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Prediction of Gas Hydrate Formation Temperature in Pipelines using Artificial Neural Network (ANN) and Firefly Algorithm (FA)

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Abstract

Natural gas hydrate is a major flow assurance problem encountered in the transportation of natural gas, onshore and most especially offshore and cold environment. The formation of hydrate plugs can be a costly problem in pipelines as it impedes transmission of natural gas leading to operational and economic challenges. The prediction of natural gas hydrate formation condition is key to inhibiting their formations in pipelines. This study investigates the prediction of gas hydrate formation temperature using artificial neural network (ANN) and firefly algorithm (FA). The effectiveness of these techniques was evaluated, and new correlations were developed. The experimental data containing specific gravity, pressure, and temperature, drawn from literature was used in the model development. Statistical and graphical performance analysis showed that ANN had the better performance with the least MSE and MAPE of 0.10376 and 0.005944 comparism FA which gave 113.00670 and 0.18479 respectively. The results showed that the ANN and FA are viable tools for natural gas hydrate formation temperature prediction.

Keywords: *Gas hydrate; Artificial neural network; Firefly algorithm; Temperature; Pressure.*

1. Introduction

Demand for cleaner energy due to the ever-increasing concern for the climate is the reason the petroleum industry is tilting towards natural gas production. Natural gas is gradually becoming the major source of energy due to its abundance, availability, economic viability, and environmental friendliness [1]. Produced natural gas needs to be transported usually over a very long distance through pipeline network from the wellhead to the treatment and process facility and sometimes to the final consumers. These pipelines can travel through cold environment while the pressure condition in them could be favourable to hydrate formation. Gas hydrates are ice-like crystalline solids formed as a result of the interaction between gas and water molecules at low temperature and high pressure [2]. Gas Hydrates are cages of water molecules (host) with gases molecules (guest) trapped in the cavities and bounded to the hydrogen bond of the water molecules. Light hydrocarbon gases, acid gases and water-soluble polar compounds are the guest molecules found in gas hydrate. Historically, Sir Humphrey Davy in 1810, discovered gas hydrate. From 1810 to 1900s other hydrate formers were discovered due to laboratory curiousity [3-5]. A technical discovery that gas hydrates were the cause of gas pipeline plugging above water freezing conditions was made by Hammerschmidt. Efforts have however been made to developed mitigation strategies and regulations been placed on water content in pipelines to control hydrate formation [3, 5-6].

Gas hydrates have three known unit crystal structures, the sI, sII, and sH. The three structures are composed of cages with cavities of different sizes. The cubic structure I or sI have 5^{12} and $5^{12}6^2$ cages with 4.0-5.5Å, and can take guests with a smaller diameter compare to the cubic structure II or sII (6.0-7.0Å) 5^{12} and larger $5^{12}6^4$ cages. The sII $5^{12}6^2$ cage is smaller than sI $5^{12}6^4$ and larger than 5^{12}. The hexagonal structure H has the largest cage $5^{12}6^8$ and

two other smaller cages 5^{12} and $4^{3}5^{6}6^{3}$. sH can take mixtures of small (4.0-5.5Å) guest molecules and larger (8.0-9.0Å) guest molecules. Most hydrates found outside the pipeline in nature are usually found to exist in sI structures while the sII structures are found to exist mostly in oil and gas operations and processes. The sH structures can occur in either environment.

For gas hydrate formation to be initiated the following conditions must be simultaneously satisfied: presence of hydrate former (like methane, ethane, carbon dioxide and hydrogen sulfide), presence of water (in the right quantity) and right combination of pressure and temperature (usually low temperature and high pressure). If any of the conditions is violated hydrate formation will not be initiated and will be discontinued when initiated already. The presence of high velocity fluid, agitation, nucleation sites and seed crystals of hydrate favors and hence enhance gas hydrate formation. Hydrate nucleate, grow, agglomerate and eventually plug pipelines when not controlled effectively. Hydrate plug pose a very great danger to the lives, environment and nearby infrastructure including the pipelines, hydrate plugs cost the industry billions of dollars in prevention and remediation. Damages caused by corrosion due to presence of hydrate are greater than hydrate plugging as plug ruptures pipeline while corrosion can go as far as the deteriorating of the pipeline and causing a larger section or the entirety of the pipeline to be replaced [7]. Hydrate, ice, hydrocarbon vapor, liquid water, and hydrocarbon liquid are usually represented by the letters H, I, V, L_W, and L_{HC} respectively on the natural gas hydrate phase diagram. The lower quadruple point, which shows the stage at which the four-phase ice, liquid water, hydrocarbon vapor and hydrate (I-L_W-H-V) are in equilibrium is usually represented by Q_1. The temperature approximates the ice point at this point. The upper quadruple point of equilibrium between the four-phase systems water liquid, hydrocarbon liquid, hydrocarbon vapor, and hydrate is usually represented as Q_2 (L_W-L_{HC}-V-H). The Q_1Q_2 line's pressures and temperatures represent the conditions that are in equilibrium between three-phase liquid water, hydrocarbon vapor and hydrate. The hydrate region exists to the left of the three phase lines (I-H-V), (L_W-H-V), (L_W-H-L_{HC}) and at the right the phases exist for liquid water or ice and the hydrocarbon liquid or vapour [8]. The temperature and pressure along line Q_1Q_2 indicates the maximum temperature at a particular pressure and the minimum pressure for a particular temperature for each hydrocarbon mixtures with water. Higher pressure is usually needed for methane to form hydrate compare to the other lager hydrocarbon. However, as the molecular size increases the pressure required for hydrate formation decreases.

