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Artificial Neural Networks for Modeling Rheological Properties under High-Temperature and High-Pressure in Gas Well Cement Slurries

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Artificial neural networks (ANN) was used to predict the rheological properties of high temperature high pressure gas well cement slurries. Seven different materials were used as additives which includes: Fresh water, dyckerhoff, silica flour, antifoam, extender, fluid loss, dispersant, retarder, anti-settling agent, gas control agent, dry viscosifier, potassium chloride and accelerator. Four recipes were prepared using these additives in different mixtures. Recipe four have all the additives. The rheological properties were investigated at different temperatures in the range of 23 to 60ºC using an advanced shear-stress/shear-strain controlled rheometer. Experimental data thus obtained were used to develop predictive models based on back- propagation artificial neural networks. It was found that ANN depicted good agreement with the experimental data, with ANN

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achieving more accurate predictions. The developed models could effectively predict the rheological properties of new slurries designed within the range of input parameters of the experimental database with an absolute error of 3.43, 3.17, and 2.82%, in the case of ANN, for the different recipes. The flow curves developed using ANN allowed predicting the Bingham parameters (yield stress and plastic viscosity) of the oil well slurries with adequate accuracy. The goal of the process is to choose the network that minimizes the prediction errors/RMSEs. There is however need to avoid an over-trained network. The result showed that over-training of the networks sets in around the scenario when the number of hidden layer neurons exceeds 9. It also demonstrates that the network with 9 hidden layer neurons gave the least RMSEs, and it is this network that has been adopted as the network for the final model development in this work.

Keywords: Multiple regression analysis; yield stress; cement slurry; gas well; artificial neural networks.

1. INTRODUCTION

The rheological properties of gas well cement slurries are important in assuring that such slurries can be mixed at the surface and pumped into the well with minimum pressure drop, thereby achieving effective well cementing operation. The rheological properties of gas well cememnt slurries depend on various factors including the water-cement ratio (w/c), size and shape of cement grains, chemical composition of the cement and relative distribution of its components at the surface of grains, presence and type of additives, compatibility between cement and chemical admixtures, mixing and testing procedures, time and temperature, etc. The interactions among the above mentioned factors play a vital role in altering the rheological properties of gas well slurries. Moreover, a wide range of bottom-hole pressure and temperature makes the characterization of the rheology of gas well cement slurries more challenging than that of normal cement paste. Therefore, a clear understanding of this complex behavior is important in order to successfully predict the rheological properties of gas well cement slurries. Much work has been conducted over the last few decades to investigate the rheological behaviour of cementitious systems such as cement paste, mortar, grout, slurry and concrete. A number of shear stress-strain rate relationships have been developed for cement slurries. However, there exists no model that explains the interactions among the materials used for preparing such slurries and test conditions such as temperature, shear rate, etc. The power-law, Bingham, and Herschel-Bulkley models are the most commonly used in the well cementing industry [1]. Such models are comprised of empirical expressions derived from the analysis of limited experimental data and based on simplifying assumptions [2]. Moreover, they do not have true predictive capability outside the experimental domain and when different materials are used [3], and do not explain the interactions among test parameters.

The first step to design a High Pressure High Temperature and gas well cementing job is to know the well construction [4]. The depth, hole size, casing hardware and deviation are the basic parameters required to start a design and these are information which must be supplied by the client in the geotechnical order before any design can be done; Temperature, Mud characteristics, Pore pressure and fracture pressure, Information about previous offset wells, Casing seat depths, Stratigraphy, Drilling data (If losses occurred or if there was influx during drilling operation), Casing types to be used and Open hole sizes with desired excesses to mention but a few. Proper prediction of Bottom Hole Circulating Temperature using Bottom Hole Static Temperature, flow rates, steel temperatures etc., is very important as this Bottom Hole Circulating Temperature determines the kind of additives to be used and it also shows cement slurry behavior during the operational and placement time of the job [5]. The operational time includes the ramp up time from when the first barrel of cement is pumped till it gets to the shoe before it turns in the annulus and up to the placement time in the annulus where it begins to develop compressive strength.

