International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 638-650 www.ijaem.net ISSN: 2395-5252

Artificial Intelligence (Ann) and Accurate Well Log Interpretation: Key To Accurate Gravel Pack Design: (A Niger Delta Case Study)

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Date of Submission: 25-12-2020 Date of Acceptance: 31-12-2020

ABSTRACT—In sand production, two kinds of solids are encountered; the load-bearing solids and the fines. In gravel packing (a mechanical sand control technique), efforts are made to select a proppant which is small enough to allow fines to be produced with the crude but also big enough to prevent the influx of the load-bearing solids into the production tubing. The goal of a sand control job seeks to control formation sand without excessively reducing well productivity. In order to achieve an effective control of the sand, accurate design and execution of the gravel pack must be achieved. This is to be done by obtaining an accurate formation sand sample, evaluating the grain sorting (size distribution) and therefore, selecting an optimum gravel size in relation to the formation sand size to control the movement of formation sand. This masterpiece “artificial neural network (ANN) and accurate well log interpretation: key to accurate gravel pack design using Niger delta wells as a case study”, in every ramification, bypasses the conventional sieve analysis used to determine the sizes of the formation sand and brings to light, the use of advanced regression analysis for accurate well log interpretation of permeability from porosity and water saturation data in predicting the formation grain size and better still, the application of the Artificial intelligence (an advanced statistical tool built with more than 10 different algorithms, with the ability to forecast, predict and interpret new data based on history matching of old available data)in predicting new and accurate proppant sizes. In conclusion, from the results obtained, this work proved that the artificial intelligence (Artificial Neural Network) is a viable tool for the industry which when utilized effectively, delivers the right results and with ease.

Keywords—Artificial Intelligemce, Artificial Neural Network, Multivariate Linear Regression

I. INTRODUCTION

In recent years, the accessing of multimedia data or digital daFormation sand production is one of the foremost problems afflicting the petroleum industry as a result of its unfavourable effects on the productivity of wells and its equipment [1]. It is mostly associated with reservoirs with unconsolidated formation (sandstones). One of the major causes of sand production in the oil and gas industry is multiphase flow i.e. water or gas being produced with the hydrocarbon fluid. If this be the case, then every reservoir in the world will need sand control measures since associated gas accompanies the hydrocarbon fluid during production. Amongst the sand control techniques available, gravel packing has proven to be highly effective as it allows for the production of fines but not the load bearing solids that damage the production equipment. In order to achieve a durable sand control, a well-executed, good gravel pack design is required. This includes obtaining a representative sample of the formation sand, analysing the formation grain distribution, and selecting an optimum gravel size in relation to the formation sand size to control formation sand movement and using the optimum screen slot width to retain the gravel because with the proppant being either too small or too big leads to either the influx of clay particles that plug the formation or no sand controlat all. Saucier [2] performed an experiment, using both linear and full scale radial cells to study the effects of gravel size, formation grain size, flow rate and gas-liquid ratio on sand production. He propounded the principle that, “optimum sand control is achieved when the median grain size of the gravel pack is no more than six times larger than the median grain size of the formation sand” which happens to be the standard in the industry till date. Therefore, to apply the above stipulated design criteria, the most important information required i.e. “knowledge of the formation sand grain size” ought to be readily available, but the reverse is often the case as core analysis is extremely expensive to conduct, especially on development wells. In majority of cases, gravel pack design have had to be based on grain size data obtained from offset wells rather than from the well in question due to the absence of specific well data and sometimes from scanty sieve analysis data from the producing well.

The use of well logs provides an alternative means to formation grain size determination as they correlate directly with porosity, pore size and permeability. With the knowledge of the above, for unconsolidated sands like those of the Niger Delta, it is possible to predict grain size if the permeability is known. The permeability can be computed using a functional equation relating permeability (K) to the porosity (Ø) and irreducible water saturation (Swi) [3,4].

The feasibility of grain size prediction from wireline logs using neural networks was shown by authors in an earlier paper.Neural network is an artificial intelligence employed in science and engineering, with the ability to forecast, predict, classify and interpret data. Using these techniques, a back-propagation neural network will be trained with available grain-size distribution and well logs from different fields and used to characterize grain size distribution in subsequent wells in the fields.

The objective of this paper is geared at designing a log interpretation model as different regression analysis (RMA, OLS, MLR etc) and different correlations (Schlumberger, Kozeny, etc) will be tested and compared in order to set a standard for the industry; which will define formation grain-size based on permeability determination from porosity and irreducible water saturation.

Furthermore, it also aims at analysis the behaviour of this artificial intelligence as it trains data points of different sizes irrespective of the fact that some are complete, incomplete, distorted and concise.

II. LITERATURE REVIEW

A. conventional gravel pack design

In case.The basic idea of gravel pack design is controlling formation sand without excessively reducing well productivity. A representative sample of formation material can be gotten on preferential order from rubber-sleeve cores, conventional cores, or sidewall cores. Produced sand samples or bailed samples are not to be used for gravel sizing. Produced sand will likely possess a larger proportion of smaller grain sizes, unlike bailed sand which will likely possess a larger portion of larger grain sizes. Conventional core are the best representative of the formation sand grain but since they are expensive to get, sidewall cores are used instead. Sidewall cores provide a better representation of the formation sand than either produced or bailed sand samples [5].

