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MODELING THE EFFECT OF TEMPERATURE ON ENVIRONMENTALLY SAFE OIL BASED DRILLING MUD USING ARTIFICIAL NEURAL NETWORK ALGORITHM

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Abstract

Due to increase in environmental legislation against the deposition of oil based mud on the environment, drilling companies have come up with an optimum drilling mud such as plant oil based mud with little or no aromatic content, which its waste is biodegradable. Optimum mud carry out the same function as diesel oil based drilling fluid and equally meets up with the HSE (Health, safety and environment) standard. It is expedient to determine the down hole mud properties such density in the laboratory or use of available correlation but most time; the range of data is not either reliable or unavailable.

In this study, artificial neural network (*ANN*) was used to address the unreliable laboratory data and unavailable correlation for environmentally friendly oil based drilling mud such as jatropha and canola oil. The new artificial neural network model was developed for predicting the down hole mud density of diesel, jatropha and canola oil based drilling mud using 30 data sets. 60% of the data were used for training the network, 20% for testing, and another 20% for validation.

The test results revealed that the back propagation neural network model (*BPNN*) showed perfect agreement with the experimental results in term of average absolute relative error returned.

Keywords:

1. Introduction

The drilling mud density is a very important physical property that controls and influences the simultaneous flow of fluids and cuttings during drilling operation and is a strong function of reservoir conditions and compositions. Drilling mud density could be determined in the laboratory studies on available bottom hole samples at reservoir temperature and pressure. In case where laboratory data are not available or unreliable, the complexity and inaccuracy can be addressed by the new predictive tool developed in this study to estimate the effect of down hole temperature on environmentally friendly oil based mud using artificial neural networks (*ANNs*). A new model was developed using 30 data sets: 60% of the data were used for training the network, 20% for testing, and another 20% for validation.

2. Theory of neural networking

An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data.

In modern software implementations of artificial neural networks, the approach inspired by biology has been largely abandoned for a more practical approach based on statistics and signal processing. In some of these systems, neural networks or parts of neural networks (such as artificial neurons) are used as components in larger systems that combine both adaptive and non-adaptive elements. While the more general approach of such adaptive systems is more suitable for real-world problem solving, it has far less to do with the traditional artificial intelligence connectionist models. What they do have in common, however, is the principle of non-linear, distributed, parallel and local processing and adaptation.

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown below. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network. Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems.

Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings. Emphasis is placed on neural network paradigms that build up to or are themselves used in engineering, financial, and other practical applications.

The figure below shows a typical Neural Network process:

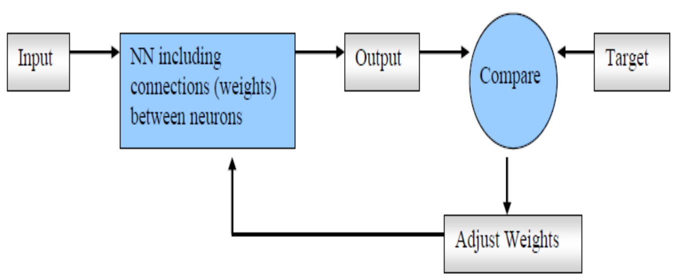

Fig 1 Neural network schematic

The word network in the term 'artificial neural network' refers to the interconnections between the neurons in the different layers of each system. An example system has three layers. The first layer has input neurons, which send data via synapses to the second layer of neurons, and then via more synapses to the third layer of output neurons. More complex systems will have more layers of neurons with some having increased layers of input neurons and output neurons. The synapses store parameters called "weights" that manipulate the data in the calculations.

3. Literature review

Over the years, a lot of research has gone into the drilling fluid industry with various outcomes and results bringing out various ways of solving different problems encountered in the industry, ranging from technical to environmental and also economical challenges. In recent times, following the outcomes of the past researches carried out, synthetic oils are now considered more environmentally friendly than the conventional diesel or mineral oil based mud.

Bailey *et al.* [1] in 1986 examined fluid viscosities of muds formulated with a low toxicity mineral oil (LTOBM) and diesel oil (OBM) with temperature and pressure. The use of mineral oils as replacements for diesel in drilling fluids was rapidly spreading at the time. They found that the greatest change in fluid apparent viscosity occurred when the testing temperatures were increased from 77°F (25°C) to 212°F (100°C), and at higher temperatures the rate of change was less.

