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Prediction of Oilfield Scale formation Using Artificial Neural Network (ANN)

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Authors' contributions

This work was carried out in collaboration among all authors. Author OAF designed the study and wrote the protocol. Author CU gave support in neural network modeling. Author FE performed the analysis and wrote the first draft of the manuscript. All authors managed the literature searches, read and approved the final manuscript.

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ABSTRACT

Scale formation and deposition is a recurring problem in many oil producing fields leading to operational problems, problems in reservoirs, pumps, valves and topside facilities. Scale is described economically as a menace to an oil-field because its build-up clogs the flow lines and causes loss of millions of dollars yearly. The ability to predict the onset and amount of scale formation has been a major challenge in the oil industry. Previous models for predicting scale formation have focused mainly on thermodynamics and limited solubility data, and can predict only the potential or tendency to form scale. However, no studies have considered the influence of kinetic and transport factors. In this paper, a comprehensive and robust model incorporating other factors that have been ignored in past studies is developed using the technique of artificial neural network (ANN).

Field data on two types of scale namely Barium and Calcium sulphate were obtained, processed, trained and tested with Artificial Neural Network. The model obtained was validated with actual data. Results show that at constant pressure, the neural network structure with optimum performance for $BaSO_4$ was ANN {1,2,1} with the lowest Mean Square Value (MSE) of 0.0025

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and the highest correlation determination (R^2) of 0.9966 while at constant temperature, it was ANN{1,1,1} with MSE of 0.0017 and R^2 of 0.9956. The neural network structure with optimum performance for $CaSO_4$ precipitation kinetics with temperature and pressure was ANN{2,5,1} with MSE of 8.7745e-005 and R^2 of 0.8206 while at constant flow rate it was ANN{1,4,1} with MSE of 2.3007e-006 and R^2 of 0.9953. This gave a very close agreement with actual data in terms of prediction and performance. The results of this study therefore will greatly help to reduce the amount of risk incurred (such as NORM, etc.) due to the deposition and formation of scale in an oil-field, the cost of stimulating an oil flow line and also improve the productivity of an oil well, hence, increase revenue to the oil industry.

Keywords: Flow assurance; scale; artificial neural network; oilfield; modelling; deposition.

NOMENCLATURES

T = *Temperature (OF), (OK)*
P = *Pressure (psia)*
ΔP = *Pressure Drawdown*
K = *Kinetic rate of reaction constant (m/min)*
Q = *Flow rate (cc/min)*
Xi = *Amount of X standardized*
Xmax = *Maximum amount in all data*
Xmin = *Minimum amount in all data*
R2 = *Correlation determination*
MSE = *Mean Square Error*
T-test = *Statistical hypothesis test with t-distribution*
F_cal = *Fischer calculation*
AIC = *Akaike Information Criterion*
SIC = *Schwarz Information Criterion*
NIC = *Network Information Criterion*
Tansig = *Tangent Sigmoid*
BaSO4 = *Barium Sulphate*
CaSO4 = *Calcium Sulphate*

1. INTRODUCTION

Oilfield scale formation represents a very significant flow assurance challenge to the oil and gas industry, with increasing water production worldwide. When producing oil and gas, there will in most cases also be produced some water, which contains dissolved inorganic salts. These salts may precipitate out of solution and tend to deposit on surfaces. Deposition of inorganic minerals from brine is called SCALE, and its formation causes flow reduction or even blocking of pipes, valves and other equipment [1-3]. Barium sulfate ($BaSO_4$) is the most insoluble scale that can be precipitated from oilfield waters. It forms a hard scale which is extremely difficult to remove. The solubility of barium sulfate is about a thousand times less than that of calcium sulfate ($CaSO_4$), at surface conditions. Barium sulfate scale (barite) in oil fields can be precipitated easily on the basis of already available information relating to thermodynamic conditions and the kinetics of precipitation [1,4]. Calcium sulfate, which is important in desalination, geochemistry and petroleum engineering, is complicated by the fact that it can crystallize from aqueous solutions in three forms: gypsum ($CaSO_4.2H_2$ O), hemihydrate ($CaSO_4\,{}^1/_2\,H_2$ O) and anhydrite ($CaSO_4$) [2,5]. These compounds may be stable depending on temperature, pressure and on ionic strength and they have decreasing solubility with increasing temperature above 40ºC. Some other authors have also investigated other ways of predicting $BaSO_4$ and $CaSO_4$ oilfield scale, which include mathematical modeling, experimental studies, as well as development of oilfield scale software [1-5]. Mineral scale formation and deposition on downhole and surface equipment is a major source of concern because of the high cost incurred in removing the scale and the reduction in oil production. Cost effective scale control should be one of the primary objectives of any efficient water injection and normal production operation in oil and gas fields [2,4].

Artificial Neural Network (ANN) is a fast-growing method which has been used in different industries in recent years. The main idea for creating ANN, a subset of artificial intelligence is to provide a simple model of human brain in order to solve complex scientific and industrial problems [6]. ANNs are high-value and low-cost tools used in modelling, simulation, control, condition monitoring, sensor validation and fault diagnosis of different systems including different kinds of rotating equipment. They learn from the data obtained from a system instead of learning from a specific program. ANNs can solve a variety of problems in optimization, pattern recognition, clustering, function approximation, time series analysis, prediction and validation. A neural network model is a group of

interconnected artificial units (neurons) with linear or nonlinear transfer functions. Neurons are arranged in different layers including input layer, hidden layer(s) and output layer [6-8].