Commonly, a sieve analysis is performed to determine gravel size. In a sieve analysis, the cumulative weight percent of each sample retained is plotted against screen mesh size on a semi-log graph to develop a sand-size distribution. The 50% cumulative weight obtained from the graph gives the median formation grain size diameter, alternatively known as D50; which is the basis of selection of the size of gravel pack sand.

Conventionally, to determine the size of the gravel pack sand required, a sample of the formation sand must be analyzed to obtain the median grain size diameter and sorting (distribution). To achieve this, the following are done:

- A representative sample of the formation sand is obtained.
- The formation grain size distribution is analyzed.
- An optimum gravel size is selected in relation to the size of the formation sand to control movement of formation sand..
- An optimum screen slot width is used to retain the gravel.

The above technique is based on works conducted by Saucier, Penberthy, and Schwartz[217] who have attempted to develop a design criteria for gravel packs by experimentally studying the interactions between carefully sized gravel and synthetic formation materials [6]. Schwartz's technique is quite similar to that of saucier but different in that Saucier's model did not account for model formation grain size distribution and formation grain size sorting. Schwart's correlation relied on the formation's homogeneity and the velocity through the screen. But for most conditions (heterogenous sands) is:

$D_{g40} = 6D_{f40}$(1)

Where:

D_g40 is diameter of gravel grain size for which 40wt% of the grains are of larger diameter.

D_f40 is the diameter of the formation grain size for which 40wt% of the grains are of larger diameter.

To fix gravel size distribution, Schwartz[7] recommended that the gravel size distribution should plot as a straight line on the standard semi-log plot, with a uniformity coefficient, U_c, defined as:

$$U_c = \frac{Dg40}{Dg90} \qquad (2)$$

Where:
D_{g40} is Grain size at the 40% cumulative level from sieve analysis plot
D_{g90} is Grain size at the 90% cumulative level from sieve analysis plot
$U_c$should be 1.5 or less (Schwartz).
For these requirements, we find that:

$$D_{g,\,min} = 0.615 D_{g40} \quad (3)$$

$$D_{g,\,max} = 1.383 D_{g40} \quad (4)$$

Equations 3 and 4, define the range of recommended gravel size.

Saucier used both full scale and radial scale cells to study the effects of gravel size, formation grain size, flow rate and gas-liquid ratio on sand production. His linear model was a Lucite cylinder with an inner diameter of ½ inch (1.27 cm). Washed river sand was used to simulate formation material. Although the river sand and gravel were maintained in a tightly packed state, no confining stress was applied. Deionized water and CO_2 were injected from the top of the cell through the synthetic formation material and gravel respectively, saucier observed (in both linear and radial models) that sand production was minimized with a gravel whose mean size was 5 to 6 times that of the mean formation grain size.

$$D_{g50} = (5 \text{ or } 6)\, D_{f50} \quad (5)$$

Since Saucier gave no recommendation about gravel size distribution, if Schwartz's criteria are applied, then:

$$D_{g,\,min} = 0.667 D_{g50} \quad (6)$$

$$D_{g,\,max} = 1.5 D_{g50} \quad (7)$$

Penberthy[1] also used linear and radial flow cells to study pressure drop across screens, liners, perforations and the gravel/sand geometries, flow rate and multi-phase flow. He also used clean river sand to simulate formation material. The results of his extensive studies are summarized below as:

- The screen/slotted liner and the gravel pack offer no significant restriction to well productivity unless they become plugged.
- Screen/slot openings should be no larger than 75% of the smallest gravel size
- Prepacking the formation significantly reduced perforation pressure drop by preventing sand migration towards the entrance of the perforations (supports Saucier's findings).
- Effective bridging of sand particles occurs at gravel to median sand size ratios of 6:1 or less (Saucier, 1974)[2]. At ratio of 10:1 sand grains can move into the gravel pack but have trouble moving through it. At ratios above 12:1 the sand can move into and through the gravel pack.
- Multiphase flow conditions led to excessive fines migration, sand production, and perforation plugging.

Based on their findings, optimization of gravel-pack sand size can be accomplished using the following guild lines:
When $D_{50}/d_{50} < 5$: There is good sand control but restricted flow due to low gravel permeability.
When $5 < D_{50}/d_{50} < 7$: There is good sand control and maximum pack permeability
When $7 < D_{50}/d_{50} < 9$: There is good sand control but restricted flow due to formation sand invasion of gravel-pack sand.
When $D_{50}/d_{50} > 9$: There is no sand control and the formation sand passes through gravel pack sand

B. Well logging intepretation in formation grain size distribution –.

The aim of quantitative log interpretation is to provide the equations techniques with which these translations can be completed [8,9,10]. Reservoir quality in most unfractured reservoirs is controlled by grain size and grainsorting, because they correlate directly with porosity, pore-sizeand permeability. Since texture is the most important control factor for reservoir quality, investigations have shown that important textural properties can be expressed in terms of 5 variables. Namely:

1. Grain size
2. Sorting
3. Shape (sphericity)
4. Angularity
5. Packing [11].

Only the first 4 properties above are measurable [3].