Fisk and Jamison [2] used a Dynamic HPHT testing unit to measure the behavior of OBM, LTOBM, and water-based muds with pressure and temperature. Equations were developed to predict fluid PV. Coefficients for fifteen OBM having different properties were averaged to obtain constants that could be used to predict the behavior of OBM on a general basis.

Yassin *et al.* [3] carried out tests on palm oil derivatives as the continuous phase for oil based drilling fluids, and the toxicity effect on plant and aquatic life. The oils used in this case include: Methyl esters of Crude Palm Oil, and Methyl esters of Palm Fatty Acid Distilled. Tests were carried out on the physico-chemical properties of these oils such as flash point, pour point, aniline point, etc at varying temperatures and pressures.

Bleier *et al.* [4] conducted studies along with the Environmental Protection Agency (EPA) in the USA, on various technologies in the drilling fluid sector of the industry, and at that time, also analysed future projections, to encourage the adoption of emerging technologies. The studies conducted include: Biodegradability, toxicity, effects of additives, chlorides, salts heavy metals, and means of minimizing waste volumes.

Hemphil [6] carried out studies to predict the rheological properties of ester based drilling fluids under down hole conditions. Rheological tests that simulated field conditions were run in the laboratory on an ester-based drilling fluid from the field. The rheological behavior of the fluid was tested under varying ranges of temperature, pressure, and ester/water ratios. A predictive down hole rheological model of the ester-based drilling fluid was constructed using over eight hundred (800) fluid viscosity measurements. A general model has been developed to predict the downhole behavior of moderate-density ester-based drilling fluids with temperature and pressure.

Sundermann *et al.* [7] eliminated drilling problems with high temperature gas wells in northern Germany via the development and use of potassium formate ($KCHO_2$) biopolymer fluids. The formulated drilling fluid allowed a higher mud weight with fewer solids. It was then tested by drilling a 5 in section well at 16860 ft in 42 days. The ROP was 31.23 ft/D as against the 26.48 ft/D obtained using the $CaCO_3$ polymer mud. The biopolymer system proved to be very stable requiring only small chemical additions of viscosity and filtration control agents to keep the fluid properties within the desired range.

Sanchez et al [9] formulated drilling fluids from mineral oil (< 0.1% aromatics) and palm tree oil (without aromatic), both produced in Venezuela. Their work evaluated the toxicity and biodegradability of mineral and palm tree oil-base drilling fluids compared to those formulated with Diesel. Standard procedures were performed for both tests. The results indicate that mineral and palm tree oil based fluids are no toxic while diesel showed high toxicity levels.

Osman and Aggour [10] proposed an Artificial Neural Networks (ANN) model to predict mud density as a function of mud type, pressure and temperature. Data used were for temperature and pressure ranges up to 400°F and 14,000 psig respectively. The study showed the effect of temperature and pressure on the density of oil-base and water-base drilling fluids and presented experimental measurements of densities in the temperature range of 70 to 400°F and pressure range of 0 to 14,000 psig. Their finding was that the change in mud density with pressure and temperature is independent of the initial mud density (at 70°F and 0 psig). They also concluded that for equal densities at the surface conditions, oil-base drilling fluids become denser than water-base drilling fluids at high temperatures and pressures

4. Experimental procedure

4.1 Mud preparation

Three oil in water mud samples were prepared for this study: Diesel OBM- Diesel, Jatropha OBM- Jatropha oil, Canola OBM- Canola oil.The densities of the various base fluids (water, canola oil, jatropha oil and diesel) were measured using the mud balance.

1. Using the weighing balance, the various quantities of materials were measured.
2. The quantities of water and oil were measured using measuring beakers.
3. Using the Hamilton Beach Mixer, the measured materials were thoroughly mixed until a homogenous mixture was obtained.
4. The mud samples were aged for 24 hours.