Neural Networks were first formalized in a 1943 paper by McCulloch and Pitts [9]. Later in the 1960s, Rosenblat developed the perceptron convergence theorem in 1962, [10] and Minsky and Papert in [11] showed the limitation of a simple perceptron. Their results dampened the enthusiasm of most researchers in neural network research for 20 years. However, interest was renewed in the early 1980s. Major development behind this resurgence include (i) Hopfield's energy approach in 1982, [12] (ii) Werbos' back-propagation learning algorithm for multilayer Perceptron which was first proposed in 1974, [13] (iii) re-invention of Werbos' work on a number of occasions, which was then popularized by Rumelhart et al. [14] in, and (iv) detailed historical account of ANN development by Anderson and Rosenfeld in [15].

The statistical neural network (hereinafter, SNN) model was used in the analyses of the impact of the variables on the two dependent variables in this study. The choice of neural networks is because it is a very flexible and powerful model estimation which can estimate data that may fail in estimation procedure with other statistical methods. SNN has been found to be powerful in estimating imprecise and noisy data set. It has been found applicable in all fields that use data, both qualitative and quantitative.

In this study, we used the Multilayer Perceptron (MLP) model of the SNN because it provides a better basis for statistical inference. The simple model used is as proposed by Anders [16].

1.1 Theoretical Background of Artificial Neural Network

A neural network is a massively parallel distributed processor made up of simple processing units that have a natural tendency for storing experiential knowledge and making it available for us. ANNs have the ability to model linear and non-linear systems without the need to make assumptions implicitly as in most traditional statistical approaches. They have been applied in various aspects of science and engineering [17]. ANNs can be grouped into two major categories: Feed-forward and feedback (recurrent) networks. In the former network, no loops are formed by the network connections, while one or more loops may exist in the latter. The most commonly used family of feed-forward networks is a layered network in which neurons are organized into layers with connections strictly in one direction from one layer to another [18].

MLPs are the most common type of feed-forward networks. Fig. 1 shows an MLP which has three types of layers: an input layer, an output layer and a hidden layer.

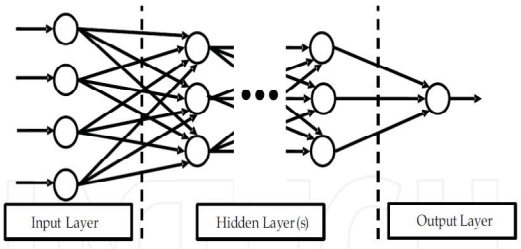

Fig. 1. A Multi-layered perceptron (MLP) network

Neurons in input layer only act as buffers for distributing the input signals x_i (i=1, 2 …n) to neurons in the hidden layer. Each neuron *j* (Fig. 2) in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function *f* of the sum.

$$y_j = f\left(\sum_{i=1}^{n} w_{ji}\, x_i\right) \quad (1)$$

f can be a simple threshold function or a sigmoidal, hyperbolic tangent or radial basis function. The output of neurons in the output layer is computed similarly. The back propagation algorithm, a gradient descent algorithm, is the most commonly adopted MLP training algorithm. It gives the change Δw_{ji} the weight of a connection between neurons i and j as follows:

$$\Delta w_{ij} = \eta\, \delta_j x_i \quad (2)$$

where η is a parameter called the learning rate and δj is a factor depending on whether neuron j is an input neuron or a hidden neuron. For output neurons,

$$\delta_j = \left(\partial f / \partial_{net\,j}\right)\left(y_j^{(t)} - y_j\right) \quad (3)$$

and for hidden neurons

$$\delta_j = \left(\partial f / \partial_{netj}\right)\left(\sum_q w_{jq}\, \delta_q\right) \quad (4)$$

In Eq. (3), net_j is the total weighted sum of input signals to neurons j and $y_j^{(t)}$ is the target output for neuron j.

As there are no target outputs for hidden neurons, in Eq. (4), the difference between the target and actual output of hidden neurons j is replaced by the weighted sum of the δ_q terms already obtained for neurons q connected to the output of j.

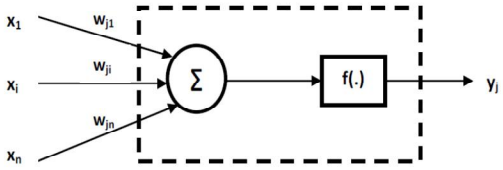

Fig. 2. Detail of the perceptron process

The process begins with the output layer, the δ term is computed for neurons in all layers and weight updates determined for all connections, iteratively. The weight updating process can happen after the presentation of each training pattern (pattern-based training) or after the presentation of the whole set of training patterns (batch training). Training epoch is completed when all training patterns have been presented once to the MLP.

A commonly adopted method to speed up the training is to add a "momentum" term to Eq. (5) which effectively lets the previous weight change influence the new weight change:

$$\Delta w_{ij}(I+1) = \eta\, \delta_j x_i + \mu \Delta w_{ij}(I) \quad (5)$$

where Δw_{ij} (I + 1) and Δw_{ij} (I) are weight changes in epochs (I + 1) and (I), respectively, and μ is "momentum" coefficient [19].

1.2 Objective of Study

The objective of this research work is to predict the formation of $BaSO_4$ and $CaSO_4$ oilfield scale using Artificial Neural network and The Statistical Neural Network taking into considerations the effect of thermodynamic, transport, and kinetic factors. This is achieved through the development of a neural network model that trained, tested and validated the obtained data using Neural Network toolbox in Matlab R2009a.

