# Chapter 4
# Artificial Intelligence Approach for Predicting TOC From Well Logs in Shale Reservoirs:
## A Review

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## ABSTRACT

*Total organic carbon (TOC) is the most significant factor for shale oil and gas exploration and development which can be used to evaluate the hydrocarbon generation potential of source rock. However, estimating TOC is a challenge for the geological engineers because direct measurements of core analysis geochemical experiments are time-consuming and costly. Therefore, many AI technique has used for TOC content prediction in the shale reservoir where AI techniques have impacted positively. Having both strength and weakness, some of them can execute quickly and handle high dimensional data while others have limitation for handling the uncertainty, learning difficulties, and unable to deal with high or low dimensional datasets which reminds the "no free lunch" theorem where it has been proven that no technique or system be relevant to all issues in all circumstances. So, investigating the cutting-edge AI techniques is the contribution of this study as the resulting analysis gives top to bottom understanding of the different TOC content prediction strategies.*

## INTRODUCTION

For gas and oil exploration, it is critical to evaluate source rock property accurately. The abundance of organic carbon can be represented by Total organic carbon as a basic and important index (Passey, Creaney, Kulla, Moretti, & Stroud, 1990),(King, 2010). Generally, from core laboratory analysis, this

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parameter is obtained which are time-consuming and expensive (Delvaux, Martin, Leplat, & Paulet, 1990; Hare et al., 2014; Johannes, Kruusement, Palu, Veski, & Bojesen-Koefoed, 2006). This constrains the quick advancement of unconventional oil and gas exploration.

Then again, permeability, thermally mature, total organic carbon (TOC) content, porosity, saturation, mechanical properties and rock mineralogy etc. define the productivity of shale quality. Further, reservoir properties which are critical can judge qualitatively of most productive shale reservoir which are commercially potential typically has at least 2% TOC and Ro (more than 1.4 in gas dry window). For a good oil and gas flow capability and storage, it needs under 40% saturation and 100 nano-darcy permeability and over 2% porosity. Further, low differential stress, a certain degree of natural fractures and over 40% quartz or carbonate in mineralogy is needed additionally for commercial shales (Sondergeld, Newsham, Comisky, Rice, & Rai, 2010). For basic and important index, TOC content is the one among the all factors representing the organic matter.

Well logging and direct geochemical analysis are utilized conventionally for TOC determination in the present petroleum industry. Whatever, core data for TOC are not available due to the time and cost required for testing and the difficulties related to gather occasion an intact and representative sample. Despite the fact that laboratory test of TOC is difficult, they are still the preferred and necessary techniques (Guangyou, Qiang, & Linye, 2003; Jarvie*, Jarvie*, Weldon*, & Maende*, 2015).

For further prediction, these lab results are regularly applied as references for the mathematical approaches. With the fast advancement of unconventional exploration of gas and oil, the accurate and continuous study on the TOC is vital. High longitudinal resolution portrays well logging. For the fact of giving continuous TOC profiles that cover the entire interval of interest when continuity of the information and log-based TOC prediction are all the more universally applicable. By comparing with surrounding rocks, some specific geophysical responses (e.g., resistivity, neutron, density, and gamma-ray) of the source rock can be recognized. During utilization of log-based TOC prediction the empirical mathematical equations are commonly utilized. Notwithstanding, equation quality are incredibly dependent by the estimation result by logging data. Meanwhile, the gamma-ray and uranium correlation technique are some of the time not reasonable for shale reservoir. Having radioactivity in phosphatic fish plates in shale reservoir elevated gamma-ray and uranium counts can't reflect TOC (Bessereau, Carpentier, & Huc, 1991; Passey et al., 1990).

A complicated non-linear function relationship is seen between the TOC content and the logging data. Between the logging data and the TOC content a complicated relationship is seen which are non-linear. By using simple linear regression, approximating the real function relationship is hard and utilizing the well log, it is impossible to predict the TOC content. Nowadays, most researchers have been attracted by AI. The real research demonstrates that AI strategies have extremely solid approximation abilities to non-linear implicit functions. On the other hand, the prediction of TOC content has been worked by AI strategies revealed by the current research result. Between TOC content and the logging parameters a correlation models have been established by utilizing the NN so as to accomplish a good prediction of TOC content. Indeed, the utilization of robust AI techniques approaches have been presented and effectively utilized in numerous engineering fields, for example, permeability estimation, lithology classification et al. (Shadizadeh, Karimi, & Zoveidavianpoor, 2010; Yuan, Zhou, Song, Cheng, & Dou, 2014; Zoveidavianpoor, Samsuri, & Shadizadeh, 2013). Table 1 abridge current TOC prediction strategies utilizing well logs.

*Table 1. Summary of log-based TOC prediction models*

| Method | Parameters | Explanation and feature | Reference |
|---|---|---|---|
| LogR method | Resistivity and Porosity | (1) TOC foundation levels and Baseline shift territorially<br>(2) LOM range varies in specific areas<br>(3) Underestimates TOC in reservoir with a plenitude of pyrite | [1], [13]– [15] |
| Bulk density method | Density | (1) Suitable for reservoirs with similar consistent mineralogy and liquid phases.<br>(2) Need a solid relationship amongst TOC and density. | (Schmoker, 1979; Schmoker & Hester, 1983) |
| Natural gamma method | Gamma intensity | (1) For non-radioactive or uranium content with phosphatic minerals has limitation.<br>(2) Better for marine source rocks (with concentrated uranium) | (Beers, 1945; Hester & Schmoker, 1987) |
| Interval transit time method | Compressional transit-time | (1) Sonic velocities can be affected significantly by many variables.<br>(2) Need a solid relationship between TOC and compressional transit time | (Autric, 1985; Decker, Hill, & Wicks, 1993) |
| Geochemical Laboratory measurements (Leco TOC and Rock Eval) | (1) Combust pulverized tock<br>(2) S1, S2, S3 peaks in rock Eval technique | (1) Discrete data points<br>(2) Direct measurements from core samples<br>(3) Expensive | (Jarvie* et al., 2015; Peters, 1986) |
| Spectral gamma ray method | Uranium, potassium, uranium content | (1) Expensive and availability is less for all wells | (Nardon et al., 1991) |
| Volume model method | Water volume and Hydrocarbon, carbonate volume, Kerogen volume clay volume, and siliceous volume | (1) Organic carbon conversion factor (K) changes territorially<br>(2) Composite well log integration | (Mendelzon & Toksoz, 1985) |
| Laser-induced breakdown spectrometry, chemostratigraphy, RockView | The carbon abundance of formation and carbonate mineral in spectroscopy | (1) International oil service companies (Schlumberger-Litho Scanner, Baker Huges-RockView services et al.) controls the Core technologies<br>(2) The chemical contents can be determined directly | (Charsky & Herron, 2013; Pemper et al., 2009) |
| Multivariate fitting | Composite well logs | (1) Need database foundation<br>(2) Hard to decide the significant parameters because of nonlinear connection between various well logs | (Heidari, Torres-Verdin, & Preeg, 2011) |
| Neural network methods | Composite well logs | (1) For over-fitting input issue data-pre-processing is essential<br>(2) Suitable at the beginning time for TOC prediction.<br>(3) Kernel functions are significant for SVR | (Huang & Williamson, 1996; Kamali & Mirshady, 2004; Tan, Song, Yang, & Wu, 2015) |

## BACKGROUND

It is evident in published literature that the utilization of AI acts to diminish the framework complexities to be modeled. For the overall framework AI can give a high level of simulated accuracy. To give some examples such studies, we note that the AI technique can be classified into these algorithms: ANNs, FL, generalized regression neural network, SVMs, radial basis function, convolutional neural networks (CNNs), Genetic calculation (GA), PSO, Neuro Fuzzy (NF), Artificial intelligence system (AIS) et al. applied to optimize the whole modeling procedure (Ardabili, Mahmoudi, & Gundoshmian, 2016; Kalantari et al., 2018). Having the amazing capability of learning the patterns AI can perceive the complex behavior in such information for modeling the objective variable. Utilizing computer-based technique research demonstrates that for accomplishing a high level of accuracy, AI models can utilize significantly large volume of data. More importantly, AI methodologies with the assistance of computer assisted facilities can also enable a variety of decision-making alternatives modeled by realistic estimates of procedures that should be applied in practical life (O'Leary, 2013).

In the same way as other different fields, AI has achieved a decent spot in the optimization, production and evaluation of source rock in shale reservoir predominantly on the grounds that the generation potential of source rock involving large volume of information with several input parameters is relatively complex process. Those can be breaking down cautiously and predict Total Organic Carbon in shale reservoir. Wang, Alizadeh, Johnson, Mahmoud, and Shi et al. utilized ANN to evaluate TOC content in shale reservoir whereas Peng, Tahmasebi, Wang et al. developed a hybrid method using FL, GA, LSSVM, PSO et al. Whatever remains of the studies, as displayed in Table 2, can be sorted dependent on the particular I approach.

## MAIN FOCUS OF THE CHAPTER

The goal of this review is to investigate the cutting-edge AI approaches utilized in TOC content prediction in shale reservoir as far as their setting of application, sensitivity and accuracy to the model's input datasets. For providing comprehensive data on the usage of AI in TOC content prediction, an extensive interpretation, review and analysis is expected where the researcher would be helped by optimizing their methodology. This review work has five stages where the first stage is about a comprehensive introduction of TOC content in shale reservoir and its prediction procedure. In second stage, an arrangement of studies dependent on the developed AI technique in a more prominent detail is provided. The next stage presents AI and TOC content prediction strategies. The criteria for assessment of models is characterized in stage four and the final stage builds up the comparison dependent on assessment criteria and the general conclusion and the synthesis of cutting-edge studies reached in the review paper in TOC prediction studies.

## METHODOLOGY

Eight recent articles of AI technique are adopted in this review which are the cutting-edge methods for TOC content prediction from well logs data. This information is gathered from IEEE, Science Direct and Springer. TOC content prediction strategy, modeling technique and the obtained results are reviewed in this paper. A list of studies on AI technique are provided in Table 2.