Prevention of hydrate formation can be done in several ways. Removal of water upon production will go a long way in preventing hydrate formation, but it is not often the most cost-effective method. Effective avoidance of hydrate formation can be done by addition of chemicals, and by heating or insulating (the thermal method) the pipeline. The thermal method makes use of hot water jacket, conductive or inductive heat tracing to add heat to the pipelines. The heat added or insulation prevent the gas from losing heat and/or keep the gas transported at a relatively high temperature, outside the hydrate formation region. Chemicals such as thermodynamic inhibitor hydrogen-bond themselves to free-water molecules, thereby reducing the water available to form hydrate. Thermodynamic inhibitors used are typically alcohols (such as methanol) and glycols (such as mono-ethylene glycol). Another chemical method used to control hydrate formation is the low dosage hydrate inhibitors (LDHI). There are two types of LDHIs: the "kinetic hydrate inhibitors" (KHIs) and the "anti-agglomerants" (AAs). The KHIs are high molecular weight polymeric chemicals such as poly [N-vinyl pyrrolidone] [9-10] that significantly delay the crystal nucleation or growth of hydrates in pipelines. The AAs are surface active chemicals (such as alkyl aromatic sulphonates), they allow hydrate crystals to form but they prevent their growth and keep them well dispersed. This prevent the hydrate crystals from agglomerating to plug pipelines, instead they will be transported with the fluids [11].

After hydrate plug discovery, studies started on various techniques to predict gas hydrate formation conditions. The method called the distribution coefficient method (K_{vsi}-value) was initiated by Wilcox in 1941, it uses the vapor/solid equilibrium ratio in equation (1) for prediction:

$$K_{vsi} = \frac{y_i}{x_{si}} \quad (1)$$

where: y_i = mole fraction of component i in the water-free vapour and x_{si} = mole fraction of component i in the water-free, solid hydrate.

The K_{vsi} values for natural gas component are presented as a function of temperature and pressure in charts.

The gas gravity method makes use of the gas-gravity chart to relate pressure, temperature, and specific gravity (molecular mass of the gas divided by that of air) of natural gases. The gas gravity chart was generated from limited available data and significant calculations based on the K_{vsi}-*value* method. The inaccuracies in this method as reported by Sloan limits this method to be used as an approximate method or an initiate estimate of hydrate forming conditions [12].

Several correlations have been proposed and developed by different authors to describe the relation between pressure, temperature and gas gravity. The proposed correlation in equation (2) for gas hydrate formation [13].

$$T = 8.9P^{0.285} \quad (2)$$

where T *and* P are temperature in °F and pressure in psi of hydrate formation respectively.

The correlation using temperature and gas gravity to calculate hydrate formation pressure [14]. This correlation in equation (3) was develop by Elgibaly and Elkame [15].

$$log\ P_m = \beta_m + 0.0497\left(T_m + kT_m{}^2\right) - 1 \quad (3)$$

where

$$\beta_m = 2.681 - 3.811\gamma + 1.679\gamma^2 \quad (4)$$

$$k_m = -0.006 + 0.011\gamma + 0.011\gamma^2 \quad (5)$$

where P_m is pressure in MPa, T_m is temperature in Celsius and γ is specific gravity

Motiee presented his correlation in equation (6) for solving for hydrate temperature using pressure and gas gravity.

$$T = -238.24469 + 78.99667\,log(P) - 5.352544(log(P))^2 + 349.473877\gamma - 150.854675\gamma^2 - 27.604065\,log(P)\gamma \quad (6)$$

where T is hydrate temperature in °F, P is the pressure in psi and γ is the gas gravity.

The correlation in equation (7) proposed by Towler and Mokhatab [16] relating hydrate temperature to pressure and gas gravity is given by:

$$T = 13.47\,ln(P) + 34.27\,ln(\gamma) - 1.675\,ln(P)\,ln(\gamma) - 20.35 \quad (7)$$

where T is hydrate temperature in °F, P is the pressure in psi and γ is the gas gravity.

The correlation temperature and pressure explicit form developed by Salufu and Nwakwo [17] is given in equation (8). They correlated hydrate formation temperature, pressure, specific gravity and water vapor pressure using gravity method and statistical analysis software.

$$T = A'[ln\,P - ln(B\gamma)] \quad (8)$$

where T is hydrate temperature in °F, P is the pressure in Psi and γ is the gas gravity.

Table 1. Correlations for predicting hydrate formation conditions [17]

$1 \geq \gamma \leq 0.59$		$0.1 \leq \gamma \leq 0.559$		$0.6 \leq \gamma \leq 0.59$	
A'	B	A'	B	A'	B
10.9529	2.4196	16.2602	105.35	12.121	8.751

1.1. Artificial Neural Network

Artificial neural networks (ANNs) are biologically inspired computing systems, which imitate the decision process in the biological central nervous system nerve cell (neuron) network. ANNs are the non-linear mathematical models that are highly regarded for their simplicity, flexibility, and availability. This model is used in predicting complex non-linear systems and discovering new patterns without using a mathematical model for the system by establishing relationships between input and output data.