4.2. Experimental procedure

1. The aged mud samples were agitated for 2 minutes using the Hamilton Beach Mixer.

Density

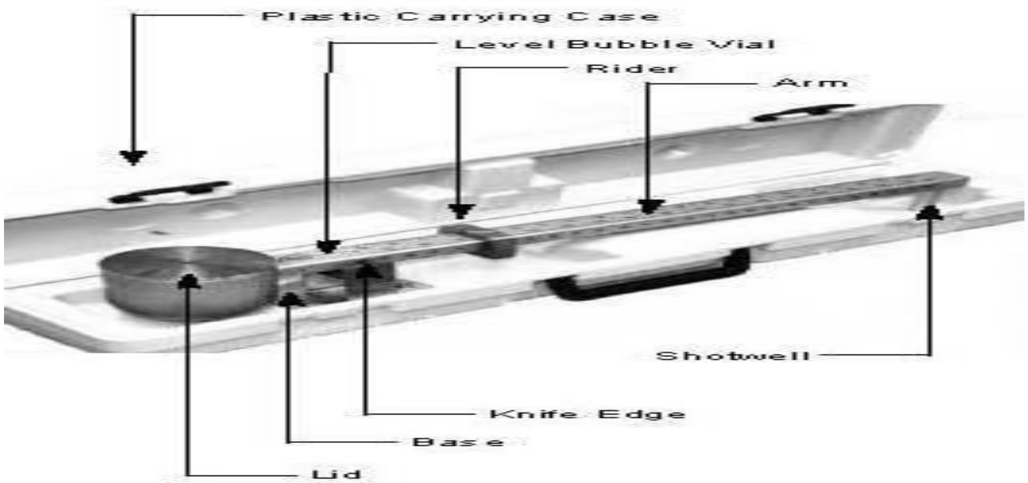

Diagram 1, 4 scale Mud Balance

2. The clean, dry mud balance cup (Diagram 1) was filled to the top with the newly agitated mud.
3. The lid was placed on the cup and the balance was washed and wiped clean of overflowing mud while covering the hole in the lid.
4. The balance was placed on a knife edge and the rider moved along the arm until the cup and arm were balanced as indicated by the bubble.
5. The mud weight was read at the edge of the rider towards the mud cup as indicated by the arrow on the rider and was recorded.
6. Steps 2 to 5 were repeated for the other samples.

Temperature effects on density

7. The newly agitated mud sample was heated using a hot plate stirrer to temperatures of $40^{O}C$, $50^{O}C$, $60^{O}C$, $70^{O}C$, and $80^{O}C$.
8. The density of the heated mud Diesel OBMt various temperatures was checked and recorded.
9. Steps 7 and 8 were repeated on other samples.
10. The values were recorded
11. The values were imputed into Microsoft Excel, and then extrapolated up to a temperature of $320^{O}C$.

Artificial neural network (ANN) predictions

After extrapolation of values in Microsoft excel, the various values were then trans-posed (still in the Microsoft excel interface), and exported to the Neural Network tool in MATLAB 2008.

The following procedures were carried out, using the Log Mean Square Error, Back Propagation.

- Input the data into the MATLAB 2008 workspace
- Type 'nntool'
- Set the Temperature values as 'INPUT DATA' P

- Set the Density values as 'TARGET DATA' T
- Data were imported from the workspace
- Varying numbers of neurons were selected in the layers- in this case, 10 neurons were used.
- The network was trained and created. Details of the codes are contained in Appendix 1D.

Density variation with temperature.

Densities were measured for the various samples at temperatures ranging from 30^{O}C to 80^{O}C and are summarized in Table 1

Table 1 Density changes at varying temperatures.

Temperature	Diesel	Jatropha	Canola
30^{O}C	10	10	10
40^{O}C	10.1	10.05	10.05
50^{O}C	10.17	10.1	10.05
60^{O}C	10.2	10.15	10.1
70^{O}C	10.2	10.15	10.15
80^{O}C	10.25	10.2	10.17

The mud samples were heated at constant pressure, and in an open space, hence the density increment.