*Table 2. Publications on AI techniques in field of TOC content prediction between 2012 and 2019*

| Row | Published Year | Author (s) | Objective |
|---|---|---|---|
| Artificial neural network | | | |
| 1 | 2019 | Huijun, Wei, Tao, Xinjun, Guangxu | To predict TOC, S1 and S2 with high accuracy based on well logs. |
| 2 | 2018 | Yousef, Ali Moradzadeh; Mohammad Reza | To estimate one dimensionally the organic geochemical parameters in one well of the Canning basin, Western Australia |
| 3 | 2018 | Bahram, Khaled, Mohamad Hossein | To estimate TOC;<br>To estimate S2 and HI factors;<br>To distinct the kerogen types |
| 4 | 2018 | Lukman, Reza, Ali, Gregory, Hongyan | To predict continuous geochemical logs in wells with no or limited geochemical information.<br>To predict TOC, S1, S2 |
| 5 | 2017 | Ahmed Abdulhamid, Salaheldin, Mohamed, Mohamed, Abdulazeez, Abdulwahab | To determine the TOC for Barnett and Devonian shale formation based on conventional logs |
| 6 | 2016 | Maojin, Xiaodong, Xuan, Qingzhao | To estimate the TOC content in gas-bearing shale (to investigate log-based TOC prediction for organic shale using the SVR method) |
| SVM, GA, PSO, ELM, FUZZY, and other methods | | | |
| 1 | 2018 | Pan, Suping | To predict TOC from well logs data |
| 2 | 2018 | Pan, Suping, Taohua | To predict TOC from well logs data |
| 3 | 2017 | Linqi, Chong, Chaomo, Yang, Xueqing, Yuan, Yuyang, Le | To predict TOC from well logs data |
| 4 | 2017 | Pejman, Muhammad | To predict TOC and FI from well logs |
| 5 | 2017 | Vahid, Ali, Reza | To formulate TOC values in the absence of laboratory TOC measurements from conventional well log data. |
| 6 | 2016 | Xian, Jian, Gang, Liu, Xinmin, | To predict TOC from well logs data |
| 7 | 2015 | Sid-Ali, Leila | To predict TOC from well-logs data.<br>To implant an intelligent system able to replace the Schmoke model in case of lack of measurement of the Bulk density. |
| 8 | 2015 | Maojin, Xiaodong, Xuan, Qingzhao | To estimate the TOC content in gas-bearing shale (to investigate log-based TOC prediction for organic shale using the SVR method) |
| 9 | 2012 | Ebrahim, Ali, Saeid | To predict TOC using intelligent systems |

## CHARACTERISTICS OF THE STUDIES

The characteristics of studies such as methodology, modeling technique, input and output criteria of every AI approaches presented in Table 3

*Table 3. Modeling characteristics*

| No | Methodology | Modeling method/ classification method/ regression method/ clustering method | Input (s)/ objective functions (s) | Output (s)/ Criteria | References |
|---|---|---|---|---|---|
| 1 | First- We made a correlation between TOC, S1, S2 and well logs to determine the suitable inputs. Second- 125 core shale samples and well logging data of Shahejie Formation from Dongying Depression, Bohai Bay, China were randomly split into 100 training samples and 25 validating samples to develop the proposed CNN for predicting TOC, S1 and S2. Third- all logs and chosen logs were used as inputs respectively for comparison. | Six Layer CNN | Density (DEN), resistivity (RT), neutron (CNL), and sonic transit time (AC) | TOC, S1 and S2 | Huijun et al (2019) |
| 2 | First, simulated annealing algorithm combined with the GA to analyze the fuzzy c-means clustering so as to classify sample data, and then to obtain the high-quality data. Then for the small sample data, LSSVM was established to predict TOC. Further, PSO-LSSVM was established to predict TOC content. At the same time, a BP-NN model for the contrastive analysis was established. | SAGA-FCM (Simulate annealing algorithm genetic algorithm-Fuzzy C mean clustering); LSSVM; PSO-LSSVM; BPNN | SP, GR, DTC, RT, U, KTH, TH, DEN, CNL | TOC | Pan et al (2018) |
| 3 | A multi-layer perceptron neural network used to predict S1, S2, S3 and TOC in presence of the petrophysical logs like GR, DT, SP, CAL, NPHI, FCNL, LLD, LLS, RHOB and MSFL as input variables. Then, the well-derived geochemical data were simulated by Sequential Gaussian Simulation (SGS) method. | MLP-NN and SGS (Sequential Gaussian Simulation) | GR, DT, SP, CAL, NPHI, LLD, LLS, RHOB, MSFL | TOC, S1 | Yousef et al (2018) |
| 4 | ANN and ΔLogR techniques were used to make a quantitative and qualitative correlation between TOC content and wireline data. Then, Artificial Neural Network and mathematical relationship between geochemical factors were used to estimate S2 and HI factors. Furthermore, estimated parameters were used to distinct the kerogen types. Finally, geochemical and depositional properties of the Pabdeh Formation were evaluated to depict applicability of the method used. | ANN; ΔLogR techniques; | (1)ΔLogR technique, sonic log (DT), corrected resistivity log (Rt) and LOM factor; GR log; (2) TOC, Rt, DT, and LOM | (1) TOC; (2) S2 | Bahram et al (2018) |
| 5 | The study investigates three types of models including PSO-LSSVM, LSSVM and ANN-BP for TOC prediction. Moreover, in this study, two cases of models will be designed. One takes the selected well logs as input, while the other takes all available well logs as input. | ANN-BP, LSSVM, PSO-LSSVM | Selected Log= (CNL, DTC, RT,U,GR,DEN) | TOC | Pan, Suping et al (2018) |
| 6 | ANN is utilized to predict organic geochemical data in two wells with no laboratory measured geochemical data, and four (4) wells with limited laboratory measured data. The distribution of these geochemical properties within the ~200m–300m thick Goldwyer 3 Shale member is subsequently modelled across the Broome Platform of the Canning Basin.The methods employed in this study can be subdivided into four main steps.<br>a. Well log to geochemical data compilation<br>b. Identification of relationship between well logs and geochemical property<br>c. Network Training<br>d. Geochemical Property Model | ANN | DTC; GR; CNL; DEN; KTH; TH; U | TOC | Lukman et al (2018) |
| 7 | Applied an ANN model with single hidden layer and 5 neurons to predict TOC in presence of the GR, $R_{ILD}$, $\Delta t_b$ as input and TOC as output of process. | ANN | Gamma ray log, deep induction resistivity log, compressional transient time, and bulk density log | TOC | Ahmed et al (2017) |
| 8 | First, a method of data mining called stepwise regression for identifying the correlations between target (i.e., dependent) parameters- the TOC and FI and the available well log data (the independent variables). Then a hybrid machine-learning algorithm (FL-GA-ANN) is also presented that models more accurately the complex spatial correlations between the input and target parameters. | Multiple linear regression (MLR); Fuzzy Logic, Genetic algorithm, ANN, Hybrid Machine Learning (FL-GA-ANN) | GR, Rhob, Nphi, DT, PE, RT10, SP, Ur, Thor, K | TOC, Fracable Index (FI) | Pejman et al (2017) |
| 9 | First- Rock-Eval pyrolysis measurements on drill cutting samples. Second, Synthesis of TOC log from conventional well log data using FL and calculating TOC applying △ log R technique. Third, grouping the synthesized TOC log data into clusters using k-means algorithm. Fourth, Training SVM and ANN classifiers to predict the source rock class membership (zones) from well log data and finally, Correlation of estimated with the achieved source rock class membership (zones) | FIS; K-means algorithm; SVM; ANN | GR, RHOB, LLD | TOC | Vahid et al (2017) |
| 10 | Two methods are mainly used in the estimation of the total organic carbon from well logs data, the first one is called the Passey's method or ΔLogR, the second method is called the Schmoker's method, it requires a continuous measurement of the Bulk density. Then, comparison between the fuzzy logic and the artificial neural network in the prediction of the total organic carbon in case of the lack of measurement of the Bulck density were established. | Fuzzy Logic; MLP-NN | Gamma ray log, deep induction resistivity log, compressional transient time, and bulk density log | TOC | Ahmed et al (2017) |
| 11 | An integrated hybrid neural network (IHNN), as an improved method, is optimized on the basis of BPNN from the following aspects including weight optimization before iteration, network structure optimization and serial-parallel integration was established for evaluating the TOC using conventional logging curves (low feature dimensions). | BP_AdaBoost; KELM; SVM; DEN; ΔlogR; IHNN | PE, KTH, AC, CNL, RD, TH, K, U, DEN, GR, SP | TOC | Linqi et al (2017) |

*continued on the following page*

*Table 3. Continued*

| No | Methodology | Modeling method/ classification method/ regression method/ clustering method | Input (s)/ objective functions (s) | Output (s)/ Criteria | References |
|---|---|---|---|---|---|
| 12 | An Extreme Learning Machine (ELM) network is a single hidden-layer feed-forward network with many advantages over multi-layer networks was employed to predict TOC from well logs data Then The results and performance characteristics of the ELM technique are compared to those obtained by the ANN method to evaluate the efficiency of these two networks during the prediction process. | ELM; ANN | DTC; GR; CNL; DEN; KTH; TH; U | TOC | Xian et al (2016) |
| 13 | Three different regression algorithm (the Epsilon-SVR, Nu-SVR, and SMO-SVR) and four different kernel functions (Linear function, Polynomial function, Gaussian function, Multilayer perceptron) used in a packet dataset validation process and a leave-one-out cross-validation process. Then, for comparison, the SVR-derived TOC with the optimal model and parameters is compared with the empirical formula and the logR methods. Additionally, the radial basis network (RBF) is also applied to perform tests with different inputs; the results of these tests are compared with those of the SVR method. | Epsilon-SVR; Nu-SVR; SMO-SVR | CNL; K; GR; U; TH; AC; DEN; PE; LLD | TOC | Maojin et al (2015) |
| 14 | An Artificial Neural Network (ANN) was applied to predict the TOC form well-logs data in case of absence of measurement of the Bulk density log. Then, different methods that are used for the determination of the TOC had been explained. The implanted neural network machine is applied to two horizontal wells drilled in the Barnett shale. | MLP-ANN | Natural gamma ray, Neutron porosity, sonic P and S wave slowness | TOC | Sid-Ali et al (2014) |
| 15 | Firstly, petro physical data were clustered into distinct groups. This classification does not require any further subdivision of the dataset but follows naturally based on the unique characteristics of well log measurements reflecting mineral and lithofacies responses within the logged intervals. Then, using an intelligent model such as Neural Network (NN) the amount of the-TOC was estimated in each individual EF(Electro-facies). | SOM; K-means clustering; Hierarchical Cluster Analysis; BP-ANN; | thermal neutron porosity (TNPHI), sonic transit time (DT), GR, CGR, SGR, K and THOR logs | TOC | Ebrahim et al (2012) |

## AI APPROACH EVALUATION CRITERIA

The viability of past AI approach connected in an issue of TOC content prediction has been assessed dependent on a correlation of the output of the developed model and the target values, utilized for most precise forecast, discovery, and streamlining and observing of the procedure in term of their measurable execution exactness. Table 4 exhibits the evaluating factors that have been utilized for looking at the productivity of the AI approach. The second segment portrays the parameters utilized in the performance indices.

