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Prediction of Dew Point Pressure for Gas Condensate Reservoirs Using Artificial Neural Network in the Niger Delta

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ABSTRACT *Dew point pressure (DPP) is one amongstthe foremostessential parameters to characterize gas condensate reservoirs. Experimental determination of DPP during a window pressure-volume-temperature cell is commonlytoughparticularlyjust in case of lean retrograde gas condensation. Therefore, checking outquick and sturdy algorithms for determination of DPP is sometimesrequired. This Paper presents a replacement approach supported artificial neural network (ANN) to work out DPP for gas condensation reservoirs specifically within the Niger delta. Therefore, it addresses the iniquality of already existing correlation within the prediction of dew point pressure. In developing the model during this work, five hundreddata sets from the Constant volume depletion experiment done from gas condensates taken from fields within the Niger Delta were used. The data sets were indiscriminately divided into four sets. For coaching, validation, testing the Neural network developed. The feedforward back-propagation learning algorithms were employed in the network because it became the best approach. The neural design used,concernedtwo hidden layers that ultimately improved the results of the network. The accuracy of this developed model was tested with fiftydata samples and also the result was compared to the results from already existing correlations and Neural network model developed. It was absolutely and clearly seen that the projected model from this work performed higher with a parametric statistic of 0.99999 and AARE of 0.039675 than alternative correlations and existing models*
KEYWORDS: *artificial neural network, condensate gas reservoir, dew point pressure*

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I. INTRODUCTION

In reservoir engineering,a rangeof informationis required to accurately estimate reserves and forecast production. Field characterization consists of reservoir rock analysis and fluid analysis. The determination of gas condensate dew-point pressure is important for fluid characterization, gas reservoir performance calculations, and for the planning of production systems. (Mohammad & Muhammad, 2011). Retrograde gas reservoirs recognized together as one of the foremost precious, and clean organic compound energy sources as compared to alternative fossil fuels. They dissent in their thermodynamic and flow behavior from alternative common gas reservoirs since they exist as a gas phase at initial reservoir pressure, where the reservoir temperature lies between critical temperature (Tc) and cricondentherm temperature (Tct). (El-hoshoudy, S2, & SM3, 2018)Gas condensate reservoirs exhibit complicatedphase and flow behaviors thanks to the formation of condensate banking within thenear well region and changing composition of everyphase dynamically. Natural production from these reservoirs results in pressure drop of the reservoir, which ends in gas condensation and liquid dropout within the reservoir. Retrograde condensate reservoirs turn out gas to liquid ratios of about 3-150 MCF/STB (McCain, 1990), or condensate surface yields thatvary from 7 to 333 STB/MMCF. The condensatemade adds economic value in addition to gas made, thuscreating the condensate recovery a key thoughtwithin the development of gas-condensate reservoirs. The phenomenon exhibits itself within theneighborhood of the wellbore initiallyand so propagates in an exceedingly cylindrical form to the reservoir volume. The foremostvitalimpact of liquid condensation is the reduction of gas relative permeability and because it results to a loss of production. So, correct determination of dew point pressure (DPP) is extensive (Kaydani, b, & Mohebbi, 2014). The dew-point of a gas condensate fluid happensonce a gas mixture containing serious hydrocarbons is depressurized till liquid is made, that is, a considerablequantity of gas phase exists in equilibrium with associatesmallquantity of liquid phase. As pressure is reduced, liquid condenses from the gas to create a free liquid within the reservoir. Normally, there's no effective permeability to the liquid phase and it's not produced. (Mohammad & Muhammad, 2011). Many studies reported the impact of dew point pressure on the well productivity in gas condensate reservoirs and made a conclusion that gas productivity, relative permeability, and gas recovery decrease below dew point pressure as condensate build up will increase around wellbore. Therefore, estimation of dewpoint pressure is decisive for fluid characterization and management of gas condensate reservoirs. (El-hoshoudy, S2, & SM3, 2018). In general, there aretwocategories of estimation strategies for calculation of dew point pressure. the primarycategoryis setthrough an experiment from collected laboratory samples andoftentimes these measurements don't seem to bereadily availabe. The second category, fluid reservoir properties are determined with the utilization of empirical correlations (explicit methods) or they'll be determined iteratively usingan equation of state (EOS) (Meisam & Farhang, 2007). Constant volume depletion (CVD) is themost typicaltest in DPP prediction. The depletion method is simulated by CVD, making assumptions on immobility of dropped out condensate in porous media. The test consists of a series of expansion followed by dischargingthe surplus gas at constant pressure in such a way that the cell volume remains constant at the topof every stage. (Kaydani, b, & Mohebbi, 2014) The experimental determination of DPP at reservoir temperature for gas condensate reservoirs is comparatively time intense, pricy and generally subject to several errors. Thus, there'sa requirement for additionalhowevernonethelesscorrectstrategies of predicting the temperature of gas condensate reservoirs. (Elsharkawy, 2001). Empirical correlations arecomparativelysimple to use, howeverto this point, they have not been ready to duplicate faithfully the temperature behaviour of constant-composition fluids. An EOS, while duplicating the behaviour of constant-composition fluids, might have convergence issues and should be graduated to existing and available experimental knowledge (Meisam & Farhang, 2007). Generally, the applied math approach is relatively anadditional versatile approach to the matter of pressure-volume-temperature (PVT) parameters prediction. However, it needsthe idea and satisfaction of multi traditional behaviour and dimensionality, and therefore it should be applied with caution. The quality and uncertainty in existence and additionally to non-linear behaviour of most reservoir parameters needa strong tool to beat these challenges. In recent years, intelligent Technique like artificial neural network (ANN) has had noticeable recognition in reservoir engineering Applications (Kaydani, b, & Mohebbi, 2014).ANN is outlined as a computer model that makes an attempt to mimic straightforward biological learning method and simulate the precisefunction of human nervous system. it'sanadaptive parallel information science system, thatis in a position to develop association and transformation between input and output knowledge (Singh, 2005) . This intelligent technique is non-linear and non-parametric, and will be applied to dew point pressure prediction from PVT knowledge. Three-layer feedforward networks aretested to be universal function. (Meisam & Farhang, 2007)This work proposes a brand new approach based on ANN to work out a formula for DDP using the Niger delta Fields in Nigeria as a case study. Alternative works done on the prediction of the dew point pressure using Neural network failed tocover a study on the Niger delta fields and as such this work seeks to find the reliabilities of the developed model from ANN on the fluid or (Soumik, Mohammad, & Syed, 2018) properties from the Niger delta fields. The benefits of ANN compared to classical methodsare the speed, the simplicity, and therefore thecapabilityto find out from examples. rather than the complicated rules and mathematical routines. ANNs areready to learn the key information patterns withindimensionalinformation domain. So, engineering effort are often reduced within the areas. Finally, the performance of this model are going to be compared with that of alternative models

