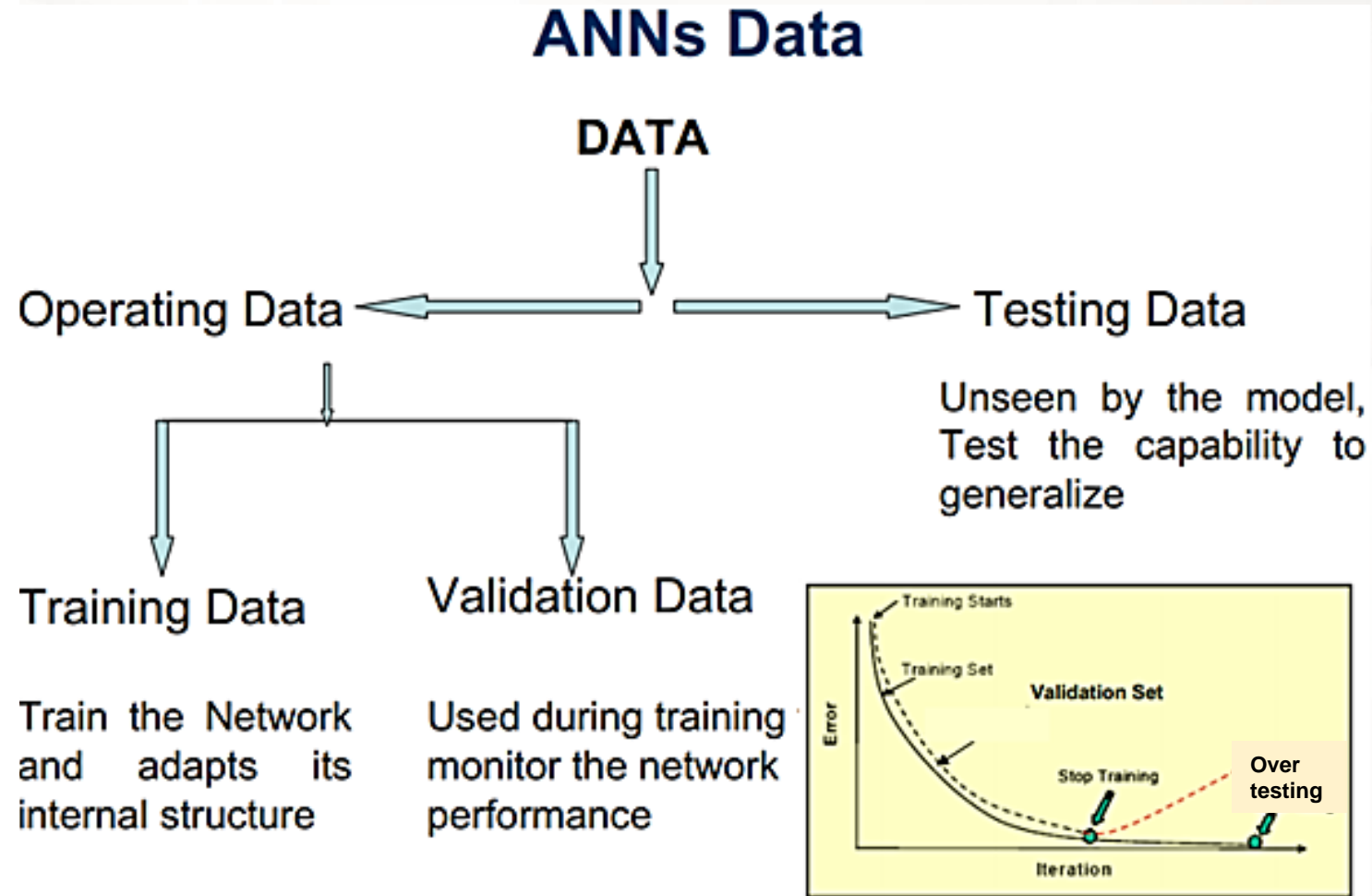
- ANN is an information processing system that roughly replicates the behaviour of a human brain by emulating the operations and connectivity of biological neurons
- It performs a human-like reasoning, learns the attitude and stores the relationship of the processes on the basis of a representative data set that already exists
- A series of connecting neuron weights are adjusted to fit a series of inputs to another series of known outputs. It means the neuron is learning.
- The adaptability, reliability and robustness of an ANN depend upon the source, range, quantity and quality of the data set.