Various authors (SPE 56626) have shown that the grain size distribution is feasible from wireline logs using neural networks. The gamma ray log is the most important log for this purpose due to its reflection of the relationship between the grain size and shale content. Selection of other logs such as density, neutron, sonic and resistivity, are based on fluid type in the reservoir in question. Based on their research, the gamma and density logs are an optimal combination in gas reservoirs [12]. Owing to the fact that permeability can be got via different means, different authors have come up with different practical relationships for relating porosity and water saturation to permeability.

The relationship between permeability and the size parameters of unconsolidated sand is approached by considering sands as logarithmic frequency distribution having the basic parameters "mean size and standard deviation" [3].

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 638-650 www.ijaem.net ISSN: 2395-5252

[4] adopted Kozeny's equation which states that permeability is a function of porosity and irreducible water saturation. The former employed the Kozeny's equation and defined the formulae below as the best estimator of permeability, based on the samples obtained from a particular field. That is:

$K = 0.136\ \emptyset^{4.4} / S^2_{wr}$ (8)

According to Kozeny,

$K = A_1 * (\emptyset^3 / S^2)$ (9)

Where:

A = constant

S = Surface area per unit bulk volume

According to him, equation 9 can be expressed in terms of surface area per unit volume of solid material and as surface area per unit volume of pore space; given as:

$K = A_1 * \emptyset^3 / (1 - \emptyset)^2 * S_0^2$ (10)

Where:

S_0 = surface area per unit volume of solid material

And also;

$K = A_1 * (\emptyset / S_p^2)$ (11)

Where:

S_p = surface area per unit volume of pore space

Irrespective of the fact that these equations are practically feasible and applicable in the industry, a perfect or rather suitable relationship between the independent and dependent variables is usually in doubt. Some authors might decide to employ the Reduced Major Axis (RMA) and propagate it as an excellent measure of the permeability-porosity-water saturation relationship [4], others are likely to adopt the Multivariate Linear Regression [13] while some might stick to the good old Ordinary Least Square regression (OLS). But the big question is, "Which of the available regression analysis provides the best measure for log interpretation"?

For this study, the RMA, OLS, MA, and Robust regression analysis, will be used.

C. Overview of the neural network.

Neural networks are information processing methods, which are parallel, distributive, analog and non-algorithmic, and have proven to be function approximation and powerful pattern recognition tools. This artificial intelligence replicates the functionality of the human neural system as it takes input, passes it down to hidden neuron layers which gets adjusted by the weights and Bias, as it trains the network iteratively, it builds an equation of its own with is later used in predicting outputs which might or might not converge accurately to the output. Neural networks possess the ability to discover highly complex relationships between several variables given to them as a result of their ability to process and learn data in a way that is both parallel and distributive. As a model-free function estimator, neural networks can map input to output no matter how complex the relationship [14].

There are several paradigms that can be used to generate neural networks. A feed- forward, back propagation neural network (which adopts a supervised training scheme) is adopted in this particular study.

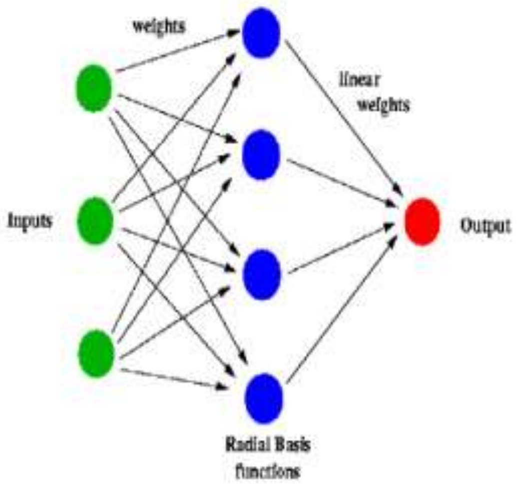

Fig 1.0: Neural network

As knowledge of the artificial neural network has grown in popularity various researchers has adopted it as a viable means to solving extremely difficult problems which conventional methods cannot. Amongst them are: [15] on "computer emulation of Human Mental processes: Application of Neural Network Simulators to Problems in Well log interpretation" (SPE 19619). "Design and Development of an Artificial Neural Network for Estimation of Formation permeability" [15] registered as SPE 28237.Faga and Onyeneyin [13] applied the neural network for improved gravel pack design, and the story continues.

D. Log interpretation and formation grain size determination

PHASES OF SOLUTION

Phase 1: Accurate Interpretation of Permeability from Porosity and Water Saturation Data via testing and comparing of different Regression Analyses and Correlations.

Phase 2; Experiment 1: Implementation of the Artificial Neural Network with an Incomplete Set of Small Distorted Data Points

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 638-650 www.ijaem.net ISSN: 2395-5252

Phase 2; Experiment 2: Artificial Neural Network Implementation with an Incomplete Set of Large Data Points

Phase 3: Implementation of the Artificial Neural Network with a Large Complete Set of Data Point

NOTE: Phases 1 through 3 cover the neural network training, aimed at analyzing the behavior of this artificial intelligence.

III. METHODOLOGY

Phase 1: Accurate Interpretation of Permeability from Porosity and Water Saturation Data via testing and comparing of different Regression Analyses and Correlations.

Data gathering was done in Microsoft excel and then transferred to DATAFIT 9.1 statistical software where a multivariate linear regression was carried out in order to generate my model which will be tested alongside other available correlations. The model generated along with other models to be tested will then be sent to PLOT statistical software, where the actual comparism among the different regression analysis and correlations will be executed as the equation defined by Kozeny and employed by [4] will be adopted (see: fig 2). 31 set of data points will be used in the regression process and all data samples are restricted to Niger delta wells.