II. THEORY OF ARTIFICIAL NEURAL NETWORK

The prediction of retrograde dew point pressure has not widely been practiced. numerous authors tried to develop a general correlation for condensate fluid dew point estimation based on temperature, organic compound composition and C7+ properties. Kurata and Katz (1942) studied the behavior of gas condensate reservoirs and volatile oils. They tried to correlate the DPP to fluid properties using measurements of forty-nine gas condensate samples. Olds et al (1945 and 1949) created the first attempts to estimate the DPP for gas condensate reservoirs. Olds et al. (1945) investigated the gas condensate fluid behavior of Paloma filed. They found that the dew point pressure is powerfully dependent of reservoir fluid composition. They discovered that the removal of the intermediate fraction from the mixture resulted in a significant increase in the DPP. They conjointly discovered that the temperature has very little result on the DPP compared to the result of the intermediate fraction. Olds et al (1949) conjointly studied the behavior of San Joaquin natural depression fields' gas condensate samples. They presented a graphical correlation of DPP as a function of API gravity, and gas-oil ratio (GOR) of the produced condensate. This correlation features a restricted application because it covers a really slender range of gas condensate composition. Organick and Sir William Gerald Golding (1952) presented a graphical correlation to estimate the saturation pressure for gas condensates and volatile oils as a function of changed weight average equivalent relative molecular mass and a molar average boiling point. Their graphical correlation is given within the sort of fourteen operating charts, each including a bunch of plots that can't be used for computer calculations. Organick and Sir William Gerald Golding declared that easy mixtures and pure components can't be properly predicted using their correlation. In 1967, Nemeth and Kennedy developed a correlation within the form of an equation, that relates the dewpoint pressure of a gas condensate fluid to its chemical composition, temperature and characteristics of C7+. the ultimate sort of the equation contains eleven constants; The dew-point pressure and temperature ranges varied from 1,270- 10,790 psia, and 40-320oF respectively. Elsharkawy (2001 & 2002) presented another mathematical correlation to see the DPP for gas condensate reservoirs that's based on an oversized data bank of experimentally measurements and picked up DPP. Elsharkawy conjointly presented calculations of DPP using SRK and PR Eos and 2 totally different characterization schemes of the alkane series and fraction. His correlation showed that DPP calculation depends on Eos and characterization strategies

For this work, the interest in neural networks comes from the networks' ability to mimic human brain furthermore as its ability to find out and respond. As a result, neural networks are employed in an oversized variety of applications and have tried to be effective in performing advanced functions during a form of fields. These include pattern recognition, classification, vision, management systems, and prediction. Adaptation or learning may be a major focus of neural net analysis that provides a degree of strength to the NN model. In predictive modeling, the goal is to map a group of input patterns onto a group of output patterns. NN accomplishes this task by learning from a series of input/output information sets (Zilouchian, 2001)

An artificial neuron is the basic component of a neural network. It is made up of three basic parts that include weights, thresholds, and one activation function. The weight Factors of The values W1, W2,W3 ,…..,Wn are weight factors related to every node to determine the strength of input row vector X = [x1 x2 x3…...,xn]T. every input is multiplied by the associated weight of the neuron affiliation XTW. Depending upon the activation function, if the weight is positive, XTW unremarkably excites the node output; whereas, for negative weights, XTW tends to inhibit the node output. . The node's internal threshold θ is the magnitude offset that affects the activation of the node output y as follows:

$Y = {}_{i=1}{}^{n}(X_iW_i) - \theta_k$ **1.0**

An activation function performs a mathematical operation on the signal output. Additional subtle activation functions also can be used depending upon the sort of problem to be resolved by the network. All the activation functions as represented such as the sigmoid functions, linear, threshold, piecewise functions are supported by MATLAB package.