## STATE-OF-THE-ART OF AI APPROACHES IN TOC PREDICTION

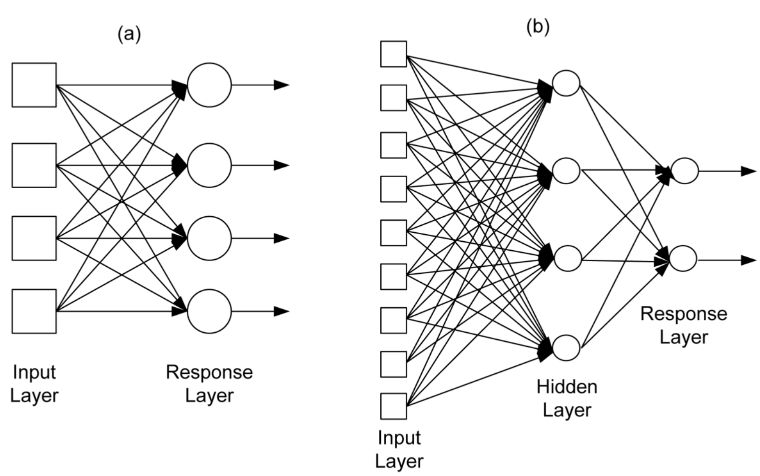
### Artificial Neural Network (ANN)

For learning and analyzing information features and subsequently implementing non-linear approximation function ANNs have a decent capacity and are being considered as a standout amongst the most effective strategies contrasted with statistical models. By working based on the biological neural system ANNs has prompted their effective applications in numerous regions, for example, image analysis, pattern recognition, adaptive controls and so forth. Any initial assumption does not require for ANN for the nature of the information distribution or fitting function and making the model a primary advantage over the counterpart are statistical. Then again, experimental data can be trained by ANN. Importantly, complex frameworks can be demonstrated in an easy way by ANNs requiring no parametric form of complex physical equations, data assumption, and initial or on the other hand boundary conditions con-

*Table 4. Model evaluation criteria*

| Accuracy and Performance Index | Description |
|---|---|
| $MSE = \frac{1}{N \times p}\sum_{i=1}^{p}\sum_{j=1}^{N}\left(T_{ij} - L_{ij}\right)^2$<br>$RMSE = \sqrt{\frac{1}{N \times p}\sum_{i=1}^{p}\sum_{j=1}^{N}\left(T_{ij} - L_{ij}\right)^2}$<br>$MAE = \frac{1}{N \times p}\sum_{i=1}^{p}\sum_{j=1}^{N}\left\|T_{ij} - L_{ij}\right\|$<br>$MAE = \frac{1}{N \times p}\sum_{i=1}^{p}\sum_{j=1}^{N}\left\|T_{ij} - L_{ij}\right\|$<br>$MAPE = 100 \times \frac{1}{N \times p}\sum_{i=1}^{p}\sum_{j=1}^{N}\left\|\frac{T_{ij} - L_{ij}}{T_{ij}}\right\|$<br>$AAD = \frac{1}{N}\sum_{i=1}^{N}\left\|T_{ij} - \overline{T_i}\right\|$<br>$R = \frac{\sum_{i=1}^{n}\left[\left(p_{Mi} - \overline{p_M}\right)\left(p_{pi} - \overline{p_p}\right)\right]}{\sum_{i=1}^{n}\left[\left(p_{Mi} - \overline{p_M}\right)^2 \sum_{i=1}^{n}\left(p_{pi} - \overline{p_p}\right)^2\right]}$ | • $P$, the number of data set patterns<br>• $n$ is the number of the samples<br>• $N$, the number of output units<br>• $T_{ij}$ and $L_{ij}$ are target and output values<br>• $p_p$ is the output power<br>• $p_{Mi}$ is the target power<br>• $p_m$ is the average power |

*Figure 1.*



trasted with mathematical type models. ANN can be partitioned into single/multi-layer, self-organized and recurrent in terms of the topology of networks. In Figure 1 (Heiliö et al., 2016) a schematic of single and multi-layer networks is portrayed.

In Figure 2, the different attributes of ANNs of diverse categorization is summarized. Further the common activation function utilized in the design of ANNs structures have given in Table 3.

Depending on the classification of ANN and applied activation function on the input, different structure of ANN is conceivable (see Table 5 and Figure 5).

(Basheer & Hajmeer, 2000)displayed a summarization of popular networks in Table 6.

## Support Vector Machine (SVM)

In 1960s, SVMs(Support Vector Machines) first introduced (Vapnik, 1963, 1964); nonetheless, the thought was revitalized (Cortes & Vapnik, 1995) later in 1990s when the SVM displayed better execution in various classification issues over the ANN approach, which had been acknowledged as an effective strategy. As being popular AI method SVM is applied as per statistical learning theory, has a wide application in numerous fields of science and engineering including regression and classification problem (Ebtehaj, Bonakdari, Shamshirband, & Mohammadi, 2016; Ghorbani et al., 2017). SVM prefer the generalized upper bound error for reducing than the local training error which is one of the main advantages contrasted with the traditional machine learning methods. Further, by utilizing SRMP and presenting a decent generalization capacity to conquer the deficiencies of the conventional ANN model that uses the empirical risk minimizing in modeling a given variable by SVM.

SVM can be demonstrated by the idea of classification considering a 2D simplest case input space containing class1 and class 2 data. Linearly classification can be possible with these data. SVM sim-

*Figure 2. Attributes of ANN*

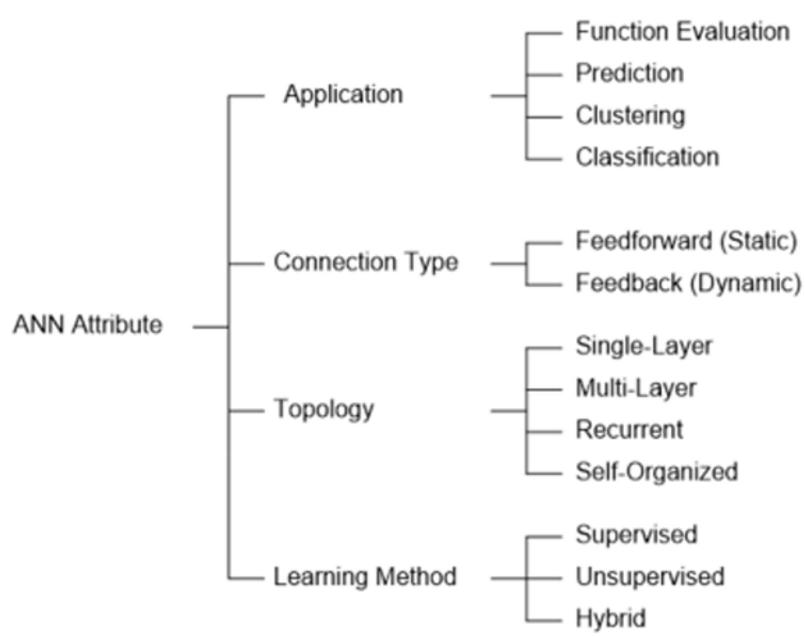


*Table 5. Activation functions of ANN (Da Silva, Spatti, Flauzino, Liboni, & dos Reis Alves, 2017)*

| Activation function | Formula | Range of output |
|---|---|---|
| Bipolar step | $f(x)=\begin{cases}1 & x<0\\ 0 & x=0\\ -1 & x>0\end{cases}$ | [-1,1] |
| Step | $f(x)=\begin{cases}1, & x\leq 0\\ -1, & x>0\end{cases}$ | [-1,1] |
| Linear | $f(x)=x$ | [-∞,∞] |
| Unit step | $f(x)=\begin{cases}1, & x\leq 0\\ 0, & x>0\end{cases}$ | [0,1] |
| Symmetric ramp | $f(x)=\begin{cases}a & x<a\\ x & -a\leq x\leq a\\ -a & x>a\end{cases}$ | [-a,a] |
| Piecewise linear | $f(x)=\begin{cases}1 & x<0\\ x+\frac{1}{2} & -\frac{1}{2}\leq x\leq\frac{1}{2}\\ -1 & x>0\end{cases}$ | [0,1] |
| Bipolar sigmoid | $f(x)=\dfrac{1-e^{-x}}{1+e^{-x}}$ | [-1,1] |
| Sigmoid | $f(x)=\dfrac{1}{1+e^{-x}}$ | [0,1] |
| Gaussian | $f(x)=\dfrac{1}{\sqrt{2\pi\sigma}}e^{\left[\frac{-(z-\mu)^2}{2\sigma^2}\right]}$ | [0,1] |
| Tangent hyperbolic | $f(x)=\tanh(x)=\dfrac{e^x-e^{-x}}{e^x+e^{-x}}$ | [-1,1] |

ply illustrated in Figure 3 (Cortes and Vapnik, 1995). In Figure 3 circle and squares are recognized as class 1 and class 2 respectively in input space. Both Figure 3(a) and Figure 3(b) represents the smallest margin and largest margin of two classes. Further, both in Figure 3(a) and Figure 3(b), there are three