According to Timur[4],

$K = A * (\emptyset^B / S^c_{wr})$ (12)

From equation 12, a generalized equation was obtained in the form:

$K = b2*(V)^{b1}$ (13)

Where $V= (\emptyset^B / S^c_w$ (14)

To obtain the values of constants A, B, and C, the multivariate linear regression will be applied.

Therefore, applying the equation of a straight line, equation 12 reduces to the form:

$\text{Log } K = \text{Log } A + B. \text{Log } \emptyset + C \text{ Log } Sw$ (15)

Equation 15 reduces further to the form:

$Y=A+B*X1+C*X2$ (16)

From the result of the multivariate linear regression, equation 12 is put into the generalized form:

$\text{Log } K = B1 \text{ Log } (V) + B2$ (17)

From equation 17, the different regression models can now be applied.

PHASES 2; EXPERIMENT 1: IMPLEMENTATION OF THE ARTIFICIAL NEURAL NETWORK WITH AN INCOMPLETE SET OF SMALL DISTORTED DATA POINTS

35 samples were employed in this training. Using already generated data from a Niger Delta well (Well X), based on the experimental fact by[3], which stipulates that permeability is proportional to the square of the mean grain size and the exponent of the standard deviation; making the mean grain size the subject of the formulae i.e. mean grain size being proportional to the permeability and the standard deviation, the permeability and the standard deviation will be trained such that the mean grain size can be determined from them.

PHASES 2; EXPERIMENT 2 AND PHASES 3 IMPLEMENTATION OF THE ARTIFICIAL NEURAL NETWORK WITH AN INCOMPLETE SET OF LARGE DATA POINTS AND A LARGE COMPLETE SET OF DATA POINT RESPECTIVELY

In order to properly train a network, there must exist a relationship between the input and the targets. Therefore, applying a total of 198 samples of well Y, the phi values at 16, 50 and 84 (as defined by Folk and Ward) will be trained against the mean grain sizes. (Supervised training)

The data points are gathered in MS Excel and transferred to MATLAB, where the neural network suite is embedded. Using the neural network tool, all input, target and sim input data are entered and then a network is created. At this, the iterative training process begins and a performance and regression plot is generated. If the regression coefficient, R, is greater than 0.93; a standard set value, the training is stopped otherwise retraining is carried out. If in the future the output converges with the target or R > 0.93, the training process is stopped. If a high error margin is encountered, a new network is created with an alteration of the training parameters such as the number of hidden neurons, the Layers, weights and bias. Once the new network is created, the training process begins iteratively again. (See: Fig 3)

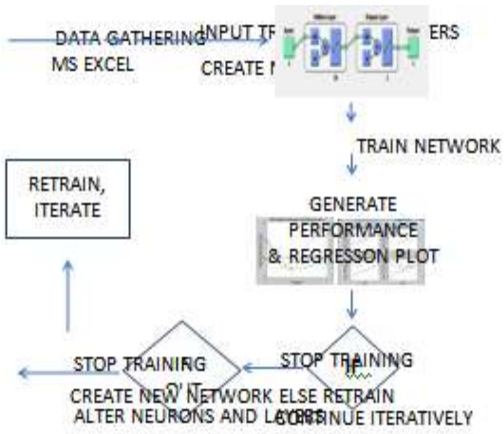

Fig 3: flow chart for neural network training of phases 2 through phases 3

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 638-650 www.ijaem.net ISSN: 2395-5252

IV. RESULTS AND DISCUSSION

Equation 18 is the model generated from the multivariate linear regression and fig 4 displays the results in the software. In order to perform a regression analysis using any linear regression model, a multivariate linear or non-linear (user defined model) regression has to be performed first such that the parameters to be correlated become linear and can easily be regressed using any of the above regression models or any other unlisted linear regression model.

Similar to Timur's work, from my analysis, the user defined correlation $Ø^4/Sw^{2.34}$ by Tochukwu, emerged best for the field being tested as RMA regression model produced the best result as compared to other models being tested. (See: table 1)

For experiment 1 of phase 2, at least 25 training sessions were carried out. From my analysis (fig 5 and 6), the first to fifth training sections gave results whose outputs appeared higher than the target with an average error of 0.4. At this, training parameters were altered as a new network was created as the number of neurons and layers were increased. Similar results for the sixth to tenth training sections as in the first to fifth training section were obtained. Yet again, the training parameters were altered as with the number of neurons in the hidden layer being reduced to below the standard number of neurons i.e. 10. At this, the results tried converging to the target as the average error reduced but by an insignificant value I.e. 0.3. This process of altering training parameters, creating of new networks and retraining continued till the twenty fifth training sections where continual trainings were halted and discontinued as the possibility of convergence appeared minimal. The results of the last training carried out appeared similar to other training results as the average error remained within the range of 0.3 to 0.6. (See: tables 2). Table 3 is the validation set which proves the lack of convergence.