The neurons form several connections with one another and exhibit different architecture. The common neural architecture includes the Feed forward single layer perceptron and the multilayer perceptron. The original plan of the single layer perception was developed by Rosenblatt in the late 1950s along with a convergence procedure to modify the weights. In Rosenblatt's perception, the inputs were binary and no bias was enclosed. It absolutely was supported by the McCulloch-Pitts model of the neuron with the onerous limitation activation function. the one layer perception is incredibly just like ADALINE aside from the addition of an activation function. Multi-layer perceptions represent a generalization of the single-layer perception as delineated within the previous sentence above. The one-layer perceptron forms a half–plane decision region. On the opposite hand, multi-layer perceptrons will form arbitrarily advanced decision regions and may separate varied input patterns. the potential of multi-layer perceptron stems from the non-linearity used within the nodes. If the nodes were linear elements, then a single-layer network with appropriate weight can be used rather than two- or three-layer perceptron.the figure below shows a typical multi-layer perceptron neural network structure. As discovered, it consists of the subsequent layers: Input Layer: A layer of neurons that receives information from external sources, and passes this information to the network for processing. This maybe either sensory inputs or signals from different systems outside the one being modeled. Hidden Layer: A layer of neurons that receives data from the inputlayer and processes them in a hidden method. it has no direct connections to the outside world (inputs or outputs). All connections from the hidden layer are to other layers inside the system. Output Layer: A layer of neurons that receives processed information and sends output signals out of the system. Bias: Acts on a neuron like an offset. The function of the bias is to produce a threshold for the activation of neurons. The bias input is connected to every of the hidden and output neurons during a network

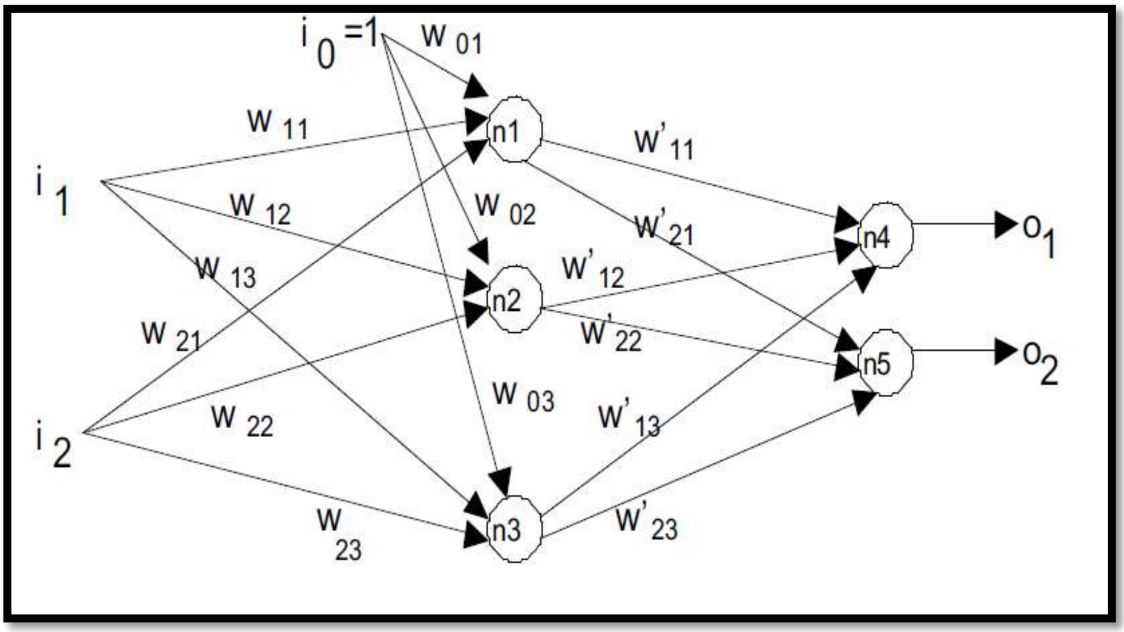

Figure.1. An example of a multilayer perceptron

The input/output mapping of a network is established per the weights and also the activation functions of their neurons in input, hidden and output layers. the number of input neurons corresponds to the number of input variables within the neural network, and also the variety of output neurons is the same as the number of desired output variables. the number of neurons within the hidden layer(s) depends upon the actual NN application. for instance, think about a two-layer feed-forward network with 3 neurons within the hidden layer and 2 neurons within the second layer:

Artificial neural networks go through the optimized weight values. the strategy by which the optimized weight values are earned is called Learning. in the learning process, it tries to teach the network the way to turn out the

output once the corresponding input is given. Once learning is complete: the trained neural network, with the updated best weights, ought to be ready to produce the output at intervals desired accuracy equivalent to associate input pattern.

Learning strategies
1. Supervised learning
2. Unsupervised learning
3. Reinforced learning

Supervised learning; Supervised learning means that guided learning by "teacher"; needs a coaching set that consists of input vectors and a target vector related to every input vector

Supervised learning system:
1. feedforward
2. practical link
3. product unit
4. Recurrent
5. Time delay

Unsupervised learning
1. the target of unsupervised learning is to find patterns or options within the input data with no help from a lecturer, basically performing a bunch of input area. The system learns regarding the pattern from the data itself without a priorknowledge. this can be the same as our learning expertise in adulthood. It operates with the hebb's rule - Hebb's rule: It helps the neural network or neuron assemblies to recollect specific patterns very like the memory. From that, hold on or store data. Similar type of incomplete or abstraction patterns may well be recognized. this can be even quicker than the delta rule or the backpropagation algorithmic program due to no repetitive presentation and coaching of input–output pairs.