*Table 6. A list of popular ANN design*

| ANN designs | Characteristics | Cons and pros | Application in engineering |
|---|---|---|---|
| Backpropagation (BP) (Rumelhart, Hinton, & Williams, 1985) | • Backpropagation error with feedforward network<br>• Supervised learning<br>• MLP with more than one layer<br>•Sigmoid activation function | • Most widely, simple, and straightforward (Priddy & Keller, 2005) • Trapping in local optima and slow learning • complex non-linear mapping can be handled (Priddy & Keller, 2005) | Image processing (Hassoun, 1995) • Modelling and control (Hassoun, 1995) •Pattern recognition (Hassoun, 1995) • Forecasting and mapping (Hassoun, 1995) |
| Radial basis function (RBF)(Broomhead & Lowe, 1988) | • Feed forward with error BP(Back Propagation) •Gaussian activation function • MLPs with three layers | • Flexibility is less and slower compared to BP • Using two-step unsupervised-supervised hybrid training makes it faster in training stage than BP networks | • Function approximation (Wei, Saratchandran, & Narasimman, 1999)<br>• Adaptive control (Wei et al., 1999) • Non-linear dynamic system identification (Wei et al., 1999)•Signal processing (Wei et al., 1999) |
| Recurrent (Williams & Zipser, 1989) | • Exhibitions of memory of information sequence on network •Sigmoid activation function • Flow in both directions | • Difficulty in training and number of parameters are large (Lipton, Berkowitz, & Elkan, 2015)<br>• Time varying patterns and sequential can be modelled simultaneously (Lipton et al., 2015) | •Filtering and control (Medsker & Jain, 1999) • Dynamic system identification (Medsker & Jain, 1999) • Forecasting (Medsker & Jain, 1999) |
| Hopfield (Hopfield, 1984) | •Symmetric two-layer recurrent network •Sigmoid activation function<br>• Non-linear associative memory | • Good for noisy and incomplete data • Except bipolar and binary input other input are useless. | •Intelligent computation (Tang, Tan, & Yi, 2007)• Optimization (Hoskins & Himmelblau, 1988) |
| Kohonen (self-organizing map, SOM) (Kohonen, 1989) | • Self-organizing • 2 layer network • Unsupervisely trained | • Number of clusters can be optimized on its own• Not an incremental network (Dokur, Ölmez, Yazgan, & Ersoy, 1997) • A few numbers of clusters are not good for it • Can organize large-scale data (Recknagel, 2013) | •Data mapping (Basheer & Hajmeer, 2000)•Pattern recognition (Basheer & Hajmeer, 2000)• Classification (Basheer & Hajmeer, 2000) |
| Grossberg(Adaptive resonance theory, ART) (Carpenter & Grossberg, 2016) | Recurrent network with 2 layer • Unsupervisely trained • Feed forward and feedback weight adjustments | • Fast training and continuous plasticity (Crestani & Pasi, 2013) • Because of representing clusters by nodes, network is susceptible of degradation and failure upon damage<br>• Small clusters can be broken by large problems (Wunsch II, Hasselmo, Venayagamoorthy, & Wang, 2003) | •Classification (Basheer & Hajmeer, 2000)•Pattern recognition (Basheer & Hajmeer, 2000) |
| Counter propagation (Hecht-Nielsen, 1988) | •Combination of Kohonen (in hidden layer) and Grossberg (in output layer) networks •Sigmoid activation function • Trained by unsupervised-supervised hybrid learning | • Faster than MLP in training (Kasabov, 1996)<br>• Network optimization is time expensive and difficult (Ballabio, Vasighi, Consonni, & Kompany-Zareh, 2011) • Due to unsupervised learning the performance is better compared to BP(Taylor, 2006) | •Function approximation (Zupan & Gasteiger, 1991) •Pattern recognition (Zupan & Gasteiger, 1991) •Classification(Zupan & Gasteiger, 1991) |
| Convolutional neural networks (CNNs) (Rumelhart et al., 1985) | •Feed-forward multi-channel input •Preserves spatial dependency • Pooling operations and successive convulsion | • Large-scale problems can be handled (Kasabov, 1996) • Limited semantic generalization (Hosseini, Xiao, Jaiswal, & Poovendran, 2017) • Reduced memory size (Zhang, Wang, Tao, Gong, & Zheng, 2017) • Mathematically more complex than MLPs (Caterini & Chang, 2018) • Lower chance of over-fitting and more training (Zhang et al., 2017) | •Image processing (McCann, Jin, & Unser, 2017)•Classification (McCann et al., 2017) |
| Deep neural networks (DNNs) | • More than one hidden layer<br>• Processes data hierarchically (Cios, 2018)<br>• Usually supervised or semi-supervised training<br>• In fully supervised DNN, backpropagation with ramp activation function is used (Cios, 2018) | • Capable of large-scale data processing problems (Caterini & Chang, 2018)<br>• More details (features) can be extracted in training due to hierarchical data processing (Cios, 2018)<br>• Cautions should be made in unsupervised learning applications with modified inputs (Cios, 2018) | • Classification (Caterini & Chang, 2018)<br>• Image processing (Caterini & Chang, 2018)<br>• Multivariate regression (Du & Xu, 2017) |
| Deep belief networks (DBNs) (Hinton, Osindero, & Teh, 2006) | • Consists of a large number of layers; each layer consisting of restricted Boltzmann machines (RBMs) (Sun, Steinecker, & Glocker, 2014)<br>• Trained unsupervised layer-by-layer, and weights are adjusted top-down (Sun et al., 2014) | • Can discover a structure in data which is not labelled or structured (Sun et al., 2014)<br>• Can extract high-level features (Sun et al., 2014)<br>• Requires an additional pre-training stage to familiarize the network with data (Sun et al., 2014)<br>• Unsupervised learning in DBNs may not properly work with networks with stochastic or randomly initialized variables (Sun et al., 2014) | • Classification and clustering(Fink, Zio, & Weidmann, 2015)<br>• Image processing (Sun et al., 2014)<br>• Model discrimination (Fink et al., 2015)<br>• Monitoring and quality control (Sun et al., 2014) |

*Figure 3. Class 1 and Class 2 classification (Cortes & Vapnik, 1995)*

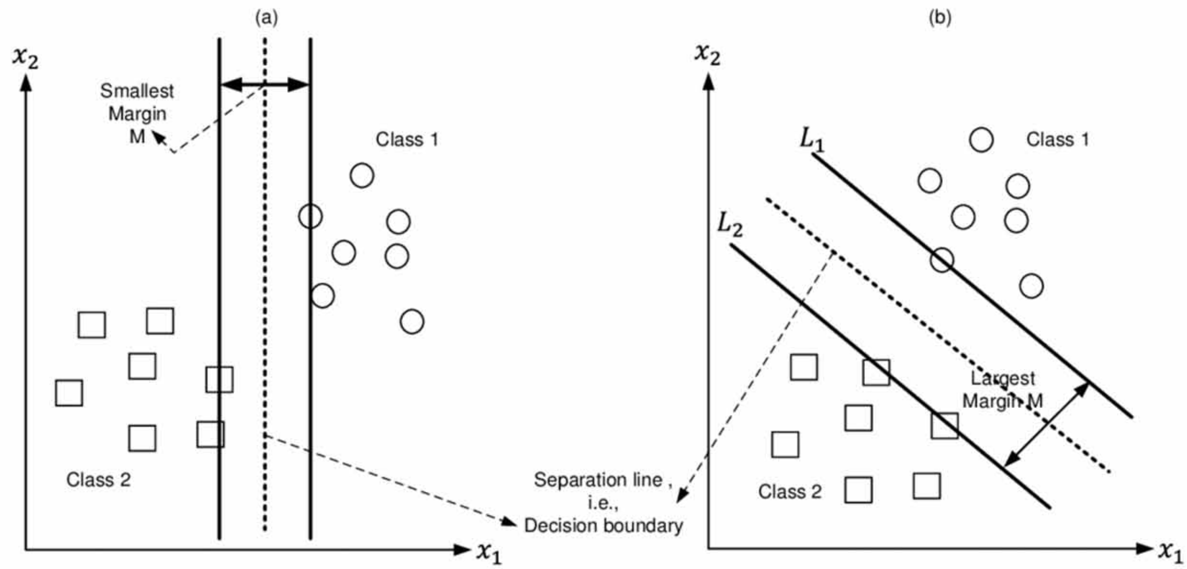
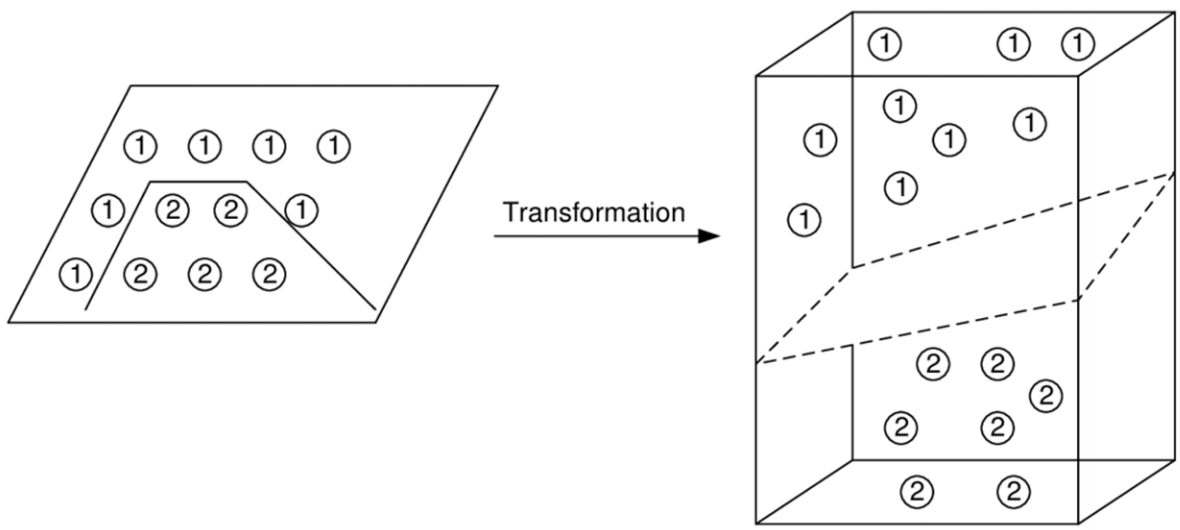



*Figure 4. Transformation in feature space*



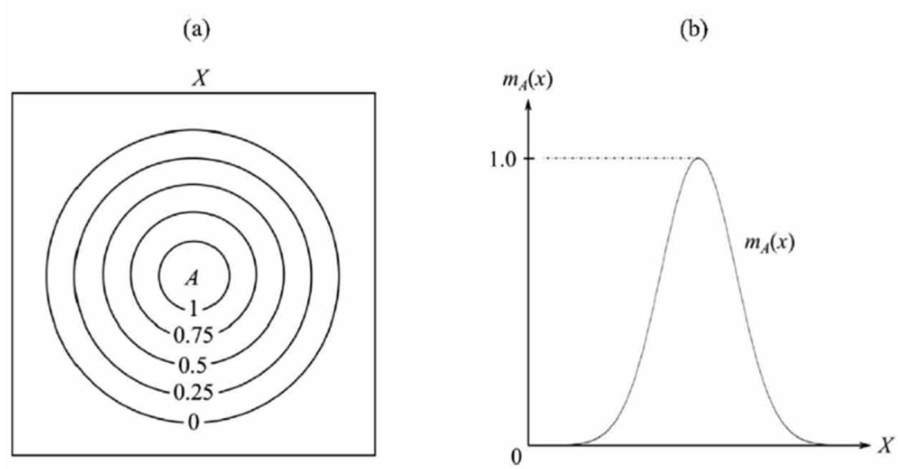

points (one circle and two squares) precisely fallen on the two lines on the two sides of the edge. These are called as the support vectors.

However, the classification of the SVM can be done in a higher dimensional space where the separation of two classes are non-linear utilizing transformation in kernel (or feature) space (sigmoid, polynomial, or/and radial basis function) delineated in Figure 4. And An outline of common kernel functions utilized in SVM is given in Table 7.