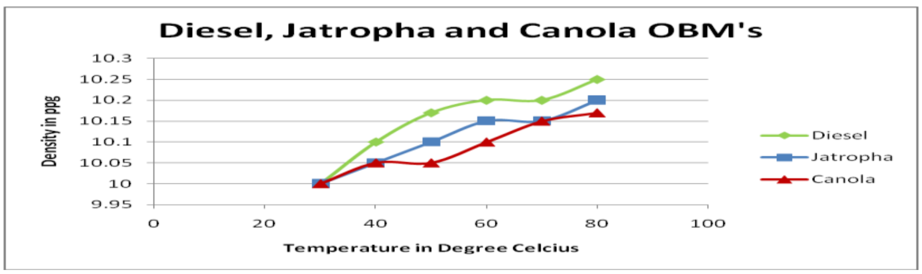

Fig 1 Plot of density against temperature (Diesel, Jatropha and Canola OBM's)

At temperatures of 60^{O}C and 70^{O}C, the densities of Diesel and Jatropha OBM's were constant, while that happened with Canola OBM at a lower range of 40^{O}C and 50^{O}C. This is shown in Figures 1. This could be due to the differences in temperature and heat energy required to dissipate bonds, which vary with fluid properties (i.e the continuous phases).

After the results were recorded, extrapolations were made in Microsoft excel, and hypothetical values were derived for temperatures as high as 320^{O}C, to enhance the prediction using Artificial Neural Network (ANN). These values are summarized Table 2.

Table 2 Hypothetical temperature-density values (extrapolated from MS Excel)

t	Diesel	Jatropha	Canola	t	Diesel	Jatropha	Canola
30^{O}C	10	10	10	180^{O}C	10.71762	10.59048	10.51524
40^{O}C	10.1	10.05	10.05	190^{O}C	10.76276	10.62905	10.54952
50^{O}C	10.17	10.1	10.05	200^{O}C	10.8079	10.66762	10.58381
60^{O}C	10.2	10.15	10.1	210^{O}C	10.85305	10.70619	10.6181
70^{O}C	10.2	10.15	10.15	220^{O}C	10.89819	10.74476	10.65238
80^{O}C	10.25	10.2	10.17	230^{O}C	10.94333	10.78333	10.68667
90^{O}C	10.31133	10.24333	10.20667	240^{O}C	10.98848	10.8219	10.72095
100^{O}C	10.35648	10.2819	10.24095	250^{O}C	11.03362	10.86048	10.75524
110^{O}C	10.40162	10.32048	10.27524	260^{O}C	11.07876	10.89905	10.78952
120^{O}C	10.44676	10.35905	10.30952	270^{O}C	11.1239	10.93762	10.82381
130^{O}C	10.4919	10.39762	10.34381	280^{O}C	11.16905	10.97619	10.8581
140^{O}C	10.53705	10.43619	10.3781	290^{O}C	11.21419	11.01476	10.89238
150^{O}C	10.58219	10.47476	10.41238	300^{O}C	11.25933	11.05333	10.92667
160^{O}C	10.62733	10.51333	10.44667	310^{O}C	11.30448	11.0919	10.96095
170^{O}C	10.67248	10.5519	10.48095	320^{O}C	11.34962	11.13048	10.99524

5. Results of neural networking

From the Artificial Neural Network Toolbox in the MATLAB 2008a, the following took place: 60% of the data were used for training the network, 20% for testing, and another 20% for validation. On training the regression values returned are summarized in Table 3

Table 3 Regression values

	Diesel	Jatropha	Canola
Training	0.99999	0.99999	0.99995
Testing	0.99725	0.99056	0.99898
Validation	0.99706	0.98201	0.99328
All	0.99852	0.99414	0.99675

Since all regression values are close to unity, this means that the network prediction is a successful one. The graphs of training, testing and validation are presented below:

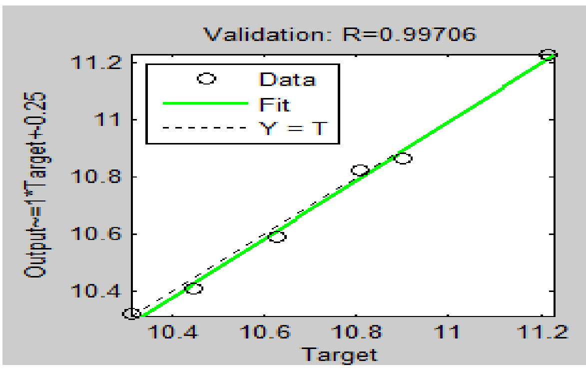

Fig 2 Estimated Data against Experimental Data (Diesel OBM Validation values)