The most common architecture is the artificial feed forward neural network, and a network with several layers is called multi-layer neural networks while one layer is referred to as single layer. The Neurons used are labelled with j collects an input from the predecessor neurons;

various components of the neurons are: activation $a_j(t)$, threshold θ_j, activation function and output function.

Representing the above scheme into a mathematical formula will give:

$$z = \sum_i w_i x_i = w^T x \quad (9)$$

To include the neuron activation, the formula becomes:

$$z = \sum_i w_i x_i + b = [w^T x] \begin{bmatrix} x \\ 1 \end{bmatrix} \quad (10)$$

The often used activation function is a threshold, sigmoidal and tangent hyperbolic functions.

Firefly algorithm (FA) on the other hand is regarded as smart, metaheuristic and inspired by natural swarm (firefly swarm), it was developed in 2008 by Xin-She Yang. It is based on swarming and light flashing patterns of fireflies. FA follows three idealized rules: all fireflies are unisex; the attractiveness is proportional to the brightness and they both decrease as their distance increases; the brightness of a firefly is determined by the landscape of the objective function.

In optimizing, random generation are used to initialise problem variables in a search place. Brightness/attractiveness of fireflies are evaluated using the light intensities, this is done after initialization. The firefly brightness is shortened and ranked based on their light intensity. The positions of the fireflies are updated based on their ranking. After updating, fireflies might occupy new positions out the defined limit.

The distance between the fireflies is given as $r_{i,j}$ in equation (11) below:

$$r_{i,j} = \|X_j - X_i\| \quad (11)$$

The movement of fireflies as a result of variation in brightness is given as X_k^{m+1}in equation (12) below

$$X_i^{t+1} = X_i^t + \beta_o e^{-\gamma r_{ij,}^2}\left(X_j{}^t - X_l{}^t\right) + \alpha \epsilon_i{}^t \quad (12)$$

where $r_{i,j}$ is the distance between two fireflies (i and j); β_o is the attractiveness of a firefly at zero distance; α is a parameter controlling the strength of the randomization term and $\epsilon_i{}^t$ is being drawn from nominal distribution.

Odutola and Aliyu [10] predicted the equilibrium hydrate formation pressure for single gases (methane and ethane) in the presence and absence of thermodynamic hydrate inhibitors (THI) using HYDOFF software and compared to the result to over 114 published experimental data points. There was a close match between the predicted and experimental data with a coefficient of determination of 0.97 for methane system and 0.90 for ethane system. Odutola and Anunihu[18] in 2019 however compared four different hydrate prediction methods (Hysys simulation, Hammerschdmit correlation, Towler and Mokhatab correlation and Katz chart) in predicting hydrate formation conditions for methane-ethane binary gas systems with varying mole fractions of methane (56.4%, 90.4%, 95.6%, 97.1%, and 98.8%). The Hysys simulation preformed best and had the least prediction error in the methane-ethane binary systems they considered. The study conducted by Heydari *et al.* [19] to determine the predictive ability of ANN in predicting the conditions in which gas hydrate occurs in flow lines. To process the 167 raw data in the ranges of 32 – 74°F, 50 – 4200 psia, and 0.554 – 1.000 for temperature, pressure, and specific gravity, respectively. The neural network was tested using 18 pieces of data. The prediction of hydrate formation in natural gas was built using two hidden layers, each of which has seven and five neurons. Each of the networks under their study was trained three times to ensure that the results could be reproduced. After a series of testing, 7-5-1 as the ideal ANN structure was chosen. The ANN model created outperforms the Sloan model as well, with an R^2 value of 0.9941 and a maximum error of 3.035 percent. Their work showed the necessity to collect a large amount of data to train the model to increase accuracy because the main drawback of the model that was demonstrated in their study and its significantly dependent on data. An investigation on prediction of hydrate formation temperature (HTF) using Artificial Neural Network used 356 input data with following range 31.95 - 78.80 ^{0}F for temperature data, 50.98 - 3874.10 psi for pressure values and 0.6 – 1.0 specific gravity values [20]. They employed back propagation architecture artificial neural network algorithm due to its effectiveness compared to other algorithms. Their results showed a higher predictive accuracy

of ANN model built in predicting gas hydrate formation condition compared to existing mathematical models.