Artificial neural networks (ANNs), also known as neural networks (NNs), neural nets, or simply neural networks, are computer architectures that take their cue from the biological neural networks that make up animal brains [6].

A Deep Learning model called an Artificial Neural Network takes its cues from the neural network of the human brain. ANNs were created to replicate how the human brain works, which involves learning from experiences and adapting to the environment. Similar to the multi-tiered structure of the human brain, which contains billions of neurons arranged in a hierarchy, the artificial neural network (ANN) similarly has a network of neurons that are connected to one another by axons [7].

These synaptically linked neurons transmit electrical signals from one layer to the next. The ANN may learn from experience without the need for human involvement thanks to this approximation of brain modeling.

Artificial neurons, which are a set of interconnected units or nodes that loosely resemble the neurons in a biological brain, are the foundation of an ANN. Like the synapses in a human brain, each link has the ability to send a signal to neighboring neurons [8]. An artificial neuron can signal neurons that are connected to it after processing signals that are sent to it. The output of each neuron is calculated by some non-linear function of the sum of its inputs, and the "signal" at a connection is a real number.

Edges refer to the connections. The weight of neurons and edges often changes as learning progresses. The weight alters a connection's signal intensity by increasing or decreasing it. Neurons may have a threshold, and only send a signal if the combined signal crosses it.

Neurons frequently group together into layers. Different layers may modify their inputs in different ways. Signals move through the layers, perhaps more than once, from the first layer (the input layer) to the last layer (the output layer).

1.1 Core Characteristics of Artificial Neural Networks

- Non-linearity imparts a better fit to the data.
- High parallelism promotes fast processing and hardware failure-tolerance.
- Generalization allows for the application of the model to unlearned data.
- Noise insensitivity that allows accurate prediction even for uncertain data and measurement errors.
- Learning and adaptivity allow the model to update its internal architecture according to the changing environment.

ANN-based computing primarily aims to design advanced mathematical algorithms that allow Artificial Neural Networks to learn by imitating the information processing and knowledge acquisition functions of the human brain.

1.2 Components of Artificial Neural Networks

ANNs are comprised of three core layers or phases – an input layer, hidden layer/s, and an output layer.

- Input Layer: The first layer is fed with the input, that is, raw data. It conveys the information from the outside world to the network. In this layer, no computation is performed – the nodes merely pass on the information to the hidden layer.
- Hidden Layer: In this layer, the nodes lie hidden behind the input layer – they comprise the abstraction part in every neural network. All the computations on the features entered through the input layer occur in the hidden layer/s, and then, it transfers the result to the output layer.
- Output Layer: This layer depicts the results of the computations performed by the network to the outer world.

1.2.1 Training

When processing samples that each have a known "input" and "result," neural networks learn (or are trained) by creating probability-weighted associations between the two that are then stored within the net's data structure. In order to train a neural network from a given example, one often compares the processed output of the network—often a prediction—against the desired output. The error is in this discrepancy [9]. The network then modifies its weighted associations using this error value and a learning strategy. The neural network will provide output that is more closely related to the goal output with each change. The training can be stopped once it has undergone a sufficient number of these changes and meets specific requirements. This is a form of supervised learning. possibly after traversing the layers multiple times.

Artificial neural network (ANN) is a powerful computational tool that allows overcoming the difficulty of assessing the complex and highly nonlinear relationships among model parameters through self-organization, pattern recognition, and functional approximation. ANN simulates the structure and internal functions of the biological brain. Unlike conventional models, ANN does not assume a model structure between input and output variables. It rather generates the model based on the database provided for training the network. An ANN solves problems by creating parallel networks and the training/learning of those networks, rather than by a specific programming scheme based on well-defined rules or assumptions [10].