From experiment 2 of phases2, only 2 training sessions were carried out. The outcome very appeared dissimilar to that of phase 1 as the error range fell within an average of 0.00170380 to 0.0057106 and the output's convergence to the target produced a perfect result as seen in the second training section (see: Tables 4). Table 5 is the simulated output/validation data which proves the convergence between output and target. From the analysis, it appeared that training an incomplete set of data with the artificial intelligence could produce an excellent result as long as the data points used is large as seen in the result of the second training, in which the correlation coefficient for all regression i.e. Training (blue line), validation (green line) and Testing (red line) was exactly 1 (see: fig 7 and 8).

From phases 3, only one training session (see: Table 6) was required to produce the desired output whose correlation coefficient was one; a perfect convergence, with an average error of -0.000314826 (see: fig 9 and 10). Table 7 shows the simulated output/validation data which proved the convergence of the data points.

NOTE: Tables 3, 5 and 7 are all unsupervised learning.

V. CONCLUSION

From phase 1 which is the accurate interpretation of permeability from porosity and water saturation data, based on my analysis and result which verified Tumur's (1946)[4] claim it has been proven that the optimum porosity-water saturation relationship for the prediction of permeability for any field is the correlation generated based on the data points got from that field and the RMA regression regresses accurately for any field in question.

From the results of phase 2; experiment 1 and experiment 2, and phase 3, which comprises of the neural network training with complete, incomplete, small and large set of data points, it can be inferred that an optimum training/convergence can be obtained if the input training sets are large, irrespective of the fact that some data points might be missing.

VI. RECOMMENDATION

Phase one is a work in progress. In the statistical world, there exists various regression analysis tool of which only 4 was used in this work. Investigation into the use of others and the measure of their accuracy should be research.

Further work can be done on the use of:

1. Generalized regression
2. ANCOVA
3. ANOVA etc.

From phase two, the data points used involves only a total of 31 samples. Therefore, for a better and more improved generalized porosity-water saturation relationship, a larger set of data points should be employed, comparing the already used regression models in addition to new one and also researching on more parameters by different author which should be included in the analysis, in addition to those already used above.

From the results of phases 2 and 3, all training based on the use of the artificial intelligence must involve the use of a large data set of at least 200

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 638-650 www.ijaem.net ISSN: 2395-5252

data points, for an effective, optimum and perfect convergence of the output with the target.
Furthermore, an investigation can be conducted to analyze the behavior of the artificial intelligence in training a small set of complete but disjointed data points.

NOMENCLATURE
ANN: Artificial Neural Network
MLR: Multivariate Linear Regression
OLS: Ordinary Least Square regression
RMA: Reduced Major Axis Regression
MA: Moving Average Regression
D_{50}: Diameter of gravel at the 50^{th} percentile point
Dg, $_{min}$: Minimum gravel size diameter
Dg, $_{max}$: Maximum gravel size diameter
CO2: Carbon (IV) Oxide

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International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 638-650 www.ijaem.net ISSN: 2395-5252

Table 1: Results of the test and comparative analysis of the different regression analysis and correlations used

PARAMETER		NUMBER OF SAMPLES	REGRESSION COEFFICIENT		R	STANDARD ERROR OF ESTIMATE		REGRESSION
			B1	B2		A	B	
Schlumberger **$Ø^6/Sw^2$**	Niger Delta	31	1.0305	5.0339	0.96795	0.048054	0.011778	RMA
			0.99745	4.9613	0.96795	0.048054	0.10858	OLS
			1.0315	5.0362	0.96795	0.049282	0.012356	MA
			0.8922	4.6691	0.96795			ROBUST
KOZENY 1 **$Ø^3/((1-Ø)^2*Sw^2)$**	Niger Delta	31	1.2577	2.99691	0.99445	0.024572	0.00012186	RMA
			1.2507	2.968	0.99445	0.024572	0.011191	OLS
			1.2592	2.9693	0.99445	0.024708	0.00012218	MA
			1.2288	2.9575	0.99445			ROBUST
KOZENY 2 **$Ø/Sw^2$**	Niger Delta	31	1.5546	1.5742	0.96181	0.079023	0.0044157	RMA
			1.4953	1.6198	0.96181	0.079023	0.066532	OLS
			1.5804	1.5545	0.96181	0.082838	0.0047947	MA
			1.4725	1.729	0.96181			ROBUST
TIXIER **$Ø^3/Sw$**	Niger Delta	31	2.061	5.0339	0.96795	0.096108	0.011778	RMA
			1.9949	4.9613	0.96795	0.096108	0.10858	OLS
			2.1033	5.0805	0.96795	0.10082	0.012917	MA
			1.7844	4.6691	0.96795			ROBUST
TUMUR **$Ø^{2.25}/Sw$**	Niger Delta	31	2.3435	4.3017	0.98796	0.067332	0.0021721	RMA
			2.3153	4.2832	0.98796	0.067332	0.046676	OLS
			2.3633	4.3146	0.98796	0.068619	0.0022497	MA
			2.1888	4.1813	0.98796			ROBUST
TOCHUKWU **$Ø^4/Sw^{2.34}$**	Niger Delta	31	1.1	3.6269	0.99588	0.01853	0.00028831	RMA
			1.0955	3.6233	0.99588	0.01853	0.017055	OLS
			1.1004	3.6272	0.99588	0.018595	0.00028982	MA
			1.0036	3.572	0.99588			ROBUST

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 638-650 www.ijaem.net ISSN: 2395-5252