A new correlation developed by Seyyed and Dehghani [21] for predicting gas hydrate formation temperature using Genetic Algorithm (GA), PSO and Imperialist Competitive Algorithm (ICA) with the use of Gaussian equation. Over 120 data points were gathered with pressure range of 2.77 to 1000 bar and temperature range of 275 to 330K. An effective comparative analysis of different models observed based on GA, PSO and ICA was also performed. The results showed PSO algorithm gives the best prediction of the hydrate temperature with the highest co-efficient of determination and the lowest root mean square error compared to GA and ICA. Hashim *et al.* [22] came up with an empirical model for predicting gas hydrate formation temperature based on Genetic Algorithm (GA), PSO algorithm with the use of Gaussian equation. Pressure and temperature ranges of 1.30 - 10.82 MPa and 259.10 to 292.35 K respectively were used. They observed PSO algorithm gave the best prediction of the hydrate temperature with the least minimum error of 0.6 and 0.1. This is a positive result for natural gas industry as the Particle Swamp Optimization algorithm is very good for prediction of hydrate formation conditions with maximum accuracy. A system to predict hydrate formation that are been formed in pipe lines [23]. Prototype and regression model associated with Wireless Sensor Network (WSN) was compared to Artificial Neural Network (ANN) Model. The result of the investigation shows that Wireless Sensor Network (WSN) prediction of hydrate formation is of higher capability when compared to ANN.

However, economic analysis is required to determine most suitable one for industrial purposes. The importance of the *e*stimation of the temperature and pressure at which hydrates are formed which is the first measure that is usually taken to prevent hydrate formation, and the importance of using a correlation or model with high accuracy. Megat [24] in his research, two alternative methods that use empirical data to estimate hydrate formation pressure for diverse gas systems were devised, namely artificial neural network (ANN) and adaptive neuro-fuzzy interference system (ANFIS model). The ANN model divides all data into three groups at random: training, cross-fitting (monitoring), and test, which account for 60%, 20%, and 20% of the total data utilized in the project, respectively. The results show that the outcomes of data-driven models are more accurate than those achieved from the three experimental models, which were created [23,25-26]. His study showed that Hammerschmidth [25] model could only be used to make educated guesses about the hydrate formation circumstances because it gave inaccurate estimations of the hydrate formation pressure. The models of Kobayashi and Motiee [23,26] made precise predictions about the pressure at which hydrates form. The ANFIS model surpasses the ANN model among the two data-driven models he utilized in terms of response. This can be attributed to the fact that the ANFIS system is designed for each data set under different rules and fuzzy inference system parameters set during the training phase. Data in the ANFIS model are classified according to the degree of dispersion around some data that are known as the cluster center. He also emphasized that ANN needs too much information to deliver a trustworthy, low-error complete response.

Moreover, Odutola *et al.* compared the effectiveness of artificial neural network for predicting hydrate formation temperature to that of Mokhtab, Hammerschmidt, Bahadori, Vuthalaru using 459 experimental points from Katz and Wilcox *et al.* chart [27]. The temperature range was 49 – 4000 psia and 0.5539 - 1.0 specific gravity. Observation from their result shows a 3.5 mean absolute percentage error and a reduction in R^2 as the specific gravity of the natural gas increases. The efficiency of ANN in predicting hydrate formation condition reduces with increasing specific gravity of the gas. The ANN gave 0.0149 average deviation, SEM 0.0043 and MAPE 3.5185.15, Megat [24] used ANN tool command in Matlab software to predict the methane gas hydrate growth rate with temperature and pressure input data using the multilayer perceptron (MLP) back propagation method. The training produced a lower mean square error thus suitable for training and prediction of hydrate growth rate. The three models gave R^2, MSE are 0.999, 0.0005995; 0.999, 0.001698 and 0.989. 0.0005937. The limitation of the model prediction however shows model is only valid for a range of input pressure and temperature and thus cannot predict where pressure and temperature is not trained as input data.

2. Methodology

2.1. Data collection and preparation

In this research, 142 data points are gathered [28] on hydrate formation conditions. This data includes actual pressure and temperature for natural gases with different specific gravities in conditions that gas hydrate form (the three phases are in equilibrium). The input variables for this data is the gas specific gravity and pressure, while the output is the temperature of the gas. This data covers a pressure range of 58.5 - 4200 psia, temperature range of 32 – 74 °F and specific gas gravity range of 0.554 to 1.

Table 2. Statistical summary of the 142 data set

Parameter	Specific gravity	Pressure (psia)	Temperature (°F)
Mean	0.7340	842.8	52.8
Median	0.7000	469.0	53.0
Standard Deviation	0.1490	941.7	12.6
Variance	0.0220	886843.7	159.0
Minimum	0.5540	58.5	32.0
Maximum	1.0000	4200.0	74.0
Percentile 25%	0.6000	216.8	42.0
Percentile 50%	0.7000	469.0	53.0
Percentile 75%	0.9000	1000.0	63.5
Range	0.4460	4141.5	42.0

2.2. Artificial neural network model development

The following properties determines the structure of the ANN model: number of input layer, hidden layer and output layer, network type, number of neurons, transfer function, training function and adaption learning function. In developing the model 70% of the datasets was used to train the model, the training data set covered the entire data range. 15% each of the remaining dataset was used to validate the model and test the model. The network type used in developing this model is the feed-forward back propagation. The best network was obtained by trial and error by changing one of the properties while keeping the others constant till the lowest prediction errors were obtained. The performance of each network was examined using mean square error (MSE) and other performance criteria to determine the best network.