The ability of the models thus developed to evaluate the sensitivity of rheological properties to the variation of shear rate, admixture dosage, and test temperature was investigated. Hence, a shear stress-shear rate curve for gas well cement slurries can be predicted at different temperatures prior to fitting the data to conventional rheological models. Consequently, the rheological properties of gas well cement slurries can be predicted as a function of mixture composition and test conditions for the first time.

This research is centered on Modeling rheological properties of High temperature and high pressure gas well cement slurries using artificial neural networks. Eleven recipes were prepared but for the purpose of this work, only four recipes that showed the wanted properties were used.

2. MATERIALS AND METHODS

The materials used for this research are as follows: Antifoam/Defoamer, Fluid Loss Additive, Retarder, Gas Migration Control Additive, Fresh Water/Seawater, API Class “G” Cement, Extenders, Accelerators and Strength Retrogression Material. While the equipment/apparatus that were used includes: Syringes, Plastic Petri dishes, Automated Weighing Balance (Kern Model), Viscometer (Fann 35), Warring Blender, Atmospheric Consistometer (Fann Model 165 AT Consistometer), High Pressure High Temperature Consistometer (Chandler Model 7025 Dual Cell HPHT Consistometer), Multiple Analysis Cement System (MACS II), Multiple Analysis Cement System (MACS II).

2.1 Methodology

2.1.1 Cement slurry selection

Cement slurries are usually selected based on well objectives and requirements. The following would be used for this study.

2.1.2 Preparation of cement slurry

The recommended cement slurry volume for laboratory testing is 600ml (API RECOMMENDED PRACTICE 10B-2). The preparation of cement slurries varies from that of classical solid/liquid mixtures due to the reactive nature of cement, shear rate and time at share are important factors in the mixing of cement slurry in the laboratory. Before any test is carried out, a laboratory calculation sheet is designed which shows the required volumes of the mix water and additives as well as specified temperature, pressure and time. The Warring blender is placed on the scale and set to zero, then fresh water/seawater is added to the blender on top of the scale till it reaches the desired weight on the laboratory calculation sheet for each of the designed cement slurry. Syringes are used to weigh liquid additives. It is recommended to use new syringes each time an additive is to be measured to ensure that there is no form of contamination. To measure the liquid additive, the syringe is used to siphon some product into it and emptied, the dead weight is measured by setting scale to zero and measuring this emptied syringe containing particles of the future fluid to be measured, then the desired volume of liquid additive from the laboratory calculation sheet is measured and kept aside till all liquid additive to be added to the mix water are measured and weighed. This pattern of measurement is done for all liquid measurement to be used per cement slurry. Plastic petri dishes are cleaned and placed on the measuring scale which is then set to zero. The dry additive is then added to the plastic petri dish till the desired volume from the laboratory calculation sheet is reached. The dry additive is kept aside until it is time to be added to the mix water in the warring blender. The recommended API mixing and blending procedure would be followed:

1. The Warring blender containing only the mix water is placed in the mixing chamber.
2. The motor is turned on and kept at 4000 r/min ± 250 r/min mixing speed.
3. The liquid additives are added into the warring blender still on low speed in the specified order that they would be added on the field.
4. Add Cement into the mix water which now contains other liquid additives and ensure the addition doesn’t exceed 15secs. (This is to cater for flash setting which is a factor

of Time to Add Cement). Cover the warring blender.

5. Turn the speed on the motor to high speed 12000 r/min ± 250 r/min for not more than 35s ± 1s to get a vortex in the blender.
6. Stop the mixer after 35 secs and proceed with desired test.

2.1.3 Procedures for the tests

2.1.3.1 Surface rheology test

The recommended API procedure for determining surface rheological properties would be followed:

1. Ensure that the rotor and bob are clean and free from any form of debris.
2. The cement slurry is poured from the warring blender into the viscometer cup to a level adequate to raise the fluid to the scribed mark on the rotor without the rotor or bob touching the bottom of the cup.
3. Turn on rotor and ensure dial is at 3rpm, raise the cup till the cement slurry is on the scribed line on the rotor.
4. Take the initial reading still at 3rpm after about 10secs of continuous rotation of cement slurry.
5. Take upward reading after 10 secs for each rpm starting from 3rpm. Take downward reading after 10 secs for each rpm starting from 300rpm. The different rpm readings are 3,6,30,60,100,200,300 rpm respectively.
6. Calculate the ratio of the dial readings during ramp-up to ramp-down at each speed. This ratio would be used to help qualify certain fluid properties.