*Table 7. Kernel functions of SVM*

| Kernel | Kernel function | Parameters |
|---|---|---|
| Linear | $K(x_i,x_j) = (x_i,x_j)^a$ | $A \in N$ |
| Polynomial | $K(x_i,x_j) = (c + x_i x_j)^a$ | $A, c \in N$ |
| Gaussian | $K\left(x_i, x_j\right) = \exp\left[-\frac{x_i - x_j}{2\sigma^2}\right]$ | $\sigma \in R$, $\sigma > 0$ |
| Sigmoid | $K(x_i,x_j) = \tan h(\eta(x_i x_j)+\theta)$ | $\eta, \theta \in R$ |

*Figure 5. Bell-shape membership function of (a) contours and (b) distribution by fuzzy sets (Terano et al., 2014)*




## Fuzzy Logic

Zadeh (1965) first proposed Fuzzy Logic (FL) where the set theory of more than one valued logic being as a generalization. Frameworks having non-crisp boundaries are managed by it where characteristics for example being unclear/ambiguous and hazy are displayed by these frameworks (Terano, Asai, & Sugeno, 2014). Assume, in total space X, x is a member. In the crisp logic, the set A on total space (X) is defined by the characteristic function $x_A$ where the total space is being mapped to the set {0,1}, as following (Terano et al., 2014):

$x_A: X \rightarrow \{0,1\}$

$$x \rightarrow x_A\left(x\right) = \begin{cases} 0 x \notin A \\ 1 x \in A \end{cases}$$

*Figure 6. General framework of fuzzy logic*

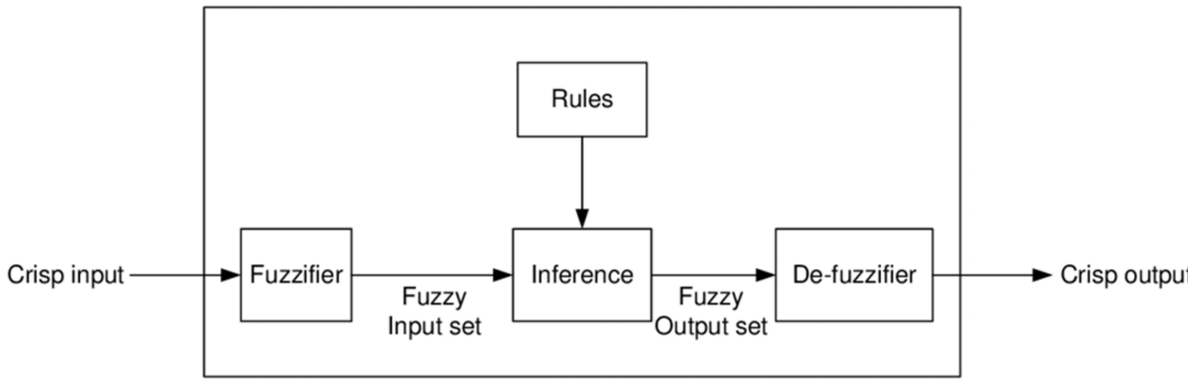



*Table 8. Standard operation in FL system (Zoveidavianpoor, Samsuri, & Shadizadeh, 2012)*

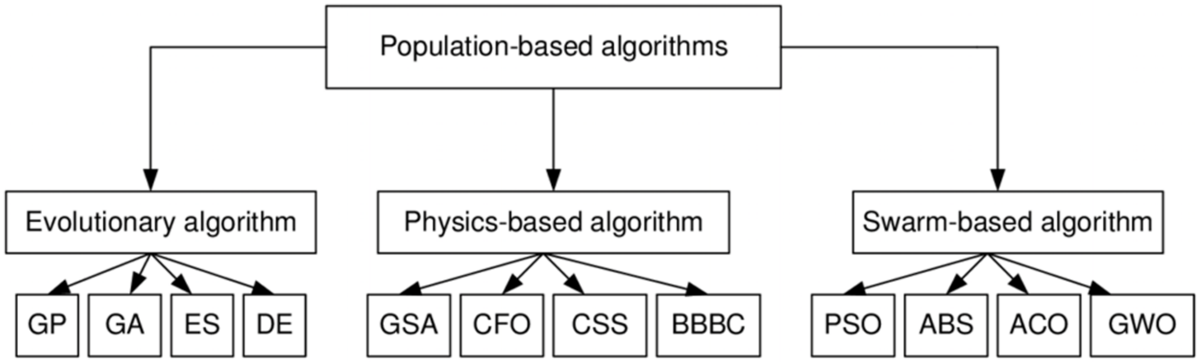
| **Fuzzy operator name** | **Algebraic operator name** | **Symbol** | **Description** | **Equation based on Algebraic** | **Equation based on Fuzzy** |
|---|---|---|---|---|---|
| Intersection | AND | $\cap$ | Applied to two fuzzy sets A and B with the membership function $\mu_A(x)$ and $\mu_B(x)$ | $\mu_{(A\cap B)} = \left\{\mu_A\left(x\right), \mu_B\left(x\right)\right\}, x \in X$ | $\mu_{(A\cap B)} = \min\left\{\mu_A\left(x\right), \mu_B\left(x\right)\right\}, x \in X$ |
| Union | OR | $\cup$ | Applied to two fuzzy sets A and B with the membership function $\mu_A(x)$ and $\mu_B(x)$ | $\mu_{(A\cup B)} = \left\{\mu_A\left(x\right), \mu_B\left(x\right)\right\}, x \in X$ | $\mu_{(A\cup B)} = \max\left\{\mu_A\left(x\right), \mu_B\left(x\right)\right\}, x \in X$ |
| Complement | NOT | NOT | Applied to fuzzy sets A with the membership function $\mu_A(x)$ | $\mu_A\left(x\right) = 1 - \mu_A\left(x\right), x \in X$ | $\mu_A\left(x\right) = 1 - \mu_A\left(x\right), x \in X$ |

In this manner, if x belongs to A, the value of 1 can be taken by the characteristic function, while if it is not a part of A, the function is 0. The following relationship is equivalent in the FL in Eq. (9):

$m_A$: $X \rightarrow [0,1]$

$x \rightarrow m_A(x)$

*Figure 7. Population based optimization algorithms (Vasant & Vasant, 2012)*




in which, the mf(membership function) is represented by $m_A$ (Terano et al., 2014). Different notation appears in the membership function in the literature, for example, fA and μA (Zadeh, 1965). From the Eq. (9) and Eq. (10), Boolean set in the crisp logic and a domain in the FL are the mapping of space X. A continuum speaks a ‘‘class’’ by Zadeh (Zadeh, 1965) work. Figure 5 outlines a portrayal of the fuzzy sets where mf as a continuum of the level of A-ness (Terano et al., 2014) or a continuum of the mg (membership grades) . Hence, the fuzzy sets consider the crisp sets as a special case.

In the theory of fuzzy logic other membership function exist beside the bell-shape membership (Figure 5 (b)).

## Evolutionary Algorithms

Numerous species over millions of years have evolved to adjust to different environments based on the Darwinian evolutionary theory. Considering the environment as a type of the problems and Evolutionary algorithm as an adaption of the population to fit the best environments, the same idea can be applied to numerical optimization. Until better solution is being achieved, the fundamental thought of evolutionary algorithm is to evolve a population of candidate solutions under a selective process analogous to the mutation, natural selection and reproduction. To generate offspring solution, parent solution is combined utilizing effective search algorithm where the offspring solution can be evaluated and may themselves produce offspring (Husbands, Copley, Eldridge, & Mandelis, 2007). Continuation of the generation prompts better solution to optimization, search and design issues. Many algorithm-like genetic algorithms, evolutionary programming, evolution programs and evolution methodologies are included by evolutionary algorithm. Both GA and DE give extraordinary performance in dealing with solutions which have variety of engineering issues. Hence, they are briefly explained in the following section.

### Genetic Algorithm (GA)

As being a prediction tool, in optimization and global search issues GA aims to create high quality solution (Salcedo-Sanz, Deo, Cornejo-Bueno, Camacho-Gómez, & Ghimire, 2018). By searching through a feature space, the nearest optimal solution is being able to deduce by this model (Eberhart & Kennedy, 1995;

Vasant & Barsoum, 2009). For candidate solution (CS) a solution needs to be chosen in GA technique where evolving towards a better solution is being set by its population. A set of properties are contained in each CS and these properties can mutate and change, in this manner the evolution is progressed as a duplicate process from a population of randomly generated individuals. Calculation of the objective function is done by each generation (the population). Then in the next iteration of the algorithm, the new generation of the candidate solution is used. The algorithm stops and uses the final model when a maximum number of generations have been produced to make the prediction. In Figure 8 and Figure 9 overall optimization process are appeared. Further a flow chart of GA is given in Fig 10.

## Differential Evolution (DE)

As a population-based model, DE uses a real-coded GA and a normal random generator for finding the global minimum of the objective function with an ARS (adaptive random search) (Maria, 1998). Mutation operation is mostly based on DE where for finding the optimal solution GA relies on crossover operation (Ab Wahab, Nefti-Meziani, & Atyabi, 2015). Like other evolutionary algorithms, DE consists of four stages: initialization, mutation, crossover, and selection. During the initialization step, a population/generation with a fixed number of candidate solutions (NP) using minimum and maximum values for each defined variable and a uniform random value in the range from 0 to 1 is created (Storn, 1995). The next step is to evolve the initial population in which every solution is mutated by adding the difference of two random solutions from the current population to a different selected random solution scaled by a factor F. Then, during the crossover process, diversity is created in the newly generated candidate