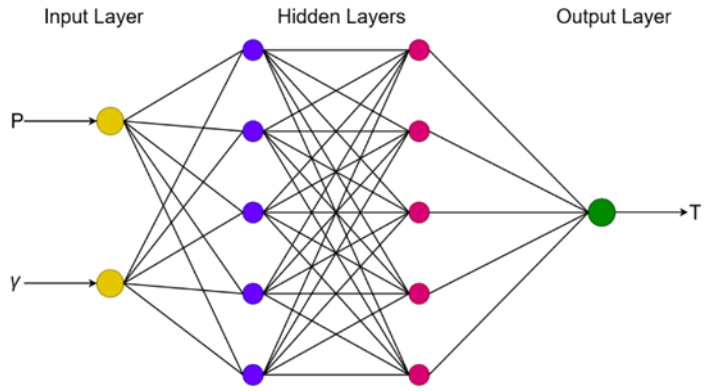

Figure 1. The Schematic Structure of the Applied Neural Network

The best network had 10, 5 neurons in each of the two hidden layer and the transfer functions used was Log-sigmoid (logsig). The tangent sigmoid (tansig) transfer function was used in the output layer. Table 3 below shows the properties of the best network. Figure 1 depicts the schematic structure of the applied neural network, with its two inputs and single output.

Table 3. Properties of the best network

Network type	Feed-forward back propagation
Training function	Bayesian regularization
Number of layers	3
Number of neurons in each lay-	5, 5, 1
Transfer function of each layers	logsig, logsig, tansig

2.3. Firefly algorithm development

Implementing firefly algorithm to develop a data driven model based on equation (13) below consist of the following steps

$$T_{(i)} = b \times \left(P_{(i)}{}^{c}\right) + \left(d \times G_{(i)}\right) + \left(e \times G_{(i)}{}^{2}\right) \quad (13)$$

Step 1: Select the FA parameters
Step 2: Calculate the predicted gas hydrate formation temperature for each sample data in the FA population applying the optimal values b, c, d, and e.
Step 3: Calculate the fitness function for each sample data. MSE is the objective function FA is aiming to minimise.
Step 4: Rank each sample in the population ascending according to its fitness function and update the firefly position.
Step 5: Repeat steps 2 to 4 for the next and subsequent iterations until all the specified iterations are completed.
Step 6: Record the lowest MSE and the best optimal values obtained in the last iteration and use the optimal values to calculate the model to evaluate the hydrate formation temperature.
Step 7: Repeat the algorithm several times to verify it is converging to a stable solution.
Step 8: Run the FA code by varying values of γ_f, α_f, β_f, nPop and MaxIt to establish the best outcome.

3. Results and discussions

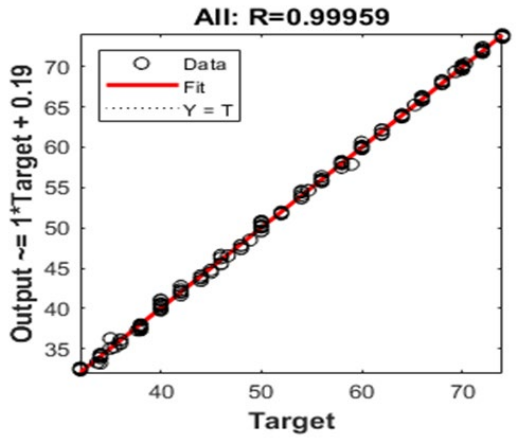

Figure 2. Regression Plot for ANN

ANN architecture used for this work was chosen based on the MSE and the R values. The network used was developed using the Bayesian Regression (trainbr) training function, Gradient descent with momentum weight and bias (learngdm) adaptation learning function, 3 layers; Log-sigmoid (logsig) transfer function and 5 neurons in the first layer and second layer, and Hyperbolic tangent sigmoid (tansig) transfer function in the third layer.The network regression plot which plots the predict data against the experimental (target) data can be shown in Figure 2, the plot shows the R value for the network was gotten as 0.99959 after 387 iterations.

Comparing the results from the ANN in this work to MLP 2-B-L (ANN) developed by Offisong [28]. The Network developed in this work produced better results, given the R value and MSE for the MLP 2-B-L are 0.99937 and 0.26763 respectively compared to the R value and MSE of 0.99959 and 0.10376 respectively gotten from this work. The differences in MLP 2-B-L model when compared to network used in this work would be responsible for the difference in results. The following are some of the similarities observed in both networks, feedforward back propagation, log-sigmoid transfer function and 2 hidden layers. MLP 2-B-L was developed using 7 and 5 neurons in the hidden layers as opposed to the 5 neurons in each hidden layer of the network in this work. Information like the training function and adaptation learning function used to developing MLP 2-B-L were not stated. For the firefly algorithm model, the parameters

assigned to the FA were the maximum number of iterations MaxIt, number of fireflies (swarm size) nPop, light absorption coefficient γ_f, attraction coefficient base value β_f, mutation coefficient α_f, mutation coefficient damping ratio (α_f _damp), uniform mutation range δ. These parameters have significant effect on the performance of FA. The performance was analyzed by evaluating the fitness function in terms of the R value and mean square error (MSE) in predicting the temperature data from the data fed to the algorithm. The firefly algorithm parameters used for this study is shown in Table 4 below;

Table 4. Firefly algorithm parameters

Parameter	Value	Parameter	Value
MaxIt	1000	α_f	0.2
nPop	40	α_f _damp	0.98
$\boldsymbol{\gamma_f}$	1	δ	0.05
$\boldsymbol{\beta_f}$	2		

The result obtained the least mean square error (MSE) in the range 113.00670. Figure 3 shows the regression plot for the FA model with a R^2 value of 0.8175.