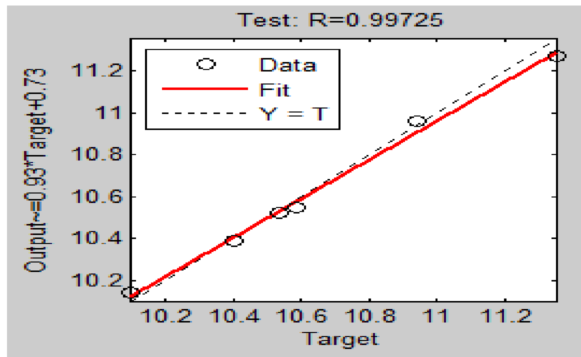

Fig 3 Estimated Data against Experimental Data (Diesel OBM Test values)

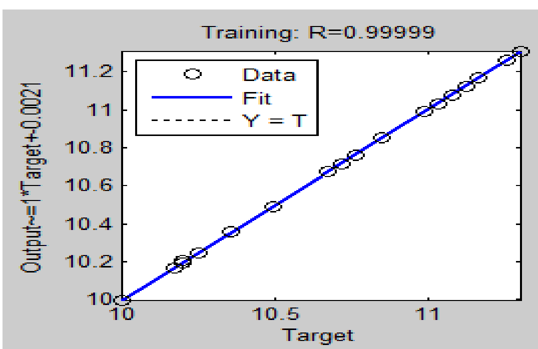

Fig 4 Estimated Data against experi-mental Data (Diesel OBM Training values)

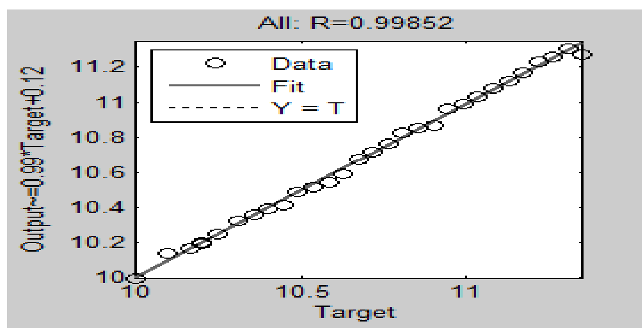

Fig 5 Estimated data against experimental data (Diesel OBM Overall values)

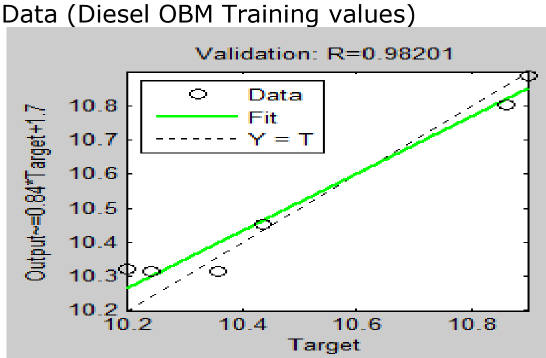

Fig 6 Estimated data against experimental data (Jatropha OBM Validation values)

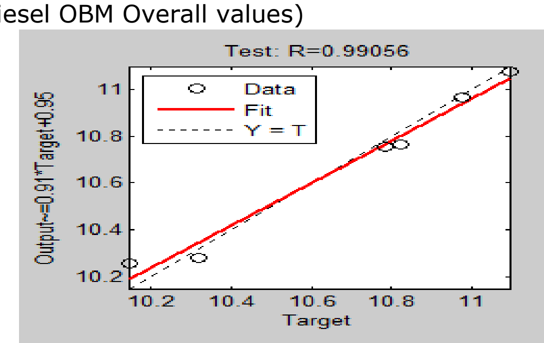

Fig 7 Estimated data against experimental data (Jatropha OBM Test values)

The values were returned after performing five iterations for each network. This also goes to say that the Artificial Neural Network, after being trained and simulated is a viable and feasible instrument for prediction.

Figures 2 to 13 present plots of Experimental data against Estimated (predicted) data for training, testing and validation processes using MATLAB 2008.