*Figure 8. GA optimization (Velez-Langs, 2005)(Chen, 2013)*

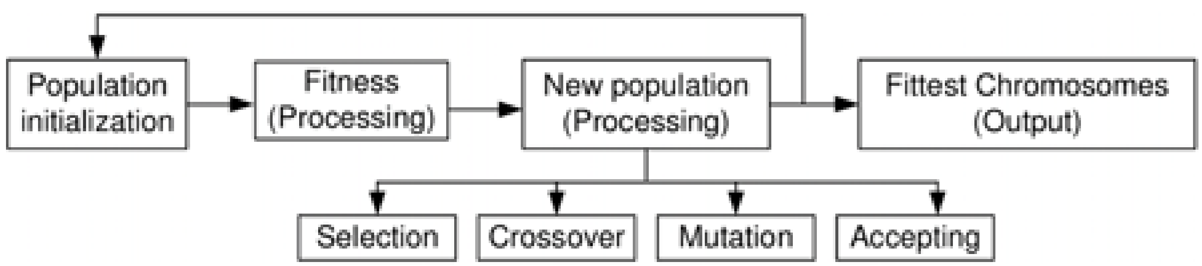



*Figure 9. (a) Crossover and (b) mutation*

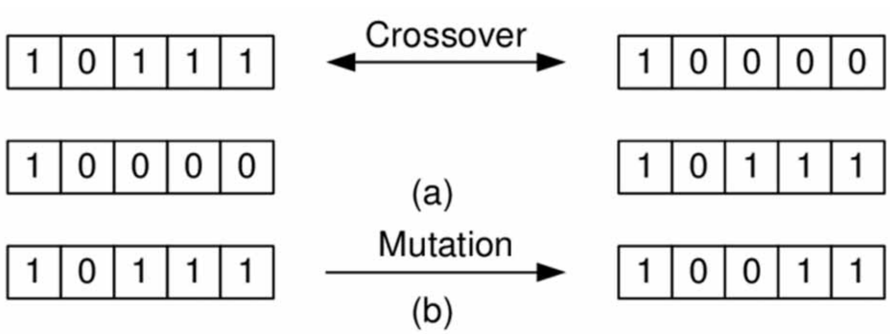
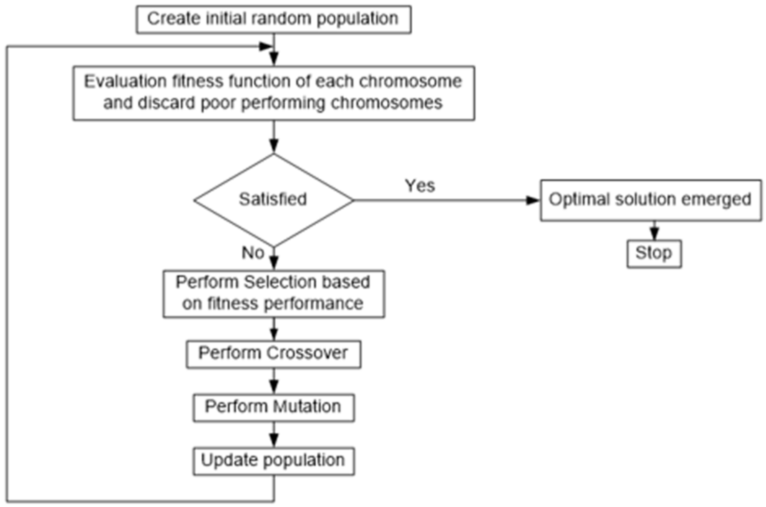


*Figure 10. The flow chart of DE algorithm (Ab Wahab et al., 2015; Khademi, Rahimpour, & Jahanmiri, 2010)*




solutions by applying the crossover probability rate (CR). There are two main crossover variants for DE: exponential and binomial. Finally, in the selection step, every solution vector in the trial population is compared with the corresponding vector in the initial population and depending on the nature of the problem (minimization or maximization), the one with the lower or higher objective function value is moved to the next generation. The four-step process repeated until the stopping criteria (reaching to the maximum number of generations or obtaining the defined different tolerance between the objective function values in the current generation and the previous one) are met. Figure 4 shows different steps of the DE algorithm.

## TOC Prediction Method

There is extensive application of artificial intelligence (AI)-based solution to complex engineering problems. In this section, we focus on the problems related to TOC content prediction in shale reservoir.

Sfidari et al (Sfidari, Kadkhodaie-Ilkhchi, & Najjari, 2012) firstly clustered Petro-physical data into distinct groups using Hierarchical cluster analysis and K-means clustering. For any further subdivision of the dataset no classification would be needed but rather pursues normally dependent on the special attributes pf well log estimation reflecting lithofacies and mineral reaction inside the logged interims. At that point, utilizing an intelligent model, for example, Neural Network (NN) the amount of the-TOC was assessed in every individual EF (Electro-facies). Here, 3 layered BP-NN model with Levenberg-Marquardt training algorithm was utilized for prediction in the clustered intervals and MSE was high. Ouadfeula and Aliouane (Ouadfeul & Aliouane, 2014) utilized ANN to predict the TOC from well-logs data if there should arise an occurrence of nonappearance of estimation of the bulk density log. The implanted NN model is applied to two horizontal wells drilled in the Barnett shale and it gave great outcomes that were exceptionally near the determined TOC utilizing the Schmoker's model. In their work, sonic P and S wave slowness logs, Neutron porosity, Natural gamma ray were utilized to predict TOC. From their work, it demonstrated the ability of the ANN to predict a TOC in case of nonappearance of the density log or a discontinuous of this log. Tan et al. (Ouadfeul* & Aliouane, 2015) presented three different regression algorithms (SMO-SVR, Nu-SVR and the Epsilon-SVR), four different kernel functions (Linear function, Polynomial function, Gaussian function and Multilayer perceptron) and a TOC prediction content that utilizes wireline logs in a leave-one-out cross-validation process and a packet dataset validation process. In following, the SMO-SVR, Nu-SVR and the Epsilon-SVR models are tested by comparison with respect to their TOC prediction accuracy. Both leave-one-out cross-validation and packet dataset validation demonstrate that the Epsilon-SVR model is superior to the SMO-SVR and Nu-SVR models. Rather than the RBF strategy, the SVR-derived TOC is in better agreement. Shi et al.(Tan et al., 2015)utilized MLP-NN and Fuzzy logic applied to two horizontal wells drilled in the lower Barnett shale formation to predict TOC from well logs data and to implant an intelligent framework ready to replace the Schmoke model in case of lack of measurement of the Bulk density where the utilization of ANN in the prediction of the TOC in shale reservoir was superior to the Fuzzy logic. Shi et al (Shi et al., 2016) used Artificial Neural Network (ANN) and Extreme Learning Machine (ELM) in TOC prediction where the Extreme Learning Machine (ELM) is a lot quicker than the Artificial Neural Network (ANN) model according to the training time comparison which made Extreme Learning Machine beneficial for practical use above ANN. For both ELM and ANN, DTC; GR; CNL; DEN; KTH; TH; U well logs data were used for training, testing and validation purpose to predict TOC. Zhu et al. (Zhu et al., 2018) utilized BP_Adaboost, KELM, SVM, DEN, $\Delta$log R and Integrated hybrid neural network (IHNN) to predict TOC content from well-logs data. The author looked at the prediction models set up in 132 rock sample in the shale gas reservoir inside the Jiaoshiba zone, rather than the established models, the accuracy of the proposed IHNN method is a lot higher and thus the generalization ability of the IHNN algorithm is also very strong. Measurements of drill cutting samples had been done by Rock-Eval pyrolysis and then FL synthesized the TOC log from conventional well log data. Further $\Delta \log R$ method had been applied for calculating TOC and then the synthesized TOC log data have been assembled into cluster utilizing k-means algorithm. Furthermore, training ANN and SVM classifiers have been utilized to predict the source rock class membership (zones) from well-log data. In Bolandi et al. (Bolandi, Kadkhodaie, & Farzi, 2017) work, both ANN and SVM were used for classification problem of source rock zonation. In term of classification accuracy, the SVM with RBF kernel readily outperformed ANN. Tahmasebi et al (Tahmasebi, Javadpour, & Sahimi, 2017) borrowed a hybrid method from machine learning and artificial intelligence proposed for accurate prediction of the parameters. The two techniques have the capacity to be tuned quickly and to utilize the more established database to precisely portray shale reservoirs. By this way, comparing with Multiple linear regression (MLR) the hybrid machine learning (HML) strategy gave considerably more accurate prediction to the TOC and FI. Mahmoud et al. (Mahmoud et al., 2017) utilized ANN model to estimate TOC for unconventional shale reservoir in Duvernay and Barnett shale formation utilizing conventional log-data (density log, gamma ray, compressional transient time, and deep induction resistivity log). ANN method gives better TOC estimations contrasted with available strategies by two criteria, higher coefficient of determination and lower average absolute deviation than accessible methods for Duvernay shale example. Furthermore, based on the weights and biases of the optimized ANN method, a new TOC empirical correlation was extracted for the first time so that without requiring the ANN model, it can be utilized with a high accuracy to estimate the TOC based on conventional log data. For accomplishing a quantitative and qualitative source rock characterization and distribution Johnson et al.(Johnson, Rezaee, Kadkhodaie, Smith, & Yu, 2018) utilized ANN across the Broome Platform of the Canning Basin. For the training, validation and test samples of the geochemical property the $R^2$ values is upwards of

75%. Further by predicting with ANN is the accomplishment of more prominent resolution between geochemical data points, as well as the time and laboratory requirements is significantly decreased in their work. Three kinds of models including LSSVM, PSO-LSSVM, and ANN-BP had utilized for prediction in Wang et al. (Pan Wang, Peng, & He, 2018) work. In their work, two cases of models had been designed where one took the selected well logs (DTC, CNL, GR, U, DEN and RT) as input and the other took all available well logs as input. In view of the outcomes, the PSO-LSSVM method beat ANN-BP and LSSVM methods. To make a quantitative and qualitative correlation between TOC content and wireline data ANN and Δ log R method were utilized in Alizadeh et al. (Alizadeh, Maroufi, & Heidarifard, 2018) work. At that point, to evaluate S2 and HI factor and to distinct the kerogen types mathematical relationship between geochemical factors and ANN were utilized. By utilizing the neural network, the mean TOC values were computed had higher correlation with real TOC determined from Rock Eval analysis. The neural network data showed better agreement in carbonate intervals with TOC calculated from Rock Eval. Nezhad et al.(Nezhad, Moradzadeh, & Kamali, 2018) utilized ANN for estimation where petrophysical logs and S1, S2, S3 and TOC data of geochemical analysis were respectively utilized as input and outputs of the models. Then Sequential Gaussian Simulation (SGS) technique simulated the well-derived geochemical data. The acquired outcome showed that MLP-ANN have a high precision in estimation of S2 and kerogen type detection and SGS acts superior to the MLP-NN technique for organic geochemical parameter evaluation. The impact of the sample data was considered in Wang and Peng (Pan Wang & Peng, 2018) work on AI modeling. The simulated annealing algorithm combined with the genetic algorithm to analyze the fuzzy c-means for improving the classification accuracy of the fuzzy c-means clustering algorithm and to classify sample data and after that to acquire the high-quality data. In this study, for the prediction of the TOC content, the TOC content prediction model was built up based on the particle swarm optimization (PSO-LSSVM). In the meantime, for the contrastive examination a BP neural network model was built up. From their outcome it could be seen that TOC could be predicted all the more precisely with PSO-LSSVM model that with BPNN and LSSVM models. A correlation between TOC, S1, S2 and well logs were made by Wang et al. (H. Wang, Wu, Chen, Dong, & Wang, 2019) to determine the suitable inputs. At that point 125 core shale sample and well logging data of Shahejei Formation from Dongying Depression, Bohai Bay, China were arbitrarily split into 100 training samples and 25 validating sample for building up the six-layer CNN for predicting TOC, S1 and S2. Further, the performance of CNN was compared with Passey technique and BP. Considering the outcomes, CNN exhibited higher prediction precision in both training and validation data for TOC, S1 and S2 contrasted with BP-ANN model and Passey technique by two criteria, higher $R^2$ and lower NRMSE.