Reinforced Learning;

A teacher is present, however do not present the expected output but or desired output. It only indicates if the computer output is correct or incorrect. The data provided helps the network in its learning method. a reward is given for proper answer and a penalty is awarded for incorrect answer

III. DEVELOPMENT OF THE NEURAL-NETWORK MODEL

ANN's ability on developing an effective model can be considered when we ignore all uncertainty and non-linearity of the system's network including complex and sophisticated mathematical correlations. Thus, this can be used to predict the DPP of retrograde condensate reservoirs. The figure below presents a flow chart that outlined the steps required to develop an ANN model

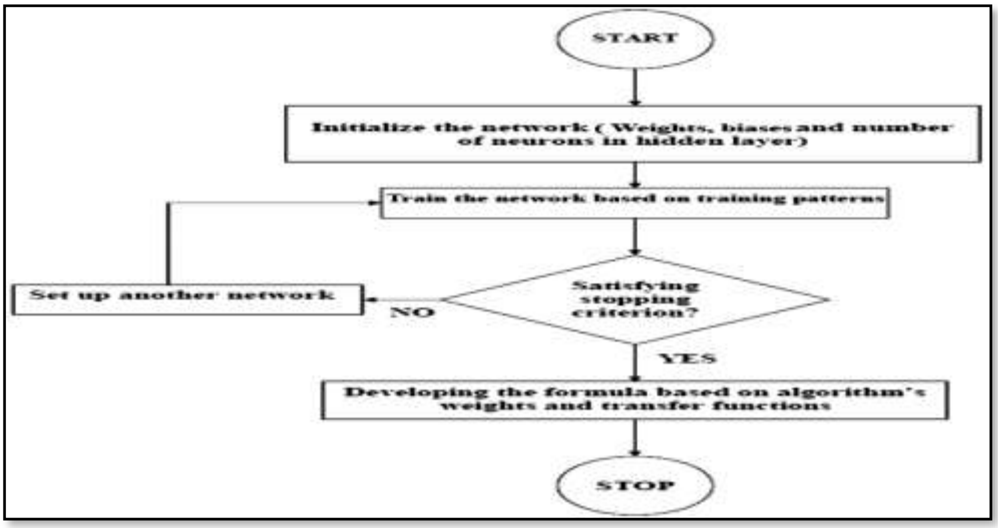

Figure 2: Flow chart on the neural network modelling

a) DATA ACQUISITION

Choosing the content and source of the data for the model is one of the most important decisions in approaching the development of an artificial neural network. In this study, a set of 500 experimental data point of CVD(constant volume depletion) has been used for developing and testing the model. The bulk of the data are from experimental measurement carried out on the fluid samples from the Niger delta basin of gas condensate fields and the rest taken from literature to improve the quality of the neural network model. Table 1 below summarized the overall range of the experimental PVT data from the CVD test used in developing the neural network

Table 1: **Summary of the range of variables**

PROPERTIES	**MINIMUM**	**MAXIMUM**
Dew point Pressure(PSI)	7030.10718	3267.0839
Temperature(F)	155	318
Methane C1	0.619	0.961
Ethane C2	0.081	0.124
Propane C3	0.008	0.089
Butane C4	0.005	0.033
Pentane C5	0.002	0.012
Hexane C6	0.002	0.021
Carbon dioxide CO2	0.14	4.37
Nitrogen N2	0	0.002
Molecular weight of Heptane Plus MC7+	126.80	168.908
Heptane Plus C7+	0.003	0.082
SG	0.776	0.812

Using linear transformation, the data were normalized between 0.2 and 1, in order to data rate reduction and avoid perturbation condition. Inputs and outputs are normalized according to Eq. (2) between 0.2 and 1 in order to alleviate the saturation problem.

$$\lambda = 0.8 \times \left\{ \frac{\lambda \mathbf{R} - \lambda \min}{\lambda \max - \lambda \min} \right\} + 0.2 \qquad 2.0$$

Where ƛR is replaced by all the input and output parameters and the values of maximum and minimum for each parameter is o btained from the table 1 above

b) Neural Network Input Data

Selecting the input variables into the model is the next step after identifying and collecting the data set. Dew point pressure prediction using established correlations are essentially based on the notion that dew point pressure for retrograde gas condensates are functions of the hydrocarbon and nonhydrocarbon reservoir fluids compositions, Reservoir temperature and the heptane plus fraction.

Pd= f{T, Xi, MWC7+, } 3.0

Where xi=MOLE FRACTION (N2+CO2) +(C1, C2, C3, C4, C5, C6 AND C7+)

Those parameters are selected as input data for training the network and dew point pressure, Pd from experimental data from the CVD test are used as a target data (Output data).

C) Neural Network Training Data And Modelling

As already stated in the section above, for obtaining ANN model to predict DPP of retrograded gas reservoirs as shown in Figure 3. Reservoir temperature, light fraction (C1, N2), intermediate fraction (C2-C6), heavy fraction (C7+), and MC7+, SG and $CO_2$are selected as input parameters