The FA model obtained is given as equation (14), repeated below

$$T_{(i)} = b \times \left(P_{(i)}{}^{c}\right) + \left(d \times G_{(i)}\right) + \left(e \times G_{(i)}{}^{2}\right) \quad (14)$$

where:$T_{(i)}$ is temperature in °F; $P_{(i)}$ is pressure in psia; $G_{(i)}$ is specific gravity; number of particles required; b = 8.4711; c = 0.2631; d = -4.1265 ;
e = 3.8689.

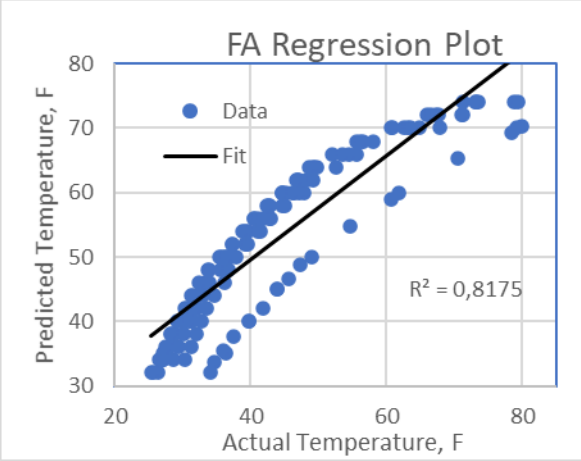

Figure 3. Regression Plot for Firefly Algorithm

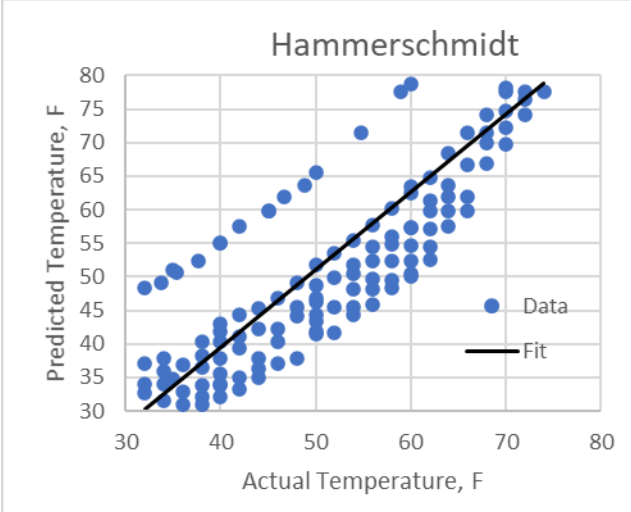

Figure 4. Regression Plot for Hammerschmidt Correlation

Hammerschmidt, Motiee, and Towler and Mokhatab's correlations in equations (3), (7) and (8) respectively were used to predict hydrate formation temperature, regression plot was generated for each of the correlations (Figure 4 to Figure 6). The results gotten from the ANN and FA models were compared to the correlations that has been used to predict hydrate formation temperature. Error analysis were performed statistically and graphically to evaluate the results gotten from the models and correlations.

Figures 7 – 11 however, are graphical evaluation, comparing the predicted hydrate formation temperature to the experimental data for the models and correlations. Prediction performance of the various model, algorithm and correlations were compared using MSE, R and R^2 values, MAPE, Chi-square and SEP (Table 5).