We can see from the Figures that the data points all align closely with the imaginary/ arbitrary straight line drawn across. This validates the accuracy of the network predictions and this also gives rise to the high regression values (tending towards unity) presented in Table 2

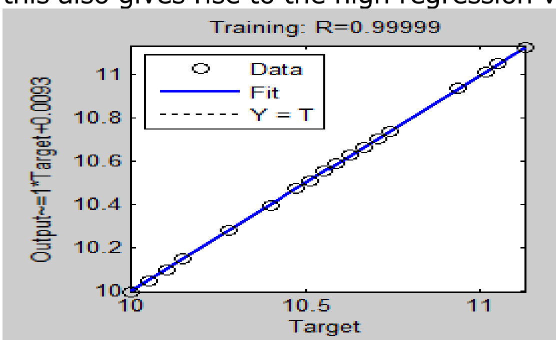

Fig 8 Estimated Data against experimental data (Jatropha OBM Training values)

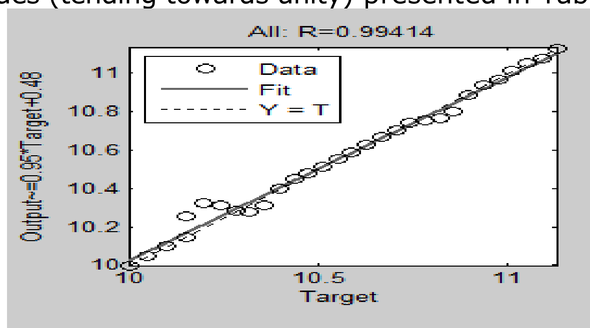

Fig 9 Estimated data against experimental data (Jatropha OBM Overall values)

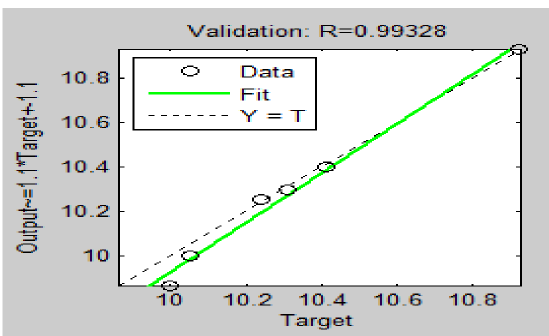

Fig 10 Estimated data against experimental data (Canola OBM Validation values)

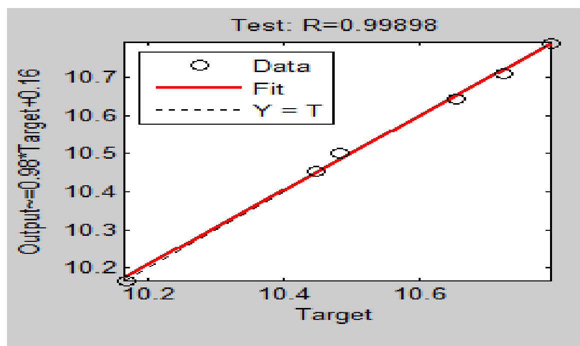

Fig 11 Estimated data against experimental data (Canola OBM Test values)

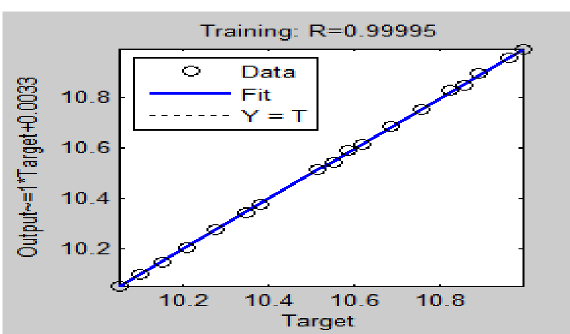

Fig 12 Estimated data against experimental data (Canola OBM Training values)

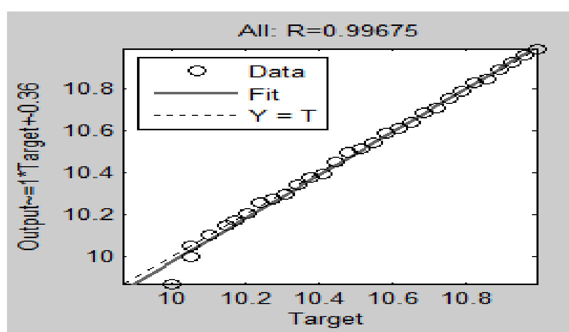

Fig 13 Estimated data against experimental data (Canola OBM Overall values)

Errors, estimated values and experimental values are summarized in Tables 4 to 6

The minute errors encountered in the predictions further justify the claim that the ANN is a trust worthy prediction tool.