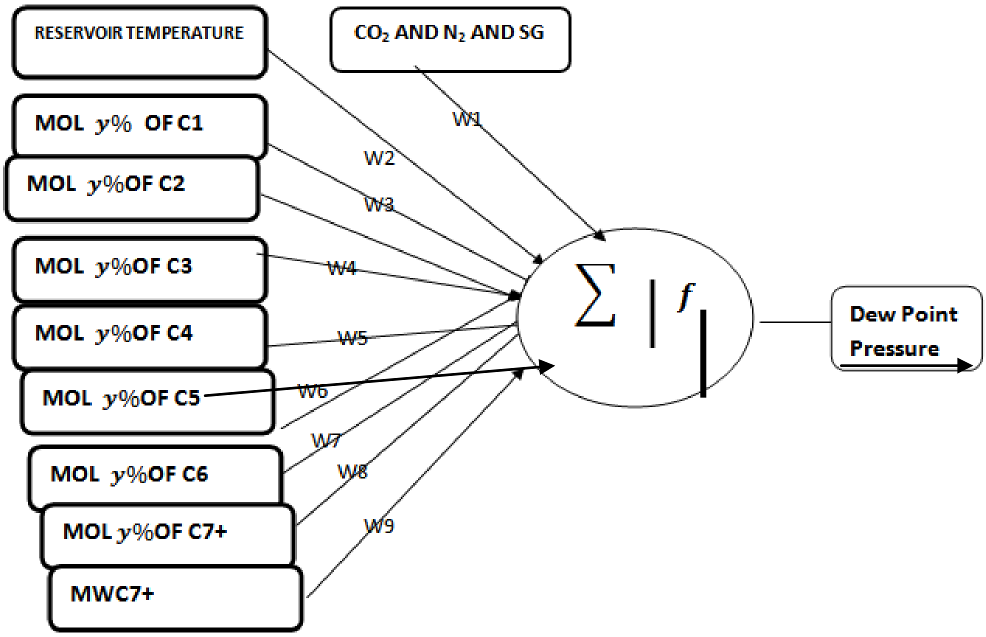

Figure 3: Mapping of input and output parameters

The back-propagation learning algorithm has been used in feed-forward neural architecture and double hidden layer network. Levenberg-Marquardt (LM) use standard numerical optimization techniques and performs better and faster than other algorithms. Tan-Sigmoid (tansig) and pure line transfer functions have been used in hidden and output layers, respectively. The computer program has been developed under MATLAB R2014a software (The MathWorks, Natick, MA).

Each feed forward network was trained by Levenberg– Marquardt algorithm and compared with other algorithms

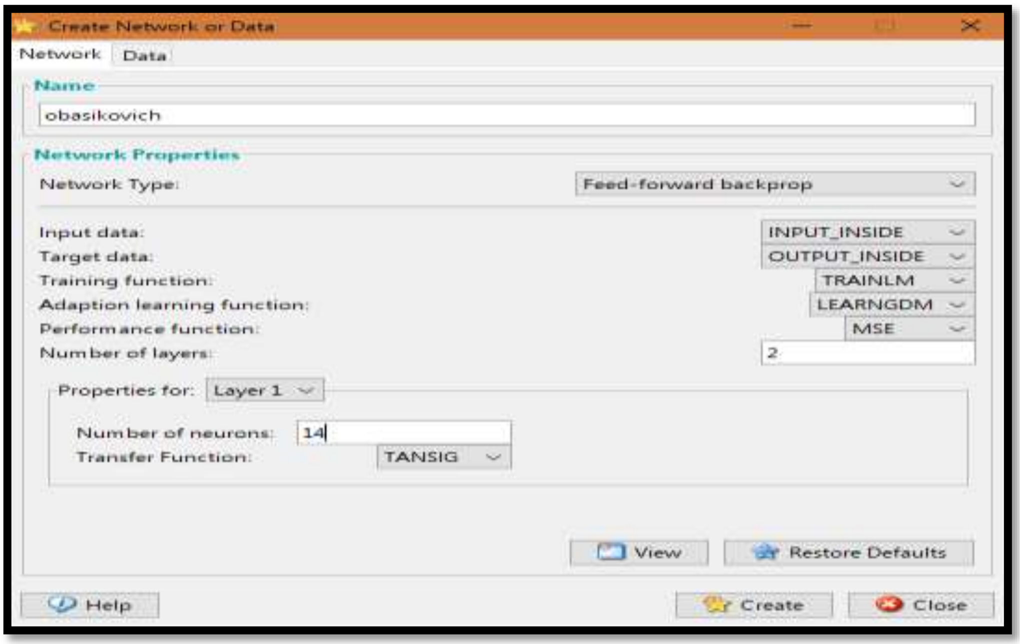

Figure 4: Neural network property

The LM algorithm training parameters used for developing the network includes the Performance function(PF), the lower limit of the performance function goal, the lower limit of the gradient grad and the maximum number of iterations epochs. The training is designed to end at each time the number of iterations surpasses epoch, if the performance function drops below goal, or if the magnitude of the gradient is less than grad.