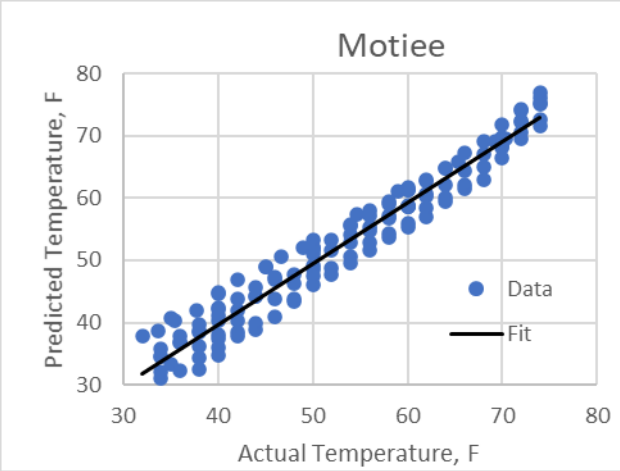

Figure 5. Regression Plot for Motiee correlation

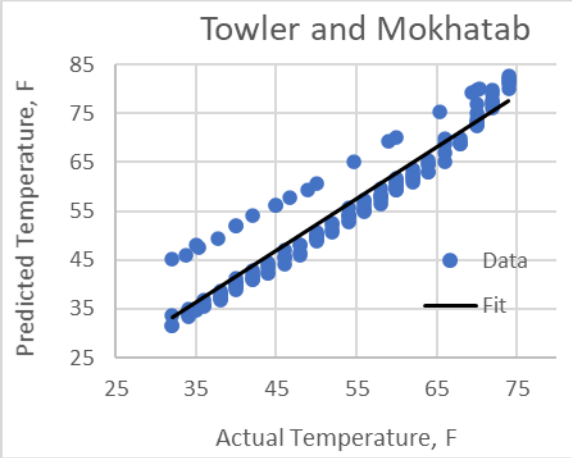

Figure 6. Regression Plot for Towler and Mokhatab correlation

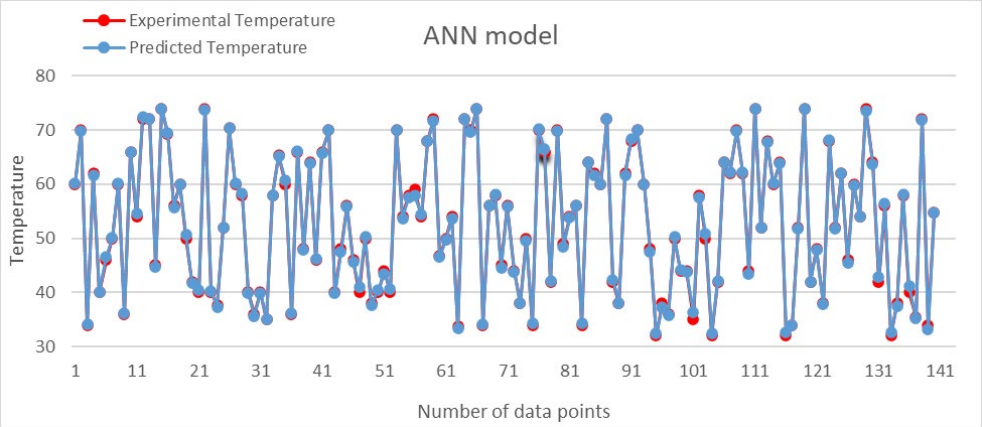

Figure 7. Comparison of experimental data and results of ANN model

Table 5. Performance and error analysis

	ANN	FA	Hammerschmidt	Motiee	Towler and Mokhatab
MSE	0.1037	113.0067	80.4110	7.9602	23.0729
RMSE	0.3221	10.6305	8.9672	2.8214	4.8034
R^2	0.9992	0.8175	0.8609	0.9761	0.9548
R	0.9996	0.9042	0.9279	0.9879	0.9772
MAPE	0.0059	0.1848	0.1329	0.0496	0.0563
Chi-square	0.4273	305.2465	214.3732	24.7447	68.0734
SEP	0.6893	20.1189	16.9712	5.3397	9.0909

The data obtained from Offisong [28] was used as the basis for prediction and comparison. The data obtained ANN had the least MSE and RMSE (0.1038 and 0.0059). followed by Motiee, Towler and Makhtab, FA and Hammerschmidt in that order. The R values indicate the relationship between the experimental and predicted data. ANN had the R and R^2 value closest to 1 (0.99959 and 0.99918 respectively) followed by Motiee, Towler and Makhtab, Hammerschmidt and FA in that order. The MAPE and SEP measure the deviation from the actual data. As seen in Table 5 ANN had the least divergence from experimental values with a MAPE and SEP of 0.005944 and 0.689312 respectively compared to the MAPE and SEP of the correlations and FA. ANN low Chi-square values of 0.42733 in comparison to FA and the correlation confirmed ANN had the best performance in prediction of gas hydrate formation temperature, while FA did not perform as well as ANN nor the correlations.