Table 2: ANN Training sessions

8TH TRAINING		15TH TRAINING		25TH TRAINING		
OUTPUT	**ERROR**	**OUTPUT**	**ERROR**	**OUTPUT**	**ERROR**	**TARGET**
2.6773	0.29269	2.7257	0.24426	2.845	0.12505	2.7033
2.6209	-0.58754	2.6704	-0.6371	**2.7592**	-0.7259	2.646633333
2.2758	0.12416	2.2987	0.10133	2.3884	0.011595	2.296933333
2.7925	0.15421	2.8006	0.14605	**2.9197**	0.026974	2.791166667
2.9125	-0.51928	2.8563	-0.45968	2.9235	-0.52682	2.867066667
2.1914	0.078633	2.1635	0.10645	**2.117**	0.058253	2.177733333
2.019	-0.24897	1.7732	-0.0031848	1.4909	0.27914	1.8461
2.6008	-0.25078	2.6512	-0.30125	**2.7357**	-0.38568	2.6272
2.2962	0.18376	2.2643	0.2157	2.2582	0.22178	2.268766667
2.7714	-0.42469	2.7709	-0.4242	**2.8133**	-0.46665	2.759466667
3.096	-0.36271	2.927	-0.19368	3.0185	-0.28516	2.980933333
2.5583	-0.39498	2.5359	-0.37255	**2.4619**	-0.29854	2.5195
1.8595	-0.34619	1.7151	-0.20172	1.92	-0.40671	1.814133333
2.8244	0.0022469	2.819	0.0076886	**2.9414**	-0.11471	2.814333333
2.6217	0.67172	2.6789	0.61448	2.7876	0.50577	2.6538
2.7861	0.22722	2.7896	0.22374	**2.8742**	0.13915	2.7799
2.5272	0.13599	2.4945	0.16884	2.4096	0.25377	2.481066667
2.9269	0.46313	2.8682	0.52183	**2.9922**	0.39776	2.882433333
2.8693	0.40928	2.8085	-0.34853	2.7188	-0.25876	2.804066667
2.7927	-0.41936	2.6638	-0.29042	**2.2959**	0.077387	2.589833333
2.5855	0.47782	2.6491	0.41424	2.7602	0.30313	2.622766667
2.959	-0.058998	2.8812	0.018841	**3.0031**	-0.10309	2.902266667
2.9594	-0.059425	2.8811	0.01889	3.001	-0.10095	2.9023
1.6794	0.063957	1.6334	0.1099	**2.0854**	-0.34203	1.629833333
3.1976	-0.0409	2.9613	0.19534	3.0842	0.072456	3.040433333
3.077	-0.020297	2.9229	0.13373	**3.0461**	0.010598	2.9721
2.6965	-0.073199	2.6315	-0.0081278	2.4226	0.20077	2.5867
2.3956	0.14441	2.4483	0.091688	**2.5451**	-0.0051078	2.4314
3.1499	-0.16986	2.9447	0.03506	3.0646	-0.084578	3.013
3.1856	-0.048227	2.9558	-0.25245	**3.0711**	-0.36773	3.0331

Table 3: ANN simulated output for phase 2, experiment 1

TRAINED OUTPUT	TARGET
2.4516	**1.106666667**
3.0785	**3.096666667**
2.6841	**3.21**
3.0944	**2.873333333**
1.2398	**1.79333333**

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 638-650 www.ijaem.net ISSN: 2395-5252