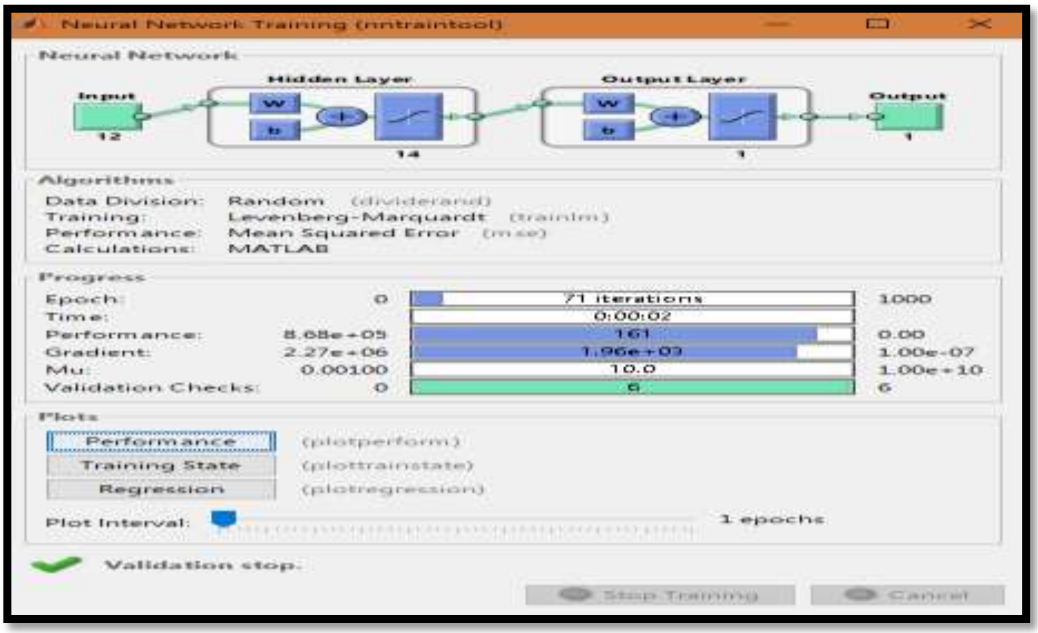

Figure 5: Neural Network training

IV. RESULTS AND DISCUSSION

This work used a novel approach on artificial neural network to determine the DPP for gas retrograde reservoirs after the normalization of the input data. The best approach that has minimum errors is performed using the LM algorithm with 14 neurons in two hidden layers

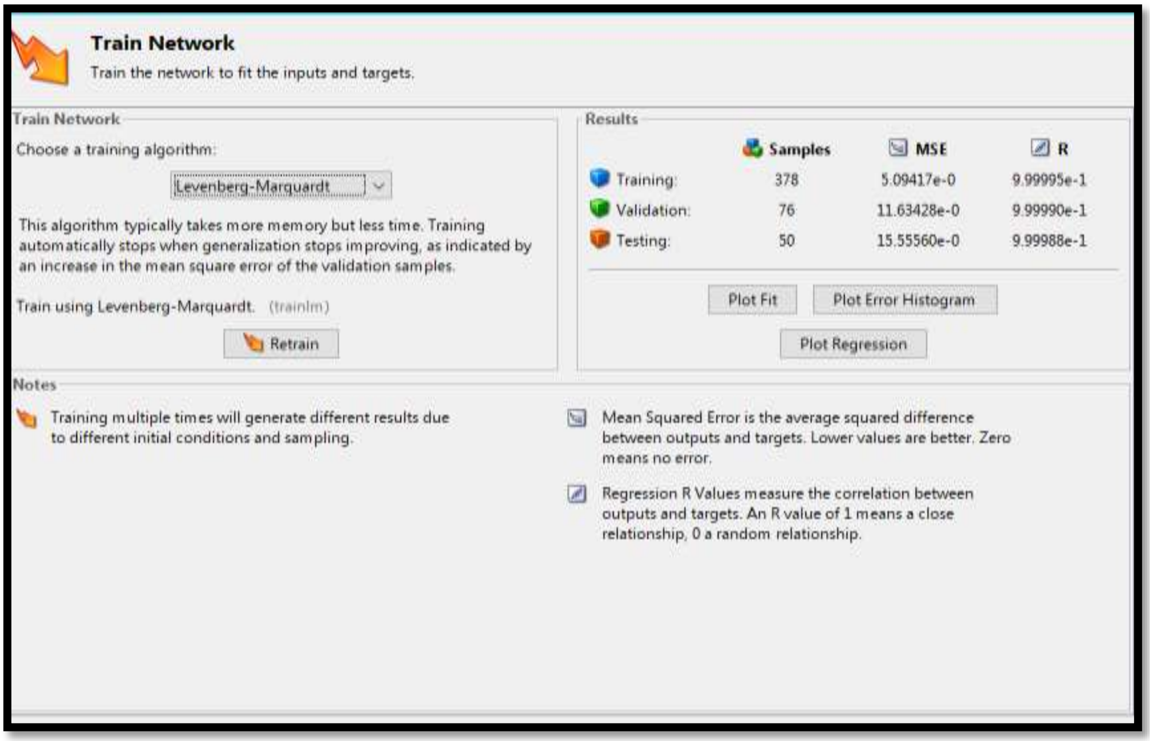

Figure 6 : Trained network Results using the Levenberg- Marquardt Algorithm

The obtained results in terms of regression analysis and mean square error with improved accuracy and better fitting for the training, validation, test and generalized samples are summarized in table 4.1 below.

Table 2 Results for the trained Neural Network

S/N	Data	Correlation Coefficient R	Mean square Error
1	Training	0.99984	5.09417
2	Validation	0.99965	11.63428
3	Test	0.99969	15.55560
	All	**0.99978**	

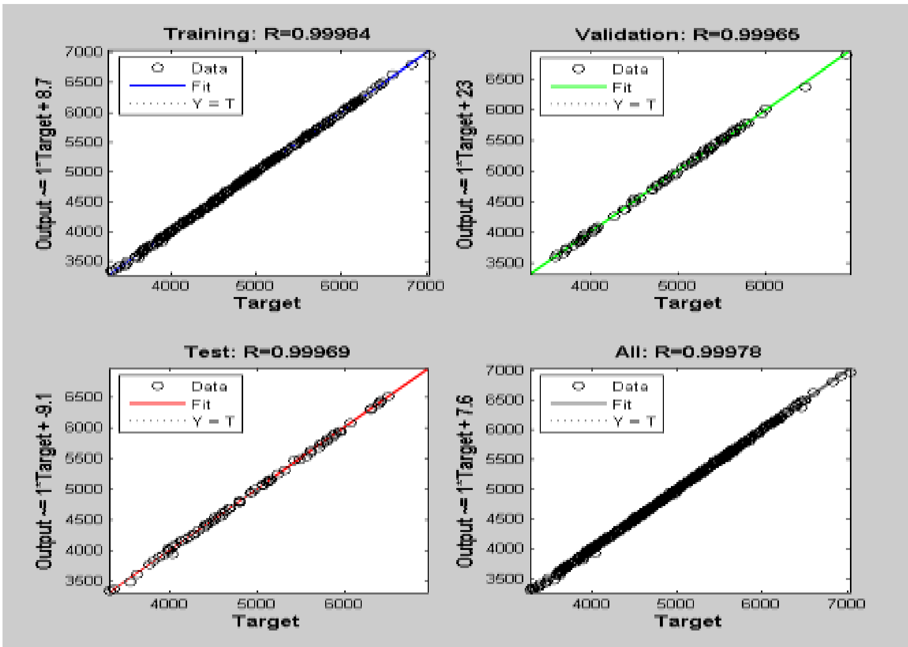

Figure 8 Regression plot of Calculated DPP vs Measured DPP for training, Validation, Test data samples.