1.3 Limitation of Study

Other types of oilfield scale were not considered in this work. These include; Calcium carbonate, Strontium Sulfate, Ferrous carbonate, Ferrous Sulfide etc. This is due to lack of sufficient data on these types of scale.

2. MATERIALS AND METHODS

2.1 Implementation of ANN Model

Designing ANN models follows a number of systemic procedures. In general, there are five basics steps: (1) collecting data, (2) preprocessing data, (3) building the network, (4) train, and (5) test performance of model.

2.2 Data Collection

Collecting and preparing sample data is the first step in designing ANN models. Measurement data of temperature, amount of $BaSO_4$ and $CaSO_4$ precipitated, pressure, kinetic rate of reaction constant and flow rate was collected from published literature.

2.3 Data Pre-processing

After data collection, three data preprocessing procedures were conducted to train the ANNs more efficiently. These procedures are: (1) solve the problem of missing data, (2) normalize data and (3) randomize data. The missing data are replaced by the average of neighboring values during the same week. Normalization procedure before presenting the input data to the network is generally a good practice, since mixing variables with large magnitudes and small magnitudes will confuse the learning algorithm on the importance of each variable and may force it to finally reject the variable with the smaller magnitude [20].

2.4 Building the Network

At this stage, the designer specifies the number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function, and performance function. In this work, a multilayer perceptron (MLP) network was used.

2.5 Training the Network

During the training process, the weights were adjusted in order to make the actual outputs (predicated) close to the target (measured) outputs of the network. A total of 24 data sets

were used for the amount of $BaSO_4$ precipitated while 20 data sets were used to generate kinetic rate of reaction constant of precipitation of $CaSO_4$. The iterations time was 1000 (i.e epoch = 1000) MATLAB provides built-in transfer functions which are used in this study; linear (purelin), Hyperbolic Tangent Sigmoid (logsig) and Logistic Sigmoid (tansig).

2.6 Testing the Network

The next step was to test the performance of the developed model. At this stage unseen data were exposed to the model. In order to evaluate the performance of the developed ANN models quantitatively and verify whether there is any underlying trend in performance of ANN models, statistical analysis involving the coefficient of determination (R^2), the root mean square error (RMSE), and the mean bias error (MBE) were conducted. RMSE provides information on the short term performance which is a measure of the variation of predicated values around the measured data. The lower the RMSE, the more accurate is the estimation. MBE is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information on long term performance of the models; the lower MBE the better is the long term model prediction.

2.7 Data Acquisition and Analysis

2.7.1 CASE 1: Prediction of amount of $BaSO_4$ precipitated

a) Twelve (12) data sets used in this work were obtained from OLI scalechem software [4]. The range of data are the following: Temperature (78 to 210°F), BaSO4 precipitated (18.0 to 20.0 mg/l). Pressure was kept constant at 4800 psia [4].

Precipitation is mathematically expressed as:

BaSO4 precipitation = f (T)

where: T = Temperature (degree fahrenheit)

b) Another set of data (12) were obtained from OLI scalechem software [4]. The range of these sets of data are the following: Pressure (0 to 5000 psia), $BaSO_4$ precipitated (15.5 to 17.0 mg/l). Temperature was kept constant at 210°F [4].

Precipitation is mathematically expressed as:

BaSO4 precipitation = f (P)

where: P = Pressure (psia)

A total of 24 data sets for predicting BaSO4 precipitation were used. In each case, the iteration time was 1000 (i.e epoch = 1000) and the Neural network formulation is:

(1-1-1), (1-2-1), (1-3-1), (1-4-1), (1-5-1), (1-6-1), (1-7-1), (1-8-1), (1-9-1), (1-10-1) for the input, hidden and output layers, respectively for each of the cases [7,8].

2.7.2 Case 2: $Caso_4$ Kinetic Rate of Reaction Constant

a) 12 data sets used in this work were obtained from Arhenius mathematical model [5] and were subsequently used to generate kinetic rate of reaction constant for CaSO4 precipitation kinetics at different temperature and pressure. The ranges of the data are the following: Temperature (323 to 353°K), Pressure drawdown (100 to 200 psig) and Kinetic rate of reaction constant (0.00357 to 0.0652 m/min).

Kinetic Rate of Reaction Constant is mathematically expressed as:

K = f (T, ΔP)

where:

T = Temperature (degree kelvin)
ΔP = Pressure drawdown (psia)
K = Kinetic rate of reaction constant(m/min)

b) 8 data sets used in this work were obtained from Arhenius mathematical model (Merdhah et al 2008). The ranges of the data are the following Flow rate (10.01 to 28.14 cc/min) and Kinetic rate of reaction constant (0.00357 to 0.0652 m/min).

Kinetic Rate of Reaction Constant is mathematically expressed as:

K = f (Q)

For $CaSO_4$ prediction, a total of 20 data sets were used. In each case, the iteration time was

1000 (i.e epoch = 1000) and the Neural network formulation is

(2-1-1), (2-2-1), (2-3-1), (2-4-1), (2-5-1), (2-6-1), (2-7-1), (2-8-1), (2-9-1), (2-10-1) for the input, hidden and output layers, respectively for each of the cases [5,7].

All input variables were standardized, that is, converting them to range (0, 1) before feeding them into the network. This is to avoid the application of extremely small weighting factors in the case of large input values.

$$X = 0.8\ (\frac{xi-xmin}{xmax-xmin}) + 0.1 \qquad (6)$$

X_i = amount of X standardized
X_{max} = maximum amount in all data
X_{min} = minimum amount in all data

Similarly, the output values were "destandardized" to provide meaningful results since all values leaving the network are in a standardized format. This is done by simply reversing the standardization algorithm used on the input nodes.