The Experimental outputs were then plotted against their corresponding temperature values, and also fitted into the polynomial trend line of order 2.

From Figures 14 to 16, which are plots of Experimental data against temperature and Estimated data against temperature on the same charts. Due to the accuracy of the networks, the graphs tend to overlap each other, except for a few minute deviations.

The equations derived are:

Diesel OBM: $\rho = -4\times10^{-7}T^2 + 0.004T + 9.915$ (1)

Jatropha OBM: $\rho = 7\times10^{-7}T^2 + 0.003T + 9.994$ (2)

Canola OBM: $\rho = -2\times10^{-6}T^2 + 0.004T + 9.827$ (3)

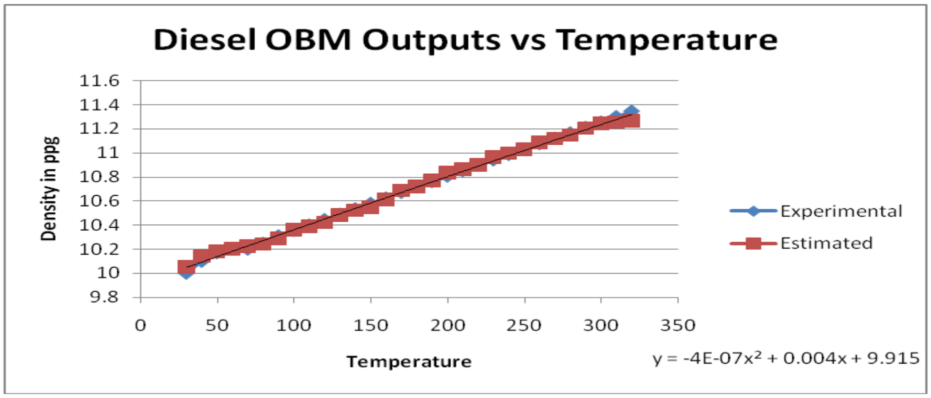

Fig 14 Graph of estimated and experimental values against temperature (Diesel OBM)

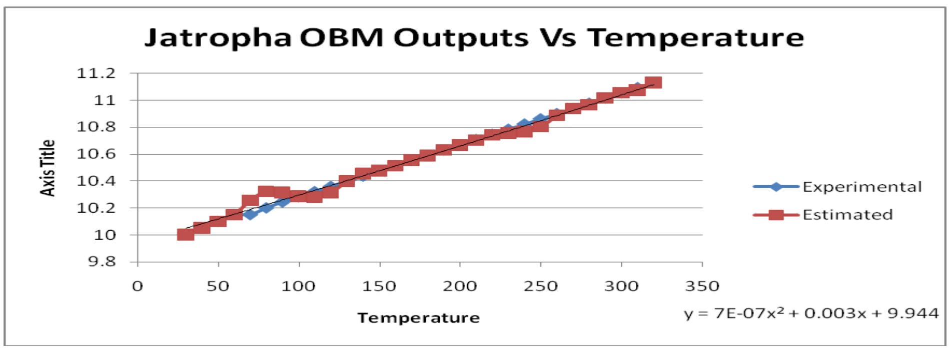

Fig 15 Graph of estimated and experimental values against temperature (Jatropha OBM)

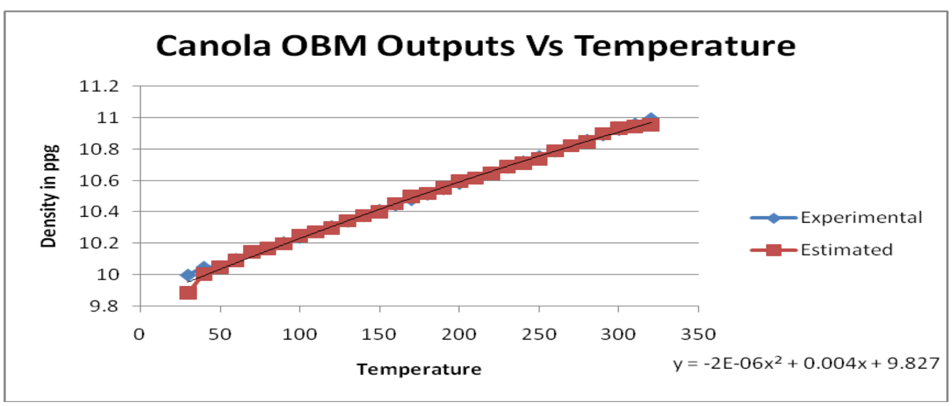

Fig 16 Graph of Estimated and Experimental Values against Temperature (Canola OBM)

Also by comparing the networks created with that of Osman and Aggour [10], we can see that this work is technically viable in predicting mud densities at varying temperatures as the network developed in the course of this project showed regression values close to those proposed by Osman and Aggour.