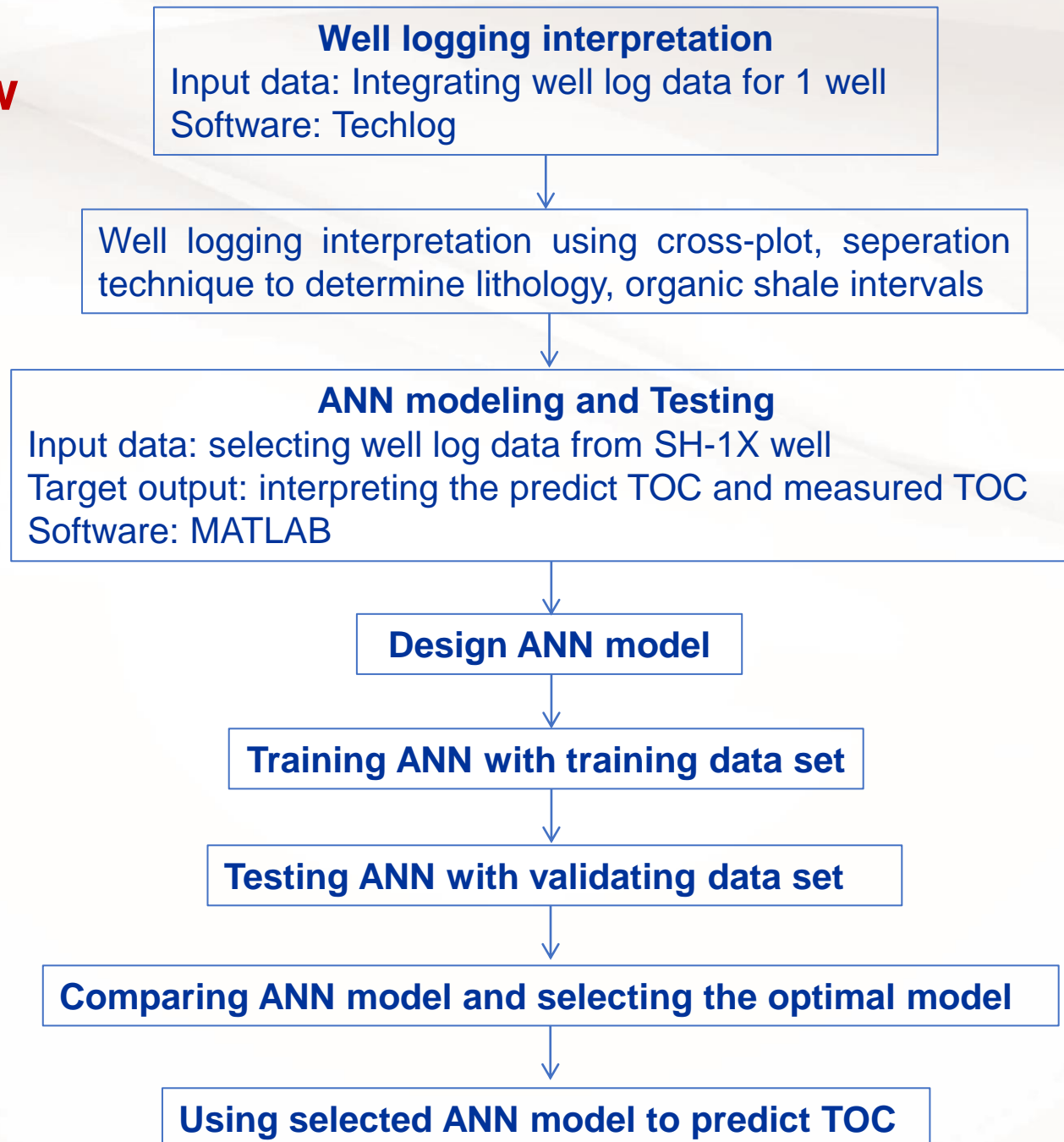


# ESTIMATION OF TOC USING ANN TECHNIQUE

How to divide the data?