Validity of the Model Developed by the Artificial Neural Network: The trained ANN model was tested with 50 data points that were not previously used during training and validation. These data were randomly selected by the MATLAB tool to test the accuracy and stability of the model. The performance of the ANN model was compared with field data and the predictions from other empirical correlations such as (Neuromorphic Method), Nementh andKennedy (1967) Elsharkawy (2001), Godwin , 2012.

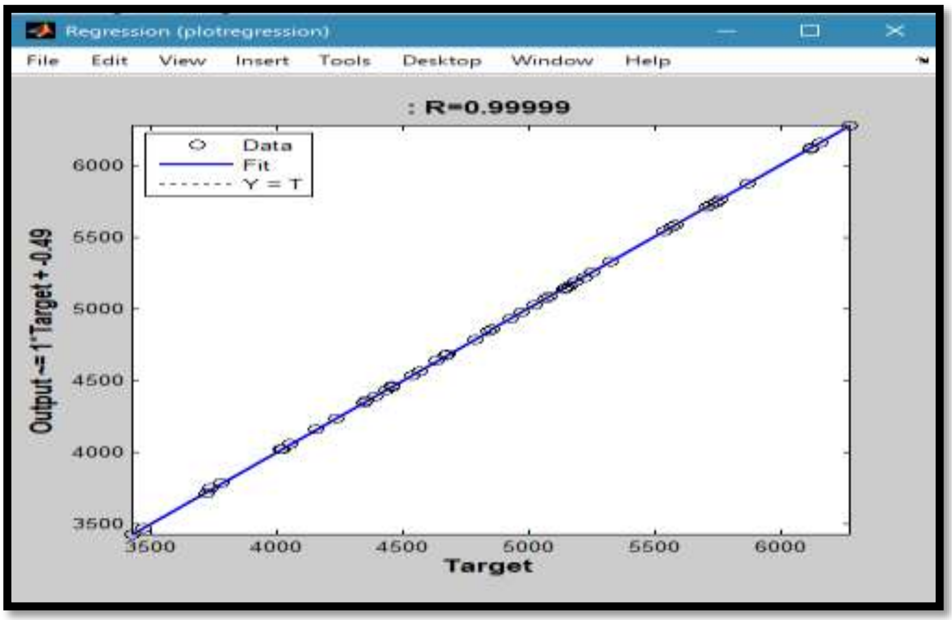

Figure 7: Regression plot of Calculated DPP vs Measured DPP to evaluate or validate neural network

The performance of the network was evaluated on the basis of an overall mean absolute error specified by the difference in the desired and actual outputs as defined below and compared with other network

Overall absolute error= $\sum \ [|\frac{Pd - Pd}{Pd}| * 100]/N$ 2

Table 3:Accuracy of the Various Methods for Predicting DPP of gsd condensate samples

Parameters	Presented Model	Nemeth and Kennedy (1967)	Elsharkawy (2001)	Godwin (2012)
AARE	0.039675	7.64	12.58	19.9
RMSE%	7.81870			
R	0.99999	0.93	0.866	0.70
R^2	0.99998	0.88	0.75	0.49

V. DISCUSSION

From the Results Shown above in Table 3 , It is clear that presented model gives a very accurate representation of the statistical values such average absolute relative error (AARE), RMSE, correlation coefficient (R), and R^2 over the full range of operating conditions for DPP prediction.The coefficient of determination (R^2) exhibits the strength of association between two variables, including the experimental and predicted data. The closer the R^2 toone, the closer the predicted values to the experimental data.