The Analysis Of The Artificial Neural Network (Ann) and The Statistical Neural Network (Tsnn) Using Neural Network Toolbox In Matlab R2009a was done and results were obtained [6-8].

2.8 Model Selection

The mean square error (MSE), and criteria such as Akaike information criterion (AIC), Schwarz information network (SIC), network information criterion (NIC), were used in model selection while the coefficient of determination (R^2) was used in determining the goodness of fit of the models [21]. The significance of the model was determined by computing the student's T test, Fisher statistic, F, and its p-value. The model with the least MSE, AIC or NIC is considered as the best. This coincides with the model that has the highest R^2.

3. RESULTS AND DISCUSSION

The neural network model used in predicting the amount of $BaSO_4$ precipitated and kinetic rate of reaction of $CaSO_4$ in this work is the multilayer perceptron model using tangent sigmoid (TANSIG) transfer function after one thousand (1000) iterations; i.e epoch = 1000. This model was chosen because it indicated the least Mean Square Error (MSE) and correlation of determination (R^2) [7].

The tangent sigmoid (**TANSIG**) transfer function is given by [7]:

$$\boldsymbol{tansig} = f_3(n) = \frac{2}{1-e^{-2n}} - 1 \qquad (7)$$

3.1 CASE 1a: Amount of $BaSO_4$ Precipitated versus Temperature at Constant Pressure (4800 psia)

The artificial neural network was run for hidden neurons ranging from 1 to 10 (i.e; ANN {1-1-1} to ANN{1-10-1). It was observed that hidden neurons ANN{*1-3-1*}, ANN{*1-4-1*}, ANN{*1-7-1*} and ANN{*1-8-1*} have correlation determination (R^2) values greater than one(1) and negative values of mean square error (MSE) which indicated over fitting so they cannot be considered. Table 1 indicates their values.

After one thousand{1000} iterations (i.e epoch=1000), the neural network structure that has the optimum performance was ANN{1,2,1} with the lowest Mean Square Value (MSE) of *0.0025* and the highest correlation determination (R^2) of *0.9966*. Other statistical criteria include T_test = *0.0023*, F_cal = *1.1890e+003*, AIC= *0.0033*, SIC= *0.0031*, NIC= *0.0799*. Figs. 3 and 4 below show the comparison between ANN{1-2-1} and Actual $BaSO_4$ precipitation against temperature and also plot of the ANN{1-2-1} against Actual BaSO4 precipitation. In Fig. 1, R^2 = 0.9789 for ANN{1-2-1)} which is greater than that of the actual (R^2 = 0.977). ANN{1-2-1} is better. Fig. 4 shows the comparison between the predicted ANN{1,2,1} and the actual $BaSO_4$.

3.2 CASE 1b: Amount of BaSO4 Precipitated versus Pressure at Constant Temperature (210°F)

The artificial neural network was run for hidden neurons ranging from 1 to 10 (i.e ANN{1-1-1} to ANN{1-10-1). It was observed that hidden neurons ANN{*1-6-1*}, ANN{*1-7-1*}, ANN{*1-**8-1***} and ANN{*1-10-1*} have correlation determination(R^2) values greater than one(1) and negative values mean square error (MSE) which indicated over fitting so they cannot be considered. Table 2 shows the results.

After one thousand{1000} iterations (i.e; epoch=1000), the neural network structure that

has the optimum performance was ANN{1,1,1} with the lowest Mean Square Value (MSE) of *0.0017* and the highest correlation determination (R^2) of *0.9956*. Other statistical criteria seen include T_test = *6.1751e-007*, F_cal = *911.5173*, AIC= *0.0021*, SIC= *0.0020*, NIC= *0.1605*. Figs. 5 and 6 below show the comparison between ANN{*1-1-1*} and actual BaSO4 precipitation with pressure change and plot of the ANN{1-1-1} against Actual $BaSO_4$ precipitation. In Fig. 5, R^2 = 0.9949 for ANN{1-1-1) higher than that of the actual(R^2= 0.9821).

Table 1. Amount of $baso_4$ precipitated using temperature with constant pressure (4800psia)

ANN structure	Alpha	Beta	R^2	MSE	T_test	F_cal	AIC	SIC	NIC
ANN (1-1-1)	21.3732	-0.0155	0.9543	0.0346	0.0023	83.5960	0.0450	0.0419	0.0868
ANN (1-2-1)	21.3732	-0.0155	0.9966	0.0025	0.0023	1.1890e+003	0.0033	0.0031	0.0799
ANN (1-3-1)	21.3732	-0.0155	1.0037	-0.0028	0.0023	1.0761e+003	-0.0037	-0.0034	0.0400
ANN (1-4-1)	21.3732	-0.0155	1.0032	-0.0024	0.0023	1.2613e+003	-0.0031	-0.0029	0.2479
ANN (1-5-1)	21.3732	-0.0155	0.9839	0.0122	0.0023	244.7309	0.0158	0.0148	0.0232
ANN (1-6-1)	21.3732	-0.0155	0.9831	0.0128	0.0023	233.1706	0.0166	0.0155	0.0238
ANN (1-7-1)	21.3732	-0.0155	1.0141	-0.0107	0.0023	287.7032	-0.0139	-0.0130	0.0058
ANN (1-8-1)	21.3732	-0.0155	1.0019	-0.0014	0.0023	2.1413e+003	-0.0018	-0.0017	0.1147
ANN (1-9-1)	21.3732	-0.0155	0.9893	0.0081	0.0023	369.6636	0.0105	0.0098	0.0644
ANN (1-10-1)	21.3732	-0.0155	0.9786	0.0162	0.0023	183.0286	0.0211	0.0196	0.0369