$$\mathbf{Y = 4007.27}\left(\frac{\text{Ø}^{4.06}}{Sw^{2.3}}\right) \quad (18)$$

PHASES 2; EXPERIMENT 1

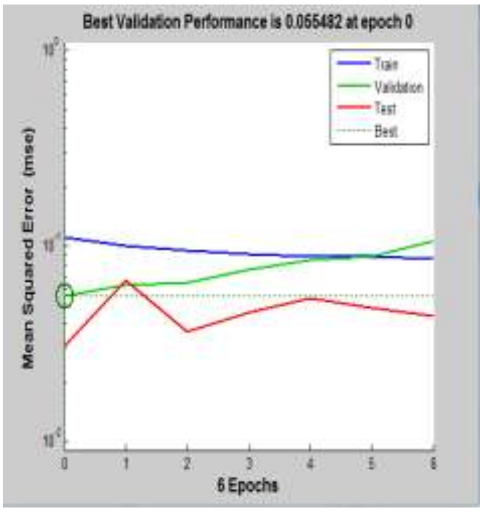


Fig 4: Performance plot

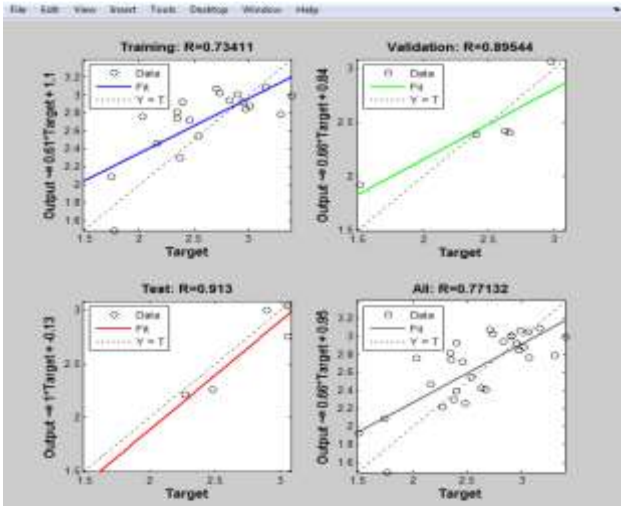


Fig 5: Regression plot

PHASES 2; EXPERIMENT 2

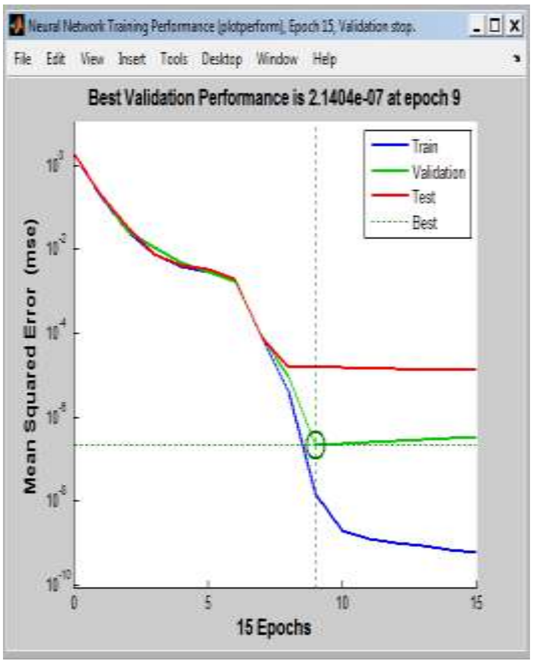


Fig 6: Performance plot

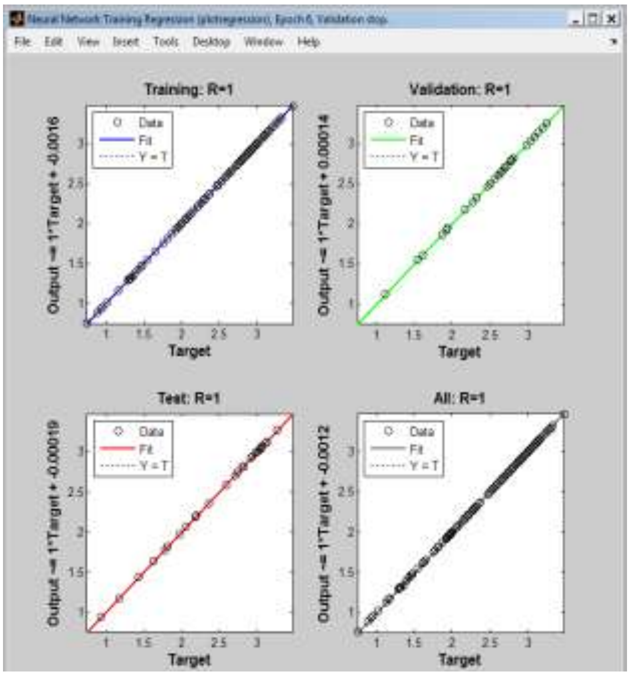


Fig 7: Regression plot

Table 4: ANN Training session

SAMPLES	1ST TRAINING		2ND TRAINING		
1	output1	Error1	output2	Error2	Target
2	3.0532	0.0001169	3.053216433	0.0001169	3.053333333
3	3.0099	0.00012133	3.00987867	0.00012133	3.01
4	2.9965	**0.000120853**	2.996545814	0.000120853	2.996666667
5	3.0099	0.000121152	3.009878848	0.000121152	3.01
6	3.0332	0.000120803	3.03321253	0.000120803	3.033333333
7	3.2165	0.000126669	3.216539998	0.000126669	3.216666667
8	2.9799	0.000107175	2.979892825	0.000107175	2.98
9	2.9899	0.000103302	2.989896698	0.000103302	2.99
10	3.1066	0.000106133	3.106560534	0.000106133	3.106666667
11	2.8765	0.000120247	2.87654642	0.000120247	2.876666667
12	2.9399	0.00011596	2.93988404	0.00011596	2.94
13	2.9166	0.000100737	2.91656593	0.000100737	2.916666667
14	2.5333	6.91E-05	2.533264203	6.91E-05	2.533333333
15	2.2898	0.000158512	2.289841488	0.000158512	2.29
16	1.8166	7.37E-05	1.816592978	7.37E-05	1.816666667
17	3.0066	9.72E-05	3.006569484	9.72E-05	3.006666667
18	2.0931	0.000191369	2.093141964	0.000191369	2.093333333
19	2.5566	7.24E-05	2.556594267	7.24E-05	2.556666667
20	3.0032	9.89E-05	3.003234411	9.89E-05	3.003333333
21	3.0799	9.49E-05	3.079905121	9.49E-05	3.08
22	2.5799	8.17E-05	2.579918329	8.17E-05	2.58
23	3.0532	0.0001169	3.053216433	0.0001169	3.053333333
24	2.8265	0.000118644	2.826548023	0.000118644	2.826666667
25	2.9232	0.000114814	2.923218519	0.000114814	2.923333333
26	2.9232	0.000114814	2.923218519	0.000114814	2.923333333
27	1.9401	-8.16E-05	1.940081585	-8.16E-05	1.94
28	1.613	0.000329853	1.61300348	0.000329853	1.613333333
29	2.7766	9.47E-05	2.776571964	9.47E-05	2.776666667
30	2.7232	8.96E-05	2.723243716	8.96E-05	2.723333333