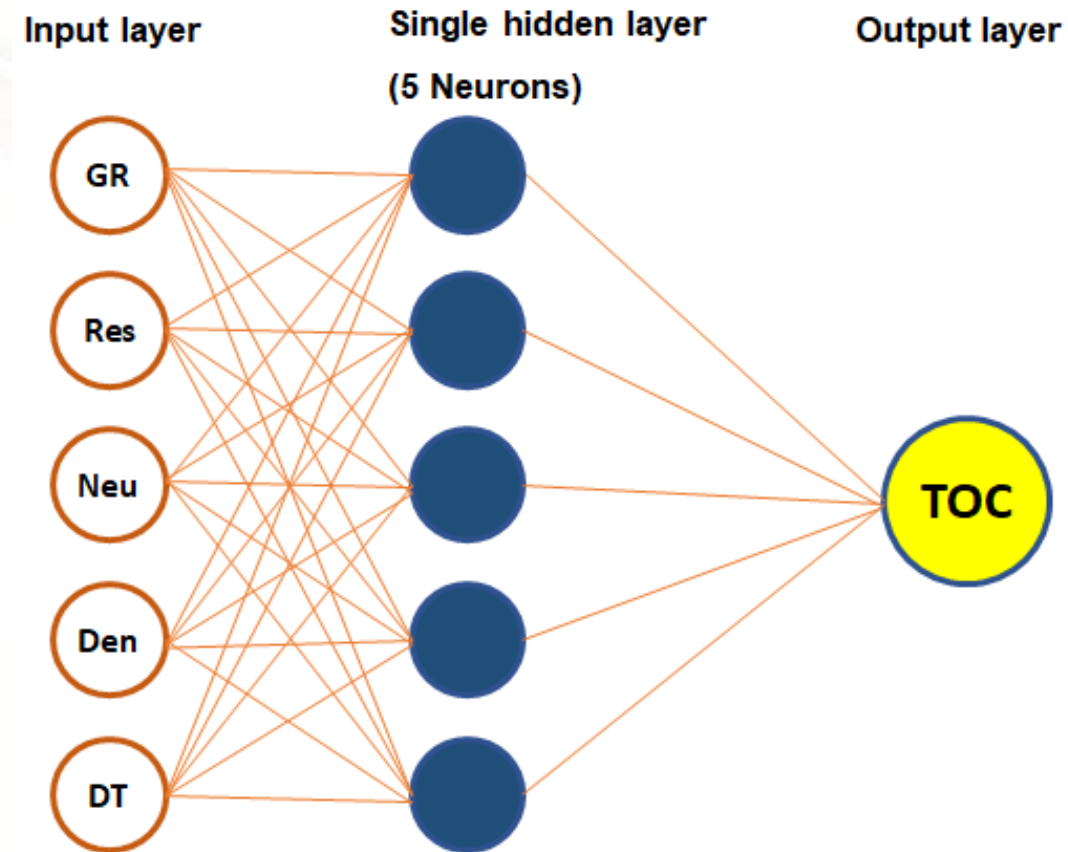
- How to select the input parameters?
- How many hidden neurons?
- How many hidden layers?
- What transfer function?
- What learning algorithms?
- How to stop the model from training?
- How to scale method?





## Designing structure for ANN model : A case study of SH-1X well, Song Hong basin

- Based on welllog curves: GR, MLR, RHOB, TNPH, DT
- ANN was trained on the data collected from shales of SH-1X well
- The model was optimized using inserted for loops built in Matlab software to consider all combinations of the possible values of different designed parameters and the ratios of the training-to-testing data
- Optimization process, the parameters were found to optimize TOC predictability for the ANN model



# ESTIMATION OF TOC USING ANN TECHNIQUE

Range of the parameters used for training the ANN model

Parameters					
	GR	Res	Sonic	Den	TOC
	(API)	(Ohm.m)	(μsec/ft)	(g/cm <sup>3</sup> )	(fraction)
Minimum	34.2	0.11	52.5	1.23	0
Maximum	150	101.2	140	2.98	0.099
Mean	113.6	2.5	92.9	2.31	0.013
Mode	115.5	0.98	79	2.46	0.001

Optimized parameters for the proposed the ANN model

Parameter	Value
Learning function	Trainlm (updates weights & bias values according to Levenberg-Marquardt optimization)
Transfer function	Tansig (calculate a layer's output from its net input. tansig (N) takes one input, N - S x Q matrix of net input (column) vector)
Number of hidden layers	1
Number of neutrons	5