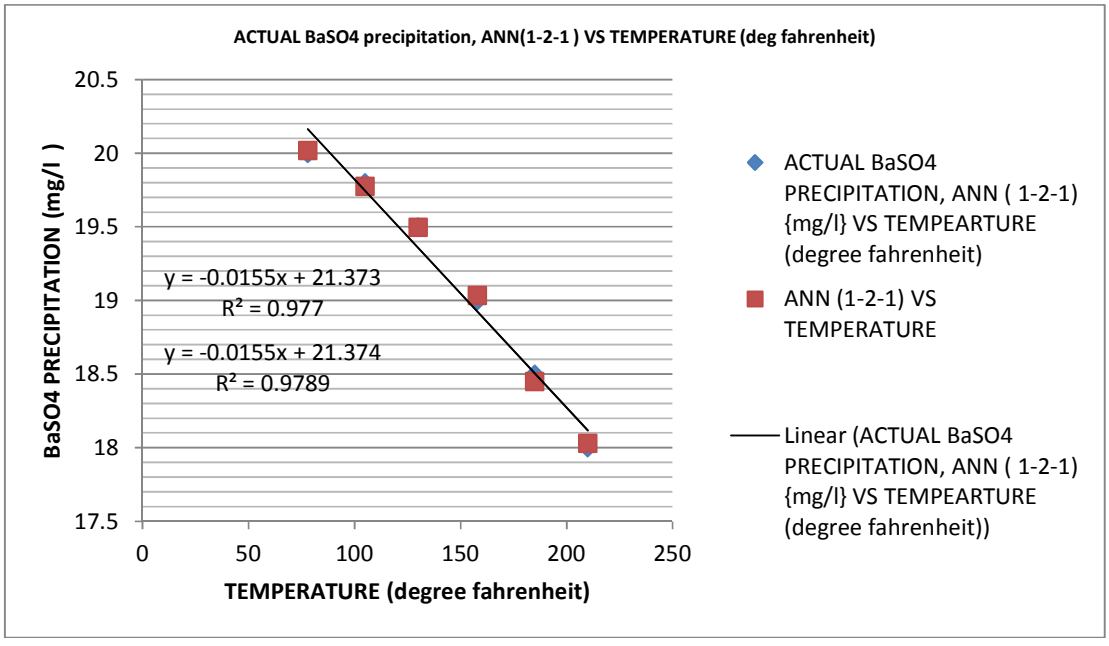

Fig. 3. Comparison between ANN{1-2-1} and actual $BaSO_4$ precipitation versus temperature
R^2 = 0.9789 for ANN{1-2-1} while R^2 =0.977 for the actual

Table 2. Amount of $BaSO_4$ precipitated using pressure at constant temperature (210°F)

	Alpha	Beta	R^2	MSE	T_test	F_cal	AIC	SIC	NIC
ANN (1-1-1)	17.0619	-2.9143e-004	0.9956	0.0017	6.1751e-007	911.5173	0.0021	0.0020	0.1605
ANN (1-2-1)	17.0619	-2.9143e-004	0.9524	0.0180	6.1751e-007	80.0058	0.0234	0.0218	0.1161
ANN (1-3-1)	17.0619	-2.9143e-004	0.9954	0.0017	6.1751e-007	865.5135	0.0023	0.0021	0.0763
ANN (1-4-1)	17.0619	-2.9143e-004	0.9816	0.0069	6.1751e-007	213.7944	0.0090	0.0084	0.0397
ANN (1-5-1)	17.0619	-2.9143e-004	0.9642	0.0136	6.1751e-007	107.6048	0.0176	0.0164	0.0624
ANN (1-6-1)	17.0619	-2.9143e-004	1.0096	-0.0036	6.1751e-007	420.1406	-0.0047	-0.0044	0.0819
ANN (1-7-1)	17.0619	-2.9143e-004	1.0370	-0.0140	6.1751e-007	111.9807	-0.0182	-0.0170	0.0350
ANN (1-8-1)	17.0619	-2.9143e-004	1.0311	1.0311	6.1751e-007	132.6493	-0.0153	-0.0143	0.0409
ANN (1-9-1)	17.0619	-2.9143e-004	0.9690	0.0117	6.1751e-007	124.8418	0.0153	0.0142	0.1896
ANN (1-10-1)	17.0619	-2.9143e-004	1.0175	-0.0066	6.1751e-007	232.5165	-0.0086	-0.0080	0.0309