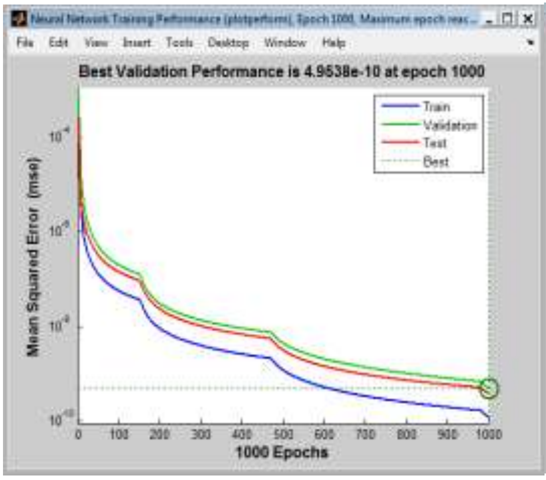
Table 5: ANN simulated Outputs for phase 2, experiment 2

SIM_OUTPUT	TARGET
1.216932941	1.216666667
2.686566734	2.686666667
1.116790268	1.116666667
1.686864945	1.686666667
0.780154426	0.78
1.29358448	1.293333333
1.850127664	1.85
0.860652422	0.86
2.746562263	2.746666667
2.833213487	2.833333333
2.469955786	2.47
1.62345604	1.623333333
1.516787438	1.516666667
2.040040091	2.04
2.543272091	2.543333333

International Journal of Advances in Engineering and Management (IJAEM)
Volume 2, Issue 12, pp: 638-650 www.ijaem.net ISSN: 2395-5252

2.283302876	2.283333333
2.363306863	2.363333333
2.579944967	2.58

PHASES 3



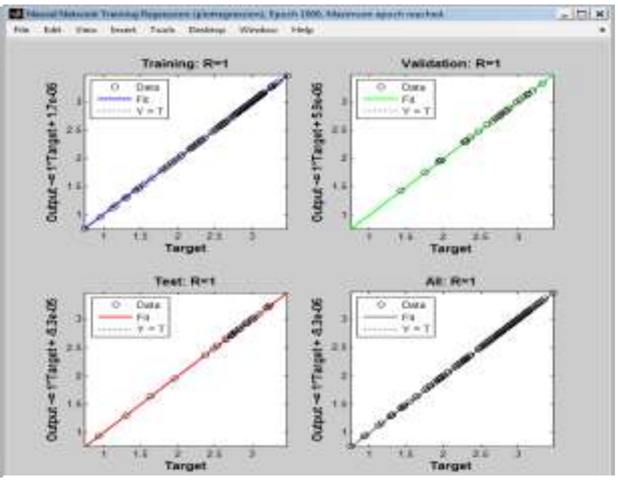


Fig 8: Performance plot of phase 3Fig 9: Regression plot

Table 6: Phase 3 neural network training session

	1ST TRAINING		
SAMPLES	**OUTPUT 1**	**ERROR 1**	**TARGET**
1	3.053336816	-3.48E-06	3.053333333
2	3.009999794	2.06E-07	3.01
3	2.996662602	4.07E-06	2.996666667
4	3.009998125	1.87E-06	3.01
5	3.033331744	1.59E-06	3.033333333
6	3.21666478	1.89E-06	3.216666667
-7	2.98000364	-3.64E-06	2.98
8	2.99000488	-4.88E-06	2.99
9	3.10666965	-2.98E-06	3.106666667
10	2.876660374	6.29E-06	2.876666667
11	2.939992368	7.63E-06	2.94
12	2.916660502	6.16E-06	2.916666667
13	2.53333812	-4.79E-06	2.533333333
14	2.290001544	-1.54E-06	2.29
15	2.749989659	1.03E-05	2.75
16	3.006662698	3.97E-06	3.006666667
17	2.889992504	7.50E-06	2.89
18	2.556672151	-5.48E-06	2.556666667
19	3.003338491	-5.16E-06	3.003333333
20	3.080015571	-1.56E-05	3.08
21	2.580002662	-2.66E-06	2.58

22	3.053336816	-3.48E-06	3.053333333
23	2.82666047	6.20E-06	2.826666667
24	2.923324499	8.83E-06	2.923333333
25	2.923324499	8.83E-06	2.923333333
26	1.939925571	7.44E-05	1.94
27	2.929985889	1.41E-05	2.93
28	2.776665409	1.26E-06	2.776666667
29	2.723328791	4.54E-06	2.723333333
30	3.079993864	6.14E-06	3.08

Table 7: Simulated output for phase 3

SIM_OUTPUT	TARGET
1.216686728	1.2166667
2.686649412	2.6866667
1.11661069	1.1166667
1.686799175	1.6866667
0.780009992	0.78
1.293449517	1.2933333
1.850001516	1.85
0.860013629	0.86
2.746662032	2.7466667
2.833323893	2.8333333
2.470007667	2.47
1.623302534	1.6233333
1.516649585	1.5166667
2.039988364	2.04
2.54333839	2.5433333