Errors, percentage errors and average errors as compared with Osman and Aggour are relatively lower, thus guaranteeing the accuracy of the newly modeled network.

Table 7 shows the regression values of Osman and Aggour for oil based mud density variations with temperature and pressure.

Table 7 Table Showing the Regression Values from Osman and Aggour

Training	Testing	Validation	All
0.99978	0.99962	0.99979	0.9998

The Relative deviation E_i was calculated using function in equation 4 and the following values were returned:

$$E_i = \left[\frac{\rho_e - \rho_p}{\rho_e}\right] \times 100 \qquad (4)$$

$$AAPE = \frac{1}{n}\sum_{i=1}^{n}\left|E_i\right| \qquad (5)$$

Table 8 Table of the Relative Deviations

Temperature	Diesel	Jatropha	Canola
30	0.49	0	1.159
40	0.40297	0	0.453731
50	0.092429	0.00198	0.0199
60	0.021569	0.014778	0.074257
70	0.231373	1.040394	0.050246
80	0.097561	1.207843	0.018682
90	0.235986	0.692808	0.078054
100	0.013748	0.031076	0.077606
110	0.107859	0.382504	0.007183
120	0.235115	0.428105	0.119538
130	0.080107	0.008473	0.006675
140	0.157991	0.157237	0.010553
150	0.346719	0.020412	0.116025
160	0.132049	0.006975	0.069241
170	0.136087	0.023647	0.176011
180	0.024081	0.019604	0.035776
190	0.080259	0.00896	0.039587
200	0.23682	0.01049	0.107622
210	0.074195	0.03447	0.03386
220	0.008346	0.035012	0.074922
230	0.173317	0.254405	0.019963
240	0.06392	0.521209	0.097495
250	0.057271	0.529223	0.174223
260	0.056307	0.108703	0.000221
270	0.039597	0.001088	0.013022
280	0.193818	0.107419	0.106789
290	0.082846	0.000346	0.043324
300	0.143289	0.000302	0.064369
310	0.442092	0.155111	0.145538
320	0.724421	0.000214	0.355045

AAPE is calculated using equation 5. Table 9 compares the AAPE, Maximum Ei and Minimum E_i for Diesel, Jatropha and Canola OBM's as well as the values from Osman and Aggour.

Table 9 Table Comparing Maximum Ei, Minimum Ei, and AAPE

	Diesel	Jatropha	Canola	Osman et al
Minimum E_i	0.008346	0.000214	0.000221	0.102269
Maximum E_i	0.724421	1.207834	1.159	1.221067
AAPE	0.172738	0.193426	0.124949	0.36037

5. Conclusion

The results of the tests carried out indicate that jatropha and canola OBM's posses great chances of being among the technically viable replacements of diesel OBM's. The results also show that additive chemistry must be employed in the mud formulation, to make them more technically feasible.

The density increased with temperature difference and became constant at some point, and begins increasing again. These temperature points of constant density varied for the different samples. The diesel OBM showed the highest variation range, while the canola OBM showed the lowest.

Artificial Neural Network works well for prediction of scientific parameters, due to minimized errors returned.

Limitation

1. The temperature-density tests were carried at surface conditions under an open system and at a constant pressure due to the absence of a pressure unit thus, the equations developed are not guaranteed for downhole circulating conditions.
2. During the temperature-density tests, it was observed that some of the mud particles settled at the base of the containing vessel, and this reduced the accuracy of the readings.
3. The mud samples were aged for only 24 hours, hence the feasibility of older muds may not be guaranteed.

Recommendations

1. This work should further be tested and investigated for the effect of temperature on other properties of the formulated drilling fluids.
2. The temperature-density tests should also be carried out at varying pressures, to simulate downhole conditions.

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