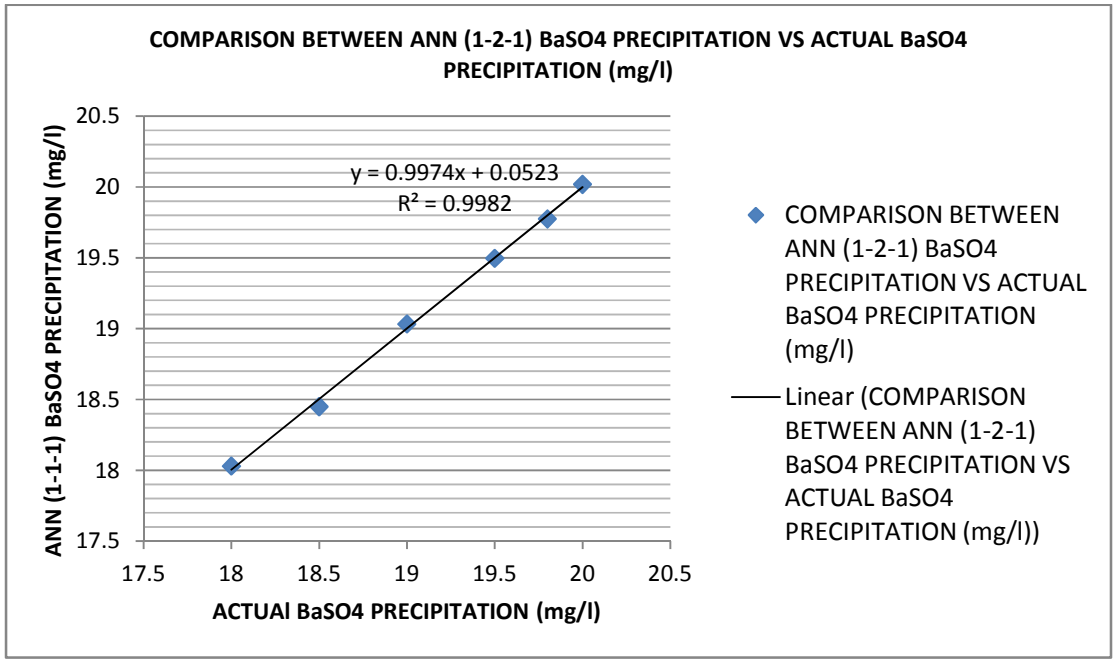

Fig. 4. ANN {1-2-1} versus actual BaSO4 precipitation

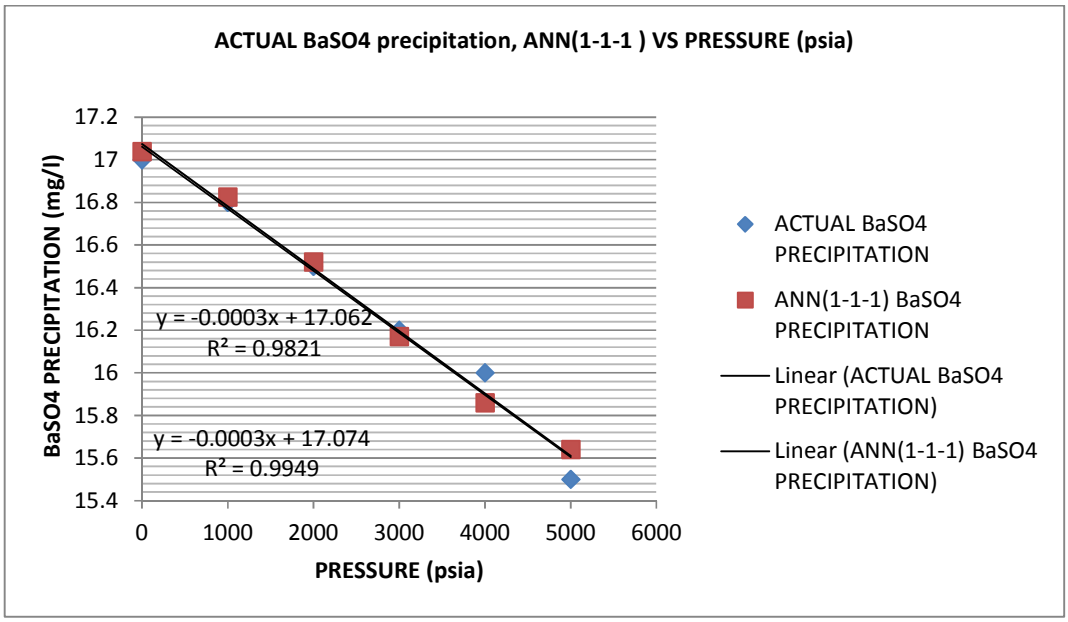

Fig. 5. Comparison between ANN{*1-1-1*} and Actual BaSO4 precipitation against pressure
R^2 = 0.9949 is for ANN{1-1-1} while R^2 = 0.9821 is for the actual

3.3 CASE 2a: $CaSO_4$ Kinetic Rate of Reaction Constant Using Temperature and Pressure

The artificial neural network was ran for hidden neurons ranging from 1 to 10 (i.e ANN {2-1-1} to ANN {2-10-1).

After one thousand {1000} iterations (i.e; epoch=1000), the neural network structure that has the optimum performance was ANN{2,5,1} with the lowest Mean Square Value (MSE) of *8.7745e-005* and the highest correlation determination (R^2) of *0.8206,* other statistical criteria seen include: *T_test_1 = 2.1130e+003*,

T_test_2 = -1.6877, T_test_3 = 50.7243 F_cal = *18.2984*, AIC= *1.1394e-004*, SIC= *1.0630e-004*, NIC= *0.0215*. Fig. 7 shows the plot of ANN {2-5-1} against Actual $CaSO_4$ Kinetic rate of reaction constant. R^2 = 0.839 for the plot.