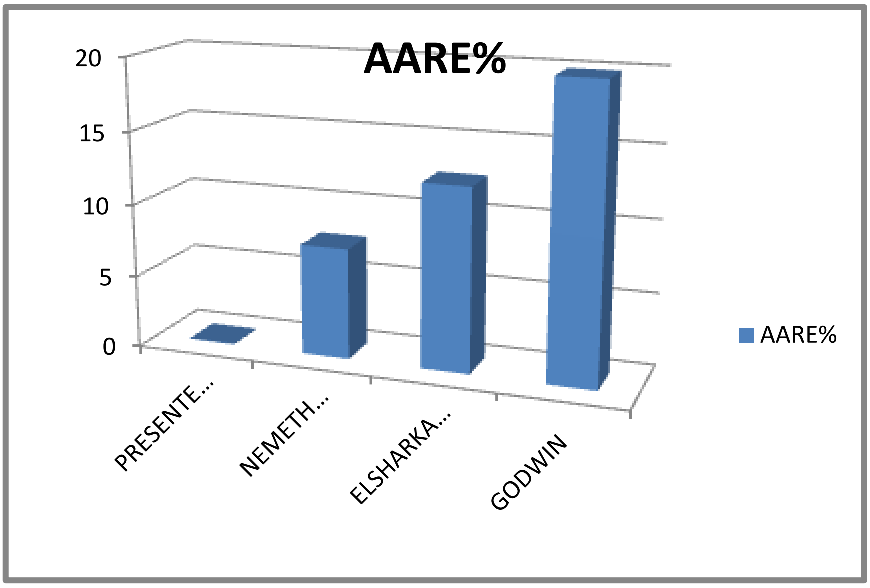

Figure 1: Absolute Average Relative percentage error for the various models

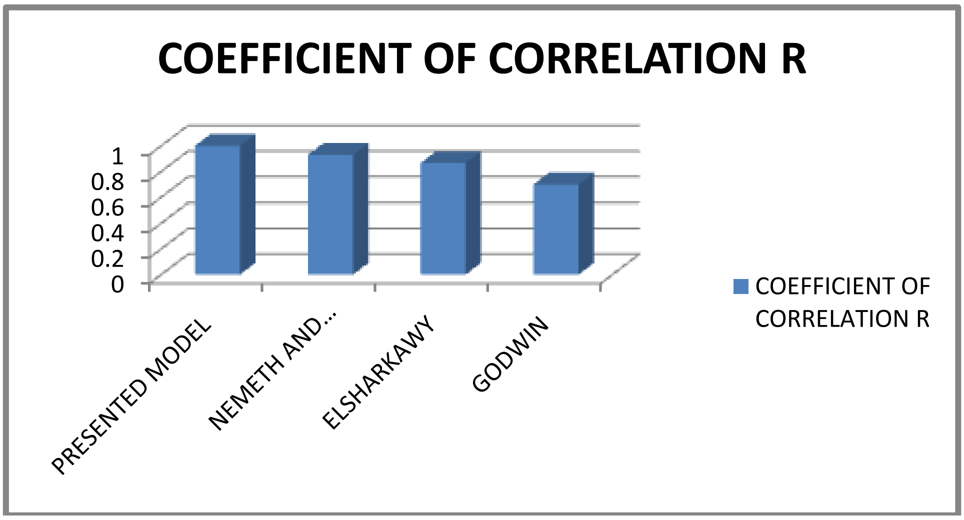

Figure2: Comparison of the Coefficient of Correlation R for the various models

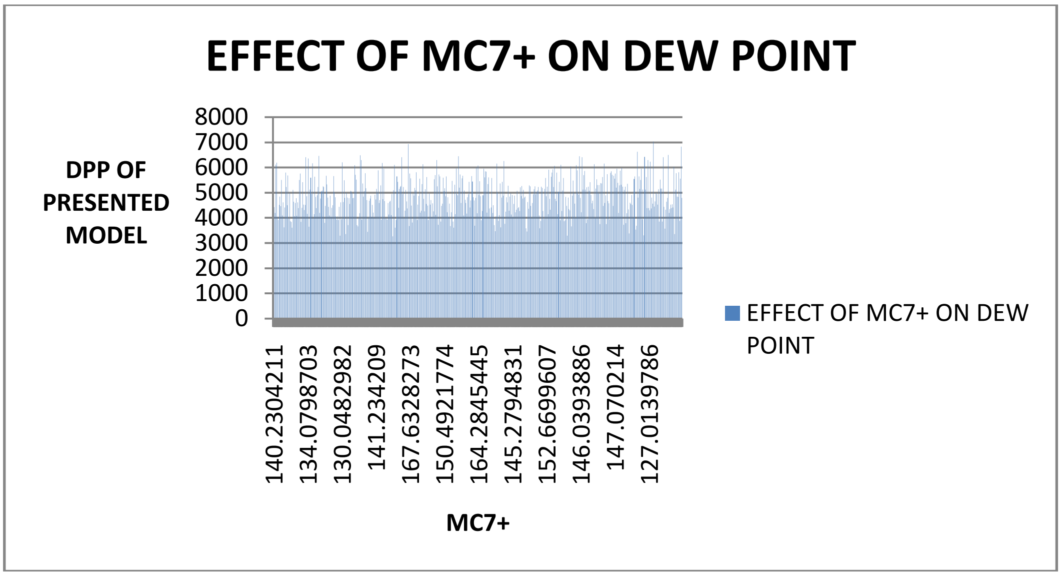

Figure 10 : Graphical representation of the Effect of MC7+ on DPP

VI. CONCLUSION

The main bottleneck of gas reservoir development is the accuracy in the determination of Dew point pressure. This project successfully addressed and have shown that the values of DPP predicted in the Niger Delta Basin using the developed ANN model is more reliable and accurate compared to empirical correlations and experimental approach that have existed long ago. Especially under confined condition with limited field information, this approach could produce a higher accuracy than other statistical method. The coefficient of correlation reached (R2= 0.9998) and the Absolute Average relative error (AARE% =0.039675) which indicates a high reliability of the presented model. The number of hidden layers used and the neural network architecture – the feed forward backward propagation contributed a lot also to the accuracy of the developed model. Model validation was carried out on 50 gas condensates samples and thus the statistical error analysis recorded a coefficient of correlation of (0.9999) which is indicative of high reliability of the developed model

VII.NOMENCLATURE

ANN	Artificial Neural Network
DPP, Pd	Dew point pressure
T_f	Reservoir Temperature
CO_2	Carbondioxide gas
N_2	Nitrogen gas
C_1	Methane
C_2	Ethane
C_3	Propane
C4	Butane
C5	Pentane
C6	Hexane
C7+	Heptane plus
MC7+	Molecular weight of C7+
YC7+	Specific gravity of C7+
AARE	Average absolute relative error
R	Coefficient of correlation
R2	Squared coefficient of correlation
RMSE	Root mean square Error
N	NO of Data set

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