## STRENGTHS AND WEAKNESSES OF ARTIFICIAL INTELLIGENCE TECHNIQUES

In this section, the common models will be deliberated briefly which can be unified into the identification, classification, estimation, mathematical modeling, clustering and function evaluation of a hybrid model with application. In this review script, sub-models, for example, ANNs, SVM, FL, Swarm intelligence and Evolutionary algorithm (EA) will be explained through delivering the principle theoretical structures.

Of the seven AI procedures featured in this work, it is important to inquire as to whether there is any of them that can be said to be 100% faultless and fit for use in all situations. In what is by all accounts a response to the above inquiry, Luchian et al. (2015) states that it is more useful concentrating on answering the problem as opposed to sitting around idly to locate the best method. Notwithstanding, a theorem yielded by Wolpert and Macready (1997) called the No Free Lunch Theorem for Optimization (NFLTO) states as follows: Given that all issues are thought to be equivalent in strength and irrespective of the criteria utilized for passing judgment on its performance, all techniques utilized for solving the issue have a similar act. In help of the NFLTO, Anifowose et al. (2016) opines that there is certainly not a solitary comprehensive AI approach that will adequately address all difficulties in all computing conditions and data since each of the AI methods is secured up its novel qualities and inevitable defects. Table 9 outlines the strengths and weakness of a portion of the AI strategies.

To demonstrate the effectiveness or otherwise of these AI procedures, a couple of researchers have endeavored to compare a couple of the AI systems.

## SYNTHESIS OF RESULTS AND CONCLUDING REMARK

This section synthesizes the discoveries and discusses about the consequences of TOC prediction in previous studies. Figure 16 shows the distribution of AI model connected in TOC prediction in shale reservoir from 2012 to 2019. This tree has been sorted dependent on a kind of strategies gathering (single or hybrid) and publication year, and they are utilized for different obligations, for example, optimizing, developing, estimating, diagnosing and designing in the prediction of TOC in shale reservoir fields. This tree additionally portrays the application patterns for every strategy in every year. As is clear, 2017 and 2018 has the most trends for applying AI techniques in TOC prediction. Likewise, the offer of utilizing single methods (78.9%) is higher than that of the hybrid methods (21.1%), then again, the assorted variety of single methods is higher than that of the hybrid methods. If there should arise an occurrence of strategy type, MLP has the most astounding utilization among different methods (both single and hybrid methods).

Table 4 shows a list of results dependents on the chosen paper number, gathered as far as the accuracy of the AI approaches and their impacts on the TOC prediction process.

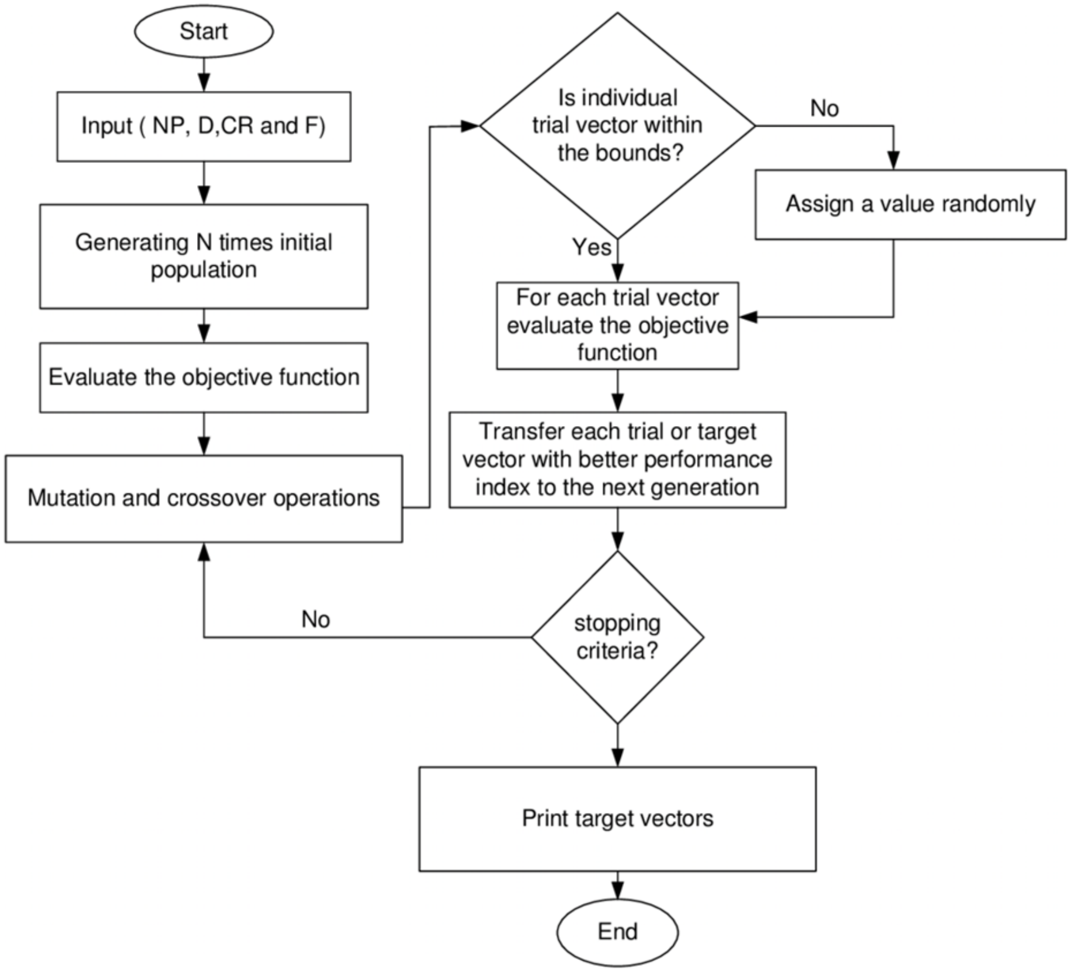
To give further bits of knowledge Table 11 has been extricated from Table 10, which introduces the productivity of every AI techniques in more prominent detail.

Considering Table 10, the utilization of LSSVM and ELM introduced the highest correlation coefficient and the lowest modeling error experienced in the prediction of the TOC content in the shale

*Table 9. Demonstrates a couple of these investigates*

| Benchmark | ANN | FUZZY | SVM | GA |
|---|---|---|---|---|
| Robustness against noise | High | High | High | High |
| Speed of convergence | Slow | Fast | - | Slow |
| Prone to over fitting? | Yes, but depends on how the training is done | - | No | - |
| Data Requirements | Huge data required | - | Small data required | - |
| Self-organization | Yes | - | - | No |
| Ability to generalize | Yes | - | Yes | - |

*Figure 11. AI methods in TOC prediction*




reservoir. In concentrates Referenced as 2, 10 and 11, the utilized techniques (for example LSSVM and ELM models) brought about the correlation coefficient values of about 0.9316, 0.9048 and 0.9493 for prediction of TOC. This value of correlation demonstrates the most noteworthy prediction ability of the developed approaches.

Then again, utilizing hybrid AI strategies, (for example, the PSO-LSSVM strategy) prompted an optimized and improved opportunity for the prediction of TOC content. For instance, in the investigation of Reference 2 and 11 that utilized PSO-LSSVM strategy, the outcome demonstrated a prediction accuracy with a correlation coefficient of 0.9451 and 0.9679 and in the investigation of Reference 5, the utilization of the FL and GA technique prompted an increase in the TOC content prediction contrasted with their Multiple Linear Regression (MLR) technique. That is, the FL-GA-ANN prompted an MSE magnitude of 0.08 for TOC content prediction, which was lower than that of the MLR method (at a value of 0.43).

In concentrates Referenced as 2, 9 and 15, the authors have utilized SAGA-FAC (Simulate annealing algorithm genetic algorithm-Fuzzy C mean clustering), K-means algorithm and K-means clustering and Hierarchical Cluster Analysis for the classification of the prediction method. This study demon-

*Table 10. Total results of the presented studies*

| Paper No | Result and evaluation |
|---|---|
| 1 | Based on the results, CNN presented higher prediction accuracy in both training and validation data for TOC, S1 and S2 compared to available methods Passey method and BP-ANN model by two criteria, lower NRMSE and higher $R^2$. |
| 2 | Based on the results, TOC could be predicted more accurately with PSO-LSSVM model than with LSSVM and BPNN models, and it had a more favorable effect from visual comparison between the prediction results and the data of measured TOC, as well as error analysis ($R^2$, RMSE, and VAF). |
| 3 | Based on the results, MLP-ANN have a high accuracy in estimation of S2 and kerogen type detection and the obtained results indicate that SGS acts better than the MLP-NN method for organic geochemical parameter evaluation. |
| 4 | Based on results, due to higher accuracy of ANN outputs and independency to the TOC content and type of lithology, author used ANN method to estimate TOC instead of ΔlogR technique. |
| 5 | Based on the results, The PSO-LSSVM model outperforms ANN-BP and LSSVM intelligent models. |
| 6 | Considering the outcome, for the training, validation and test samples the R2 value in each of the geochemical property demonstrated is upwards of 75%. A decent connection with the laboratory measured data with correlation coefficient of 0.78 and 0.83 is demonstrated by the predicted logs, especially the TOC and S2 logs. The accuracy of the predicted S1 logs might be lower-relying upon the thermal development of the examples since the S1 isn't an in-situ property. |
| 7 | Based on the results, ANN model provides better TOC estimations compared to available methods by two criteria, lower average absolute deviation and higher coefficient of determination than available techniques for Duvermay shale example. |
| 8 | Considering the outcome, the new hybrid machine (HML) technique gave considerably more exact prediction to the TOC and FI, when contrasted and those of the MLR technique are in great concurrence with the accessible experimental data for the two properties. |
| 9 | Based on results, ANN and SVM depicts that for classification problem of source rock zonation SVM with RBF kernel readily outperformed ANN in term of classification accuracy (0.9077 and 0.9369 for ANN and SVM, respectively). |
| 10 | Based on the results, author suggest the use of the artificial neural network in the prediction of the TOC in shale gas reservoirs rather than the Fuzzy logic. |
| 11 | Based on the result, it shows that TOC prediction is easier after logging prediction has been improved. Further, by comparing the prediction models established in 132 rock samples in the shale gas reservoir within the Jiaoshiba area, it can be seen that the accuracy of the proposed IHNN model is much higher than that of the other prediction models. The mean square error of the samples, which were not joined to the established models, was reduced from 0.586 to 0.442. This shows that the generalization ability of the IHNN algorithm is also very strong. Through comprehensive analysis of the results, we can see that the SVM has a poor prediction effect for data with noise and insufficient TOC information; therefore, it is not suitable for predicting the TOC problem. Because of the mechanism of random initial weights, the precision of the BP_AdaBoost algorithm is difficult to improve further, but it can better solve the problem of inaccurate calculation of the low TOC reservoir section. In addition, we can see that the KELM algorithm has a generalization ability which is inferior to that of conventional logging curves. |
| 12 | Based on result, The ELM performed slightly better in both training and validation accuracy. However, the ANN model can also produce good results. According to the training time comparison, the ELM model is much faster than the ANN model, which indicates that ELM should be chosen as the better option if processing speed is important. |
| 13 | Based on result, the Epsilon-SVR, Nu-SVR, and SMO-SVR algorithms are tested by comparison about their TOC prediction precision. Both packet dataset validation and leave-one-out cross-validation indicate that the Epsilon-SVR algorithm is better than the Nu-SVR and SMO-SVR algorithms. In contrast to the RBF method, the SVR-derived TOC is in better agreement than the RBF-based TOC, which indicates that the SVR method is more advantageous than certain neural networks. |
| 14 | Based on the results, it is clear that the implanted neural network machine is able to provide excellent results that are very close to the calculated TOC using the Schmoker's model. Obtained results clearly show the ability of the artificial neural network to predict a Total Organic Carbon (TOC) in case of absence of the density log or a discontinuous measurement of this log. |
| 15 | Results show that a three-layered back propagation neural network model with the Levenberg–Marquardt training algorithm is a high-performance learning method for this case study. Accordingly, 7 NN model were created corresponding to the identified EF groups. Comparisons show that thermal neutron porosity (TNPHI), sonic transit time (DT), GR, CGR, SGR, K and THOR logs have strong relationships with TOC within each EF. The prediction was done in the clustered intervals and the measured MSE was as high as 0.0048. |