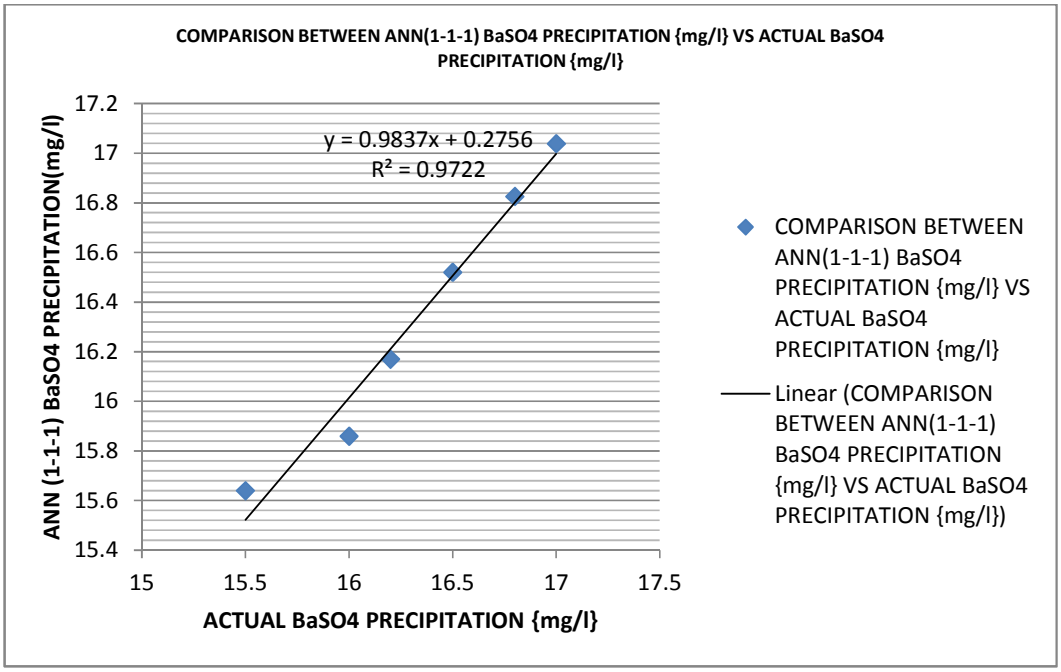

Fig. 6. ANN {1-1-1} versus actual BaSO4 precipitation

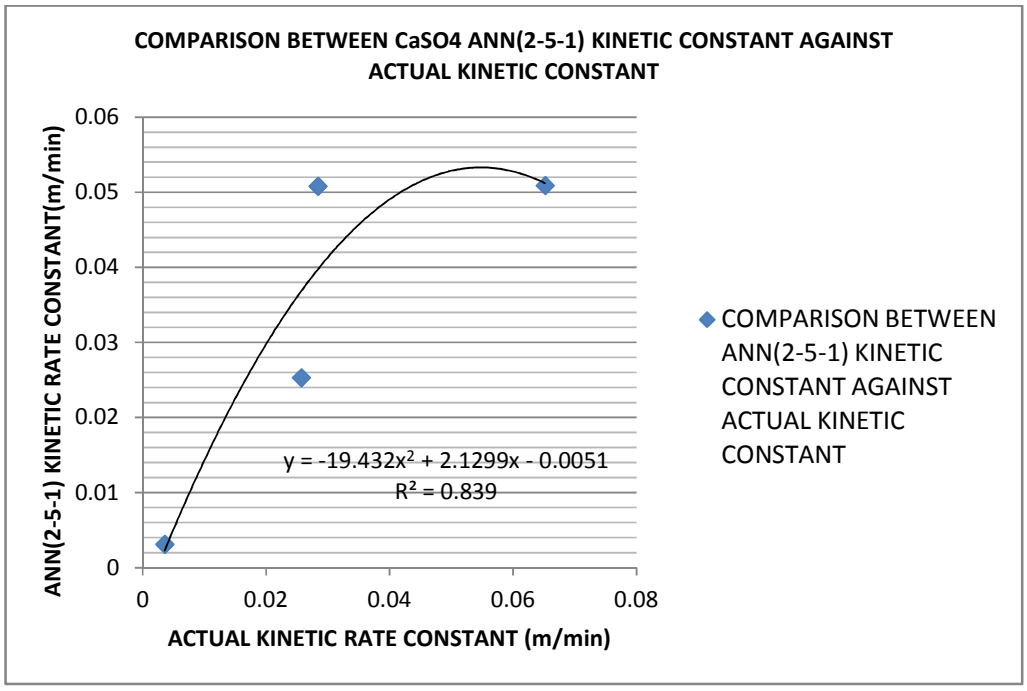

Fig. 7. ANN {2-5-1} Vs actual $CaSO_4$ kinetic rate of reaction constant

3.4 CASE 2b: $CaSO_4$ Kinetic Rate of Reaction Constant Using Flow Rate

The artificial neural network was ran for hidden neurons ranging from 1 to 10 (i.e ANN {2-1-1} to ANN {2-10-1).

After one thousand{1000} iterations (i.e; epoch=1000), the neural network structure that has the optimum performance was ANN{1,4,1} with the least Mean Square Error value (MSE) of 2.3007e-006 and the highest correlation determination (R^2) of 0.9953, other statistical criteria seen include: T_test = 0.0013, F_cal = 846.4236, AIC = 2.9874e-006, SIC = 2.7871e-006, AIC= 2.9874e-006, SIC= 2.7871e-006, NIC= 0.0020. Fig. 7 shows the plot of ANN {1-4-1} against Actual $CaSO_4$ kinetic rate of reaction constant. The R^2 value obtained was 0.9896 which indicated a good performance.