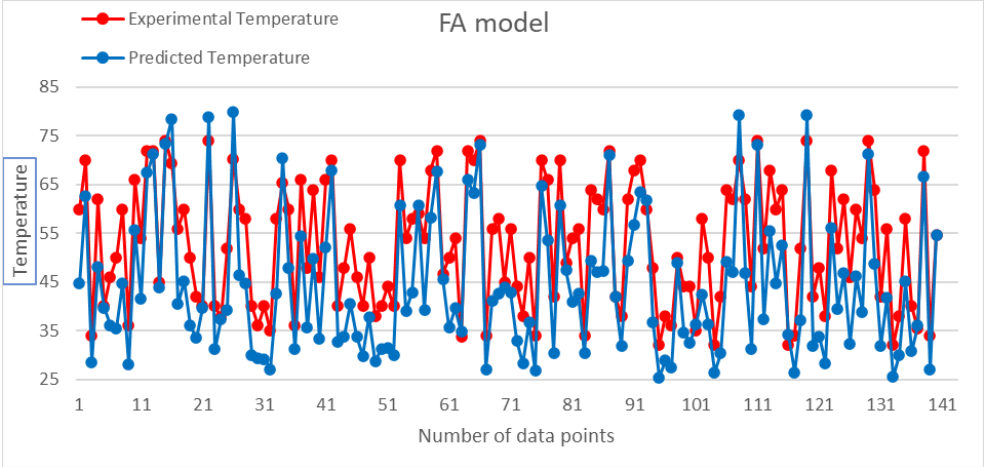

Figure 8. Comparison of experimental data and results of FA model

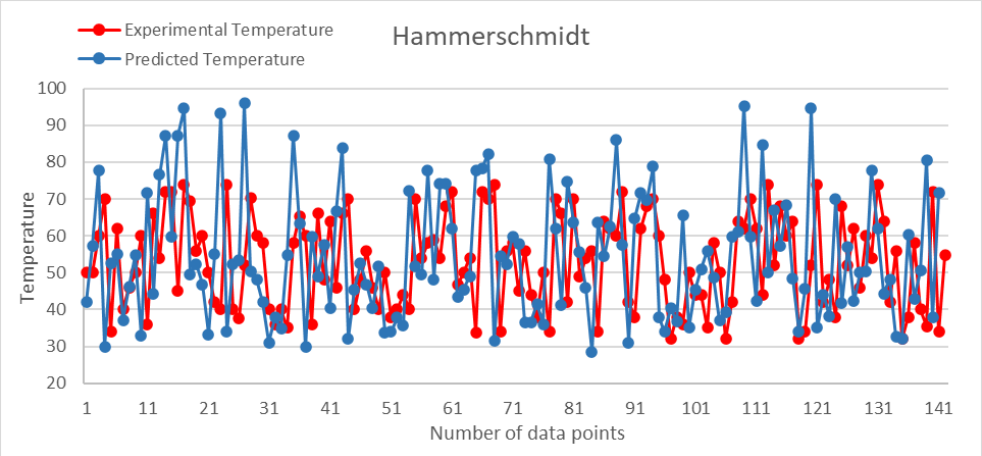

Figure 9. Comparison of experimental data and results of Hammerschmidt correlation

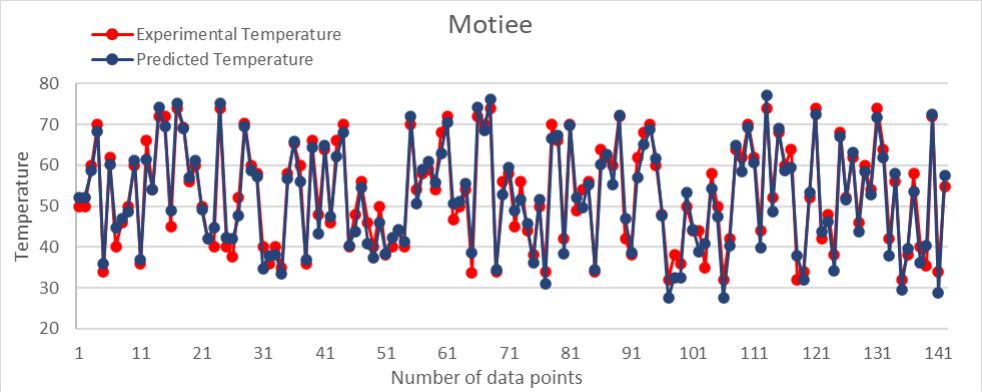

Figure 1. Comparison of experimental data and results of Motiee correlation

This work provide a confirmation to the reports made by [18, 28-29] that ANN performed better than other software and correlation in the prediction of gas hydrate formation temperature.

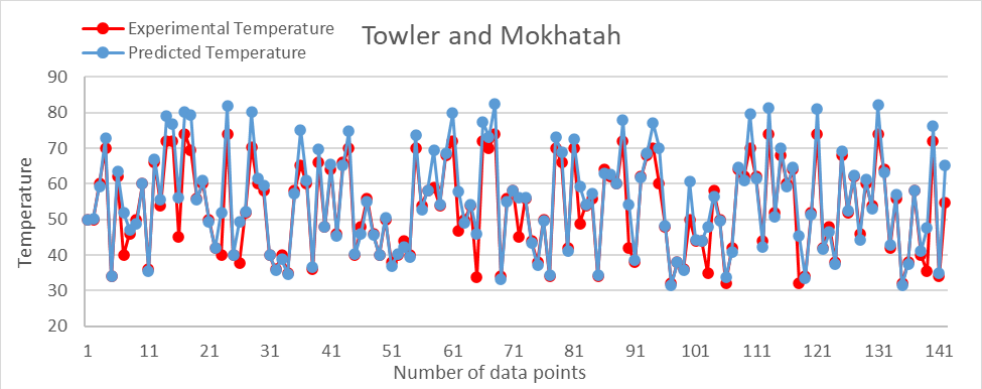

Figure 11. Comparison of experimental data and results of Towler and Mokhatah correlation

4. Conclusion and recommendation

For the prediction of gas hydrate formation temperature, the ANN model developed in this work used Bayesian regularization algorithm which obtained the best model and performed better than FA, Hammerschmidt correlation, Motiee correlation and Towler and Mokhatab's correlations. ANN performed better in comparison to FA in the prediction based on the statistical analysis, as ANN have better R, R^2, MSE, RMSE, MAPE, Chi-square and SEP values. ANN MSE of 0.10376 and R^2 of 0.99918 compared to FA MSE and R^2 value of 113.00670 and 0.8175 respectively reaffirmed the conclusion drawn by [18, 28-29] that ANN performed better in hydrate temperature prediction than any model and correlation known and available.

Both ANN and FA are very good and useful tools in predicting hydrate formation temperatures, the comparison of their performance based on their mean square error and regression value to correlations used in the industry was very good. To obtain very precise prediction, ANN is recommended. Subject to further research, the equation used for the FA can be improved upon and the use of much more datasets can help achieve better model and algorithm performance.

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