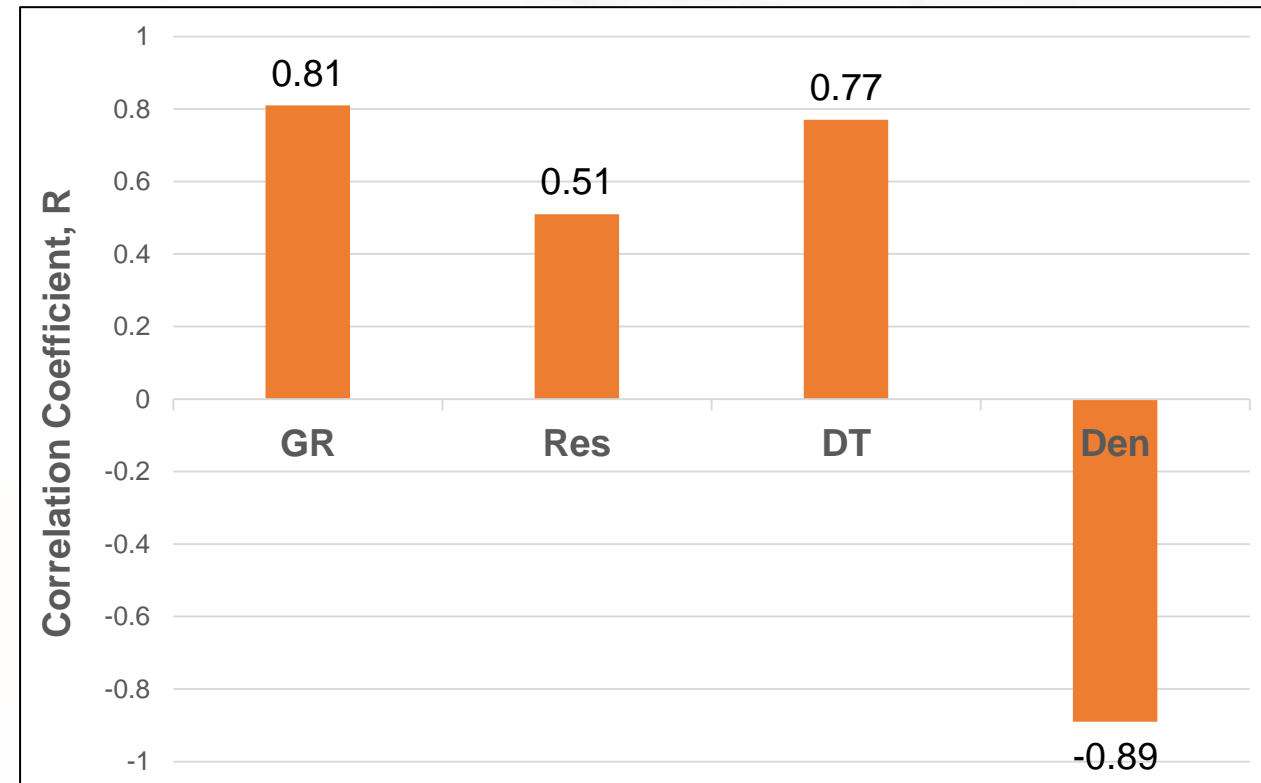


# ESTIMATION OF TOC USING ANN TECHNIQUE

## Log data collection and preparation:

- 84 data set from the well SH-1X
- The training set was evaluated statistically to remove all unrealistic values and outliers
- The outliers are removed based on the standard deviation in range of +/- 3.0
- After pre-processing, 58 of 84 data sets were selected to train the ANN model based on variables: GR, resistivity, density, sonic. The input parameters were selected based on their relative effect on the measured TOC
- TOC is strong function GR, Resistivity and density

The relative importance of the different parameters considered to learn the ANN model



# ESTIMATION OF TOC USING ANN TECHNIQUE

Building ANN model:

- Coding for this ANN model is under processing;
- The preliminary results show that the training set gave the best prediction of the measured from above *optimized parameters for the proposed the ANN model* ;
- The equations are applied for the model:

$$\frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

$$Y = \left( \frac{X - X_{\min}}{X_{\max} - X_{\min}} \right) (Y_{\max} - Y_{\min}) + Y_{\min}$$

$$\text{TOC} = \left[ \sum_{i=1}^N w_{2-i} \text{tansig} \left( \sum_{j=1}^J w_{1-ij} Y_j + b_{1i} \right) \right] + b_2$$

Y: normalized input parameter

Y<sub>min</sub>=-1; Y<sub>max</sub>=1

X: input parameter (GR, Res, density, sonic)

X<sub>min</sub>=minimum input value; X<sub>max</sub>=maximum input value

N: total number of neurons

J: number of inputs (GR, Res, sonic, density logs)

w<sub>1</sub> and b<sub>1</sub>: weight and bias of hidden



# ESTIMATION OF TOC USING ANN TECHNIQUE

The proposed ANN-based weights and biases for TOC calculations

		Input layer				Output layer		
		Weights(w1)				Biases (b1)	Weights (w2)	Bias (b2)
		j=1	j=2	j=3	j=4			
No. of neurons	i=1	0.9517	0.5817	0.9676	-2.5309	- 0.2742	-1.7182	-1.2152
	i=2	0.5742	0.6430	0.7720	-2.1296	- 0.0267	2.2211	
	i=3	5.4001	0.7938	1.0230	2.9429	0.7237	0.1883	
	i=4	0.7955	- 0.0550	- 0.4142	0.2749	1.2092	-0.9094	
	i=5	-0.1984	7.8703	- 0.4421	-0.1181	8.9550	1.7738	



## CONCLUSIONS

ANN model was proposed to estimate TOC for shales in the SH-1X well using log data.

Some obtained results can be drawn:

- Estimating TOC from well logging data shows good match with measured TOC in clean shale intervals;
- TOC empirical correlation was extracted based on the weights and biases of the optimized ANN model. The equation can be used to estimate the TOC based on log data with a high accuracy without need for ANN model
- All parameters are provided for training ANN model
- ANN model is under processing and testing, however, the initial results show a better TOC estimation compared to other methods by high coefficient of determination.





**THANK YOU**