4. DISCUSSION

Fig. 3 is a temperature plot of the precipitation of Barium sulphate. The predictions from ANN {1-2-1} fits well with the actual precipitation data with increase in temperature. R^2 of *0.9789* for ANN{1-2-1} compared with R^2 of *0.977* for the actual shows a better prediction with ANN since it is higher. This was confirmed in Fig. 4 with the regression of ANN against actual giving R^2 of 0.9982. However with change in pressure, the ANN fits well with the actual data at lower pressures, As pressure increased, the model slightly deviates from the actual data as observed in Fig. 5. This most likely is caused by equipment or human error when carrying out the experiment at higher pressures. The results of ANN{1-1-1} predictions for $BASO_4$ precipitation gave R^2 of *0.9722* in Fig. 6 compared to R^2 of 0.9982 for ANN{1-2-1}. This regression result show that the ANN{1-2-1} model is of better fit. The MSE compares the variations in the errors generated by the different models. The model with the smallest MSE in this case ANN{1-2-1} is considered a better model. To confirm model fit, AIC and SIC was considered. The AIC and SIC, like the MSE, for ANN{1-2-1} is less than the other model under comparison and thus adjured to be a better model.

The kinetic rate constant prediction obtained was less accurate for ANN {1,4,1} at higher values while it was more accurate for ANN{2,5,1} as observed in Figs. 7 and 8 respectively. Some outliers on the ANN {1,4,1} plot at higher kinetic rate constants represent overestimation in the model. The result of the entire analysis shows that as the hidden neurons increases, the values of the MSE, AIC and SIC decreases, while those of R^2 increases as also reported in previous studies [21].

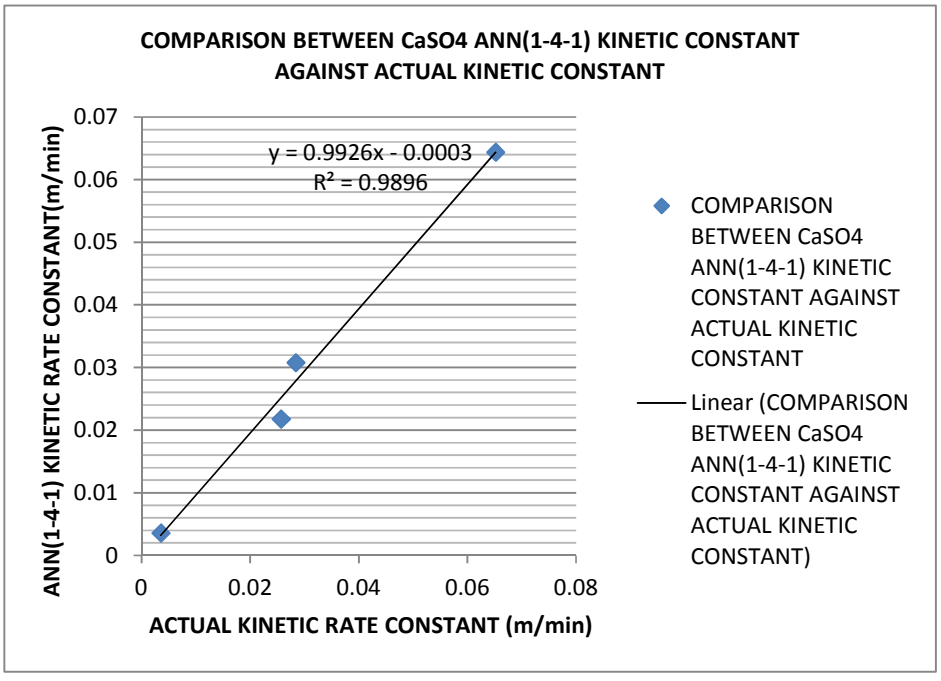

Fig. 8. ANN {1-4-1} Vs Actual $CaSO_4$ Kinetic rate of reaction constant

The Artificial Neural Network (ANN) and The Statistical Neural network (TSNN) developed here present a new and unique way in estimating the amount of Barium Sulphate ($BaSO_4$) precipitated, and also the rate of precipitation of Calcium Sulphate ($CaSO_4$) from the Kinetic rate of reaction constant. It has been established in literature that for precipitation of a compound to occur, the solubility of the compound must have been exceeded and this is caused by changes in the thermodynamic, kinetic and transport factors.

Previous models that have been utilised in predicting precipitation of oilfield scales have failed to account for the influence of kinetic and transport factors. This study has employed the technique of ANN to predict scaling while incorporating kinetic and transport factors and it has found the ANN model to be more comprehensive and robust than other models. The power of ANNs can be attributed to several features they possess, namely: ability to recognize and learn the underlying relationships between input and output without explicit physical consideration, regardless of the problem's dimensionality and system nonlinearity, and the ability to tolerate data containing noise and measurement errors due to distributed processing within the net- work.

5. CONCLUSION

Artificial neural network was successfully applied to estimate oilfield scale formation in this study. In this study, it was demonstrated that any range of input variables can be used in the predictions thus making Artificial Neural Network more robust than other prediction methods. Comparing the ANN (obtained results) with the actual results for each of the cases, it is seen that the obtained results from the network gave a better match than needed results and as such the network can be used to predict the amount of BaSO4 precipitation given temperature or pressure. Also, the kinetic rate of reaction constant was predicted for CaSO4 at given temperature, pressure drawdown and flow rate. The developed Artificial Neural Network model (ANN) and The Statistical Neural Network (TSNN), had good training and validating Results according to the data sets used in both of training and validation steps, and obtained good behavior after many trials reflecting high confidence in the prediction. Neural networks have been shown to be an efficient methodology to estimate natural gas production, utilization and flaring. Comparing model prediction in both cases show that *TSNN* performs better than *TSRM.* It is recommended that future work should consider predicting the critical value of precipitation of salts when they start posing problems in Oil and Gas Fields using ANN.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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