strated that the author of paper 2 combined simulated annealing algorithm with the GA to dissect the fuzzy c-means clustering in order to classify sample information, and after that to get the high-quality information. Further, in studies referenced as 9, combination of TOC log from conventional well log information utilizing FL and ascertaining TOC applying log R method. At that point, gathering the synthesized TOC log information into cluster utilizing k-means algorithm. Additionally, the following investigation's author clustered petrophysical data into distinct groups by utilizing k-means clustering and Hierarchical cluster analysis.

*Table 11. The values of the model evaluating factors*

| Paper No | Method | Efficiency factor | Value |
|---|---|---|---|
| 1 | BP-ANN | $R^2$ | 0.750 for TOC, 0.446 for S1 and 0.663 for S2 with all logs as input<br>0.515 for TOC, 0.384 for S1 and 0.693 for S2 with selected logs as input |
| | | NRMSE | 0.181 for TOC, 0.238 for S1 and 0.151 for S2 with all logs as input<br>0.123 for TOC, 0.226 for S1 and 0.1727 for S2 with selected logs as input |
| | CNN | $R^2$ | 0.792 for TOC, 0.740 for S1 and 0.806 for S2 with all logs as input<br>0.828 for TOC, 0.738 for S1 and 0.839 for S2 with selected logs as input |
| | | NRMSE | 0.119 for TOC, 0.120 for S1 and 0.124 for S2 with all logs as input<br>0.101 for TOC, 0.117 for S1 and 0.109 for S2 with selected logs as input |
| 2 | LSSVM | $R^2$ | 0.9316 for TOC prediction |
| | | RMSE | 0.4094 for TOC prediction |
| | | VAF | 93.4207 for TOC prediction |
| | PSO-LSSVM | $R^2$ | 0.9451 for TOC prediction |
| | | RMSE | 0.3383 for TOC prediction |
| | | VAF | 94.1019 for TOC prediction |
| | BP-ANN | $R^2$ | 0.9184 for TOC prediction |
| | | RMSE | 0.5119 for TOC prediction |
| | | VAF | 91.2551 for TOC prediction |
| 3 | MLP-NN | MSE | 7.3% for training,5.6% for validation and 9.3% for testing samples in TOC prediction |
| 4 | ANN | $R^2$ | 0.89 for TOC prediction |
| | | NRMSE | 0.0135 for TOC prediction |
| 5 | ANN-BP | $R^2$ | 0.9317 for TOC prediction |
| | | RMSE | 0.0716 for TOC prediction |
| | LSSVM | $R^2$ | 0.9493 for TOC prediction |
| | | RMSE | 0.0658 for TOC prediction |
| | PSO-LSSVM | $R^2$ | 0.9679 for TOC prediction |
| | | RMSE | 0.0526 for TOC prediction |
| 6 | ANN | $R^2$ | 0.78 for TOC, 0.83 for $S_2$ and 0.63 for $S_1$ |
| 7 | ANN | $R^2$ | 0.89 for TOC prediction |
| | | AAD | 0.99 for TOC prediction |
| 8 | MLR | MSE | 0.43 for TOC prediction & 1.12 for FI prediction |
| | HML | MSE | 0.08 for TOC prediction & 0.12 for FI prediction |
| 9 | SVM-RBF | $R^2$ | 0.9369 for TOC zonation |
| | ANN | $R^2$ | 0.9077 for TOC zonation |
| 10 | BP_Adaboost | RMAE | 0.453 for well A & 0.542 for well B for TOC prediction |
| | | MSE | 0.444 for well A & 0.586 for well B for TOC prediction |
| | | RRE | 0.250 for well A & 0.355 for well B for TOC prediction |
| | KELM | RMAE | 0.332 for well A & 0.547 for well B for TOC prediction |
| | | MSE | 0.310 for well A & 0.670 for well B for TOC prediction |
| | | RRE | 0.195 for well A & 0.523 for well B for TOC prediction |
| | SVM | RMAE | 0.371 for well A & 0.695 for well B for TOC prediction |
| | | MSE | 0.342 for well A & 0.865 for well B for TOC prediction |
| | | RRE | 0.213 for well A & 0.485 for well B for TOC prediction |
| | IHNN | RMAE | 0.303 for well A & 0.453 for well B for TOC prediction |
| | | MSE | 0.294 for well A & 0.442 for well B for TOC prediction |

*continued on the following page*

*Table 11. Continued*

| Paper No | Method | Efficiency factor | Value |
|---|---|---|---|
| | | RRE | 0.164 for well A & 0.284 for well B for TOC prediction |
| 11 | ANN | MAE | 0.0747 for input training & 0.0677 for input testing |
| | | RMSE | 0.2734 for input training & 0.2602 for input testing |
| | | VAF | 85.69 for input training & 86.30 for input testing |
| | | $R^2$ | 0.8749 for input training & 0.8682 for input testing |
| | ELM | MAE | 0.0692 for input training & 0.0827 for input testing |
| | | RMSE | 0.2631 for input training & 0.1804 for input testing |
| | | VAF | 90.41 for input training & 89.18 for input testing |
| | | $R^2$ | 0.9048 for input training & 0.9099 for input testing |
| 12 | SVR | R | 0.8284 for TOC prediction |
| | | MAE | 0.7775 for TOC prediction |
| | | RMSE | 0.9868 for TOC prediction |
| 15 | BP-ANN | MSE | 0.0048 for TOC prediction |
| | ANN | MSE | 0.0073 for TOC prediction |

In figure 3, we present the historical backdrop of AI strategies, characterizing a few outcomes started from different techniques to support the modeling efficiency and productiveness. In the present review article, an aggregate of 8 cutting edge research papers identified with the use of artificial intelligence (AI) methods for TOC prediction were gathered from highly cited publication, IEEE, Springer database and Science Direct and these were looked into regarding the prediction strategy, modeling techniques, and the acquired outcomes. The relatively low number of articles on account of utilizing AI strategies for TOC content prediction in the shale reservoir demonstrates a high research potential in this field.

The literature concerning the challenges and issues of the TOC content prediction in shale reservoir and application of AI strategies on prediction process have likewise been talked about. Because of a plenty of studies performed in the utilization of AI techniques, this article was not sorted into hybrid and single-based AI strategies. Be that as it may, the present assessment has been conducted utilizing past consequences of the most significant papers utilizing different datasets regarding the accuracy and sensitivity of the final prediction. In light of the combination of the outcomes, the utilization of hybrid strategy, for example, FL-GA-ANN or PSO-LSSVM prompts an improvement and optimization of the procedure of TOC content prediction in shale reservoir though the utilization of LSSVM and ELM techniques prompts the highest correlation and the lowest error for prediction of the TOC content in shale reservoir. In spite of various papers on different AI strategies in TOC content prediction in shale reservoir, there seems to have been an absence of concentrates if there should be an occurrence of getting to an comprehensive dataset, analyzing and classification of the AI techniques on account of TOC content prediction in shale reservoir.

## FUTURE RESEARCH DIRECTIONS

The present review study can just incompletely make up for this requirement for future researchers to concentrate in more prominent profundity on the issues brought up in this paper. Our future perspective is to build up a multi-factor system-based AI applied to TOC content prediction techniques in shale reservoir to achieve the superior in estimating and modeling and to structure a stage which contains accurate and ground-breaking strategies for unsupervised learning on TOC content prediction information.

## NOMENCLATURES

Adaptive Neuro-Fuzzy Inference System ANFIS
Artificial Neural Network ANN
Artificial Ant Colony Optimization ACO
Back Propagation Neural Network BPNN
Batch Hydrogen Production BHP
Correlation Coefficient R
Differential Evolution DE
Evolutionary Algorithm EA
Extreme Learning Machine ELM
Fuzzy Support Vector Machine FSVM
Fire Fly Algorithm FFA
Genetic Algorithm GA
Genetic Programing GP
Gray Wolf Optimization GWO
Levenberg Marquardt LM
Least Square Support Vector Machine LSSVM
Multi Layered Perceptron MLP
Monte Carlo Simulation MCS
Neuro-Fuzzy NF
Non-Dominated Sorting Genetic Algorithm NSGA
Particle Swarm Optimization PSO
Probability Distribution Functions PDF
Root Mean Square Error RMSE
Rotating Gliding Arc RGA
Self-Adaptive Gravitational Search Algorithm SAGSA
Support Vector Machines SVM
Self-Adaptive Learning Bat-Inspired Algorithm SALBIA
Teacher-Learning Algorithm TLA
Total Organic Carbon TOC

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