2.1.3.2 Downhole rheology test

The recommended API procedure for determining downhole rheological properties would be followed:

1. Condition the cement slurry to the specific temperature and pressure in the atmospheric consistometer.
   a. The cement slurry container would be placed in the heating bath or in the atmospheric consistometer with a paddle for rotational effect, preheated to the test temperature.
   b. This test temperature is held in the heating bath or in the atmospheric consistometer for 30 min ± 30 s to allow the test fluid temperature to reach equilibrium.
   c. After 30 minutes has elapsed, remove the paddle and stir the test fluid briskly with a spatula to ensure it is uniform. Continue with the desired test
2. Ensure that the rotor and bob are clean and free from any form of debris.
3. The cement slurry is poured from the conditioning cup into the viscometer cup to a level adequate to raise the fluid to the scribed mark on the rotor without the rotor or bob touching the bottom of the cup.
4. Turn on rotor and ensure dial is at 3rpm, raise the cup till the cement slurry is on the scribed line on the rotor.
5. Take the initial reading still at 3rpm after about 10secs of continuous rotation of cement slurry.
6. Take upward reading after 10 secs for each rpm starting from 3rpm. Take downward reading after 10 secs for each rpm starting from 300rpm. The different rpm readings are 3,6,30,60,100,200,300 rpm respectively.
7. Calculate the ratio of the dial readings during ramp-up to ramp-down at each speed. This ratio would be used to help qualify certain fluid properties.

2.1.3.3 Thickening time test

The recommended API procedure for determining thickening time would be followed: Preparing cement slurry for the Consistometer cup.

1. Ensure the threads of the consistometer cup are clean and free of debris.
2. The paddle shaft, diaphragm, diaphragm support ring and back up support plate are assembled and secured in the cup sleeve with the flange ring, as well as the base and center plug and ensure that the paddle turns freely.
3. The ends of the consistometer cup would be greased to ensure for easy removal of set cement after test.
4. Pour already prepared slurry into the cup to the middle of the thread, cover the cup and remove all entrained air and clean the body of the cup before putting the cup in the High Pressure High Temperature Consistometer.

Table 1. Properties of materials

Materials	Function	Specific gravity	Concentration	Units
Fresh Water	Mixing water	1.000	3.744	Gps
Dyckerhoff	Cement "G"	3.140	100.00	%
Silica Flour	Strength Retrogression	2.630	35.00	%
Antifoam	Foam Preventer	0.880	0.011	Gps
Extender	Extender	0.830	2.030	Gps
Fluid Loss	Fluid Loss	1.050	0.450	Gps
Dispersant	Dispersant HT	0.921	0.510	Gps
Retarder	Retarder MT	1.026	0.010	Gps
Anti-Settling	Extender	0.880	0.300	Gps
Gas Control Agent	Gas Control	0.902	2.800	Gps
Dry Viscosifier	Weighting Material	-	0.100	%
KCL	Salt	1.162	19.149	Kg/tonne

Table 2. Composition of cement slurry

Materials	Recipe 1	Recipe 2	Recipe 3	Recipe 4
Fresh Water	✓	✓	✓	✓
Dyckerhoff	✓	✓	✓	✓
Silica Flour	✓	✓	✓	✓
Antifoam	✓	✓	✓	✓
Extender	✓	✓	✕	✓
Fluid Loss	✓	✓	✓	✕
Dispersant	✓	✓	✓	✓
Retarder	✓	✓	✓	✓
Anti-Settling	✕	✓	✕	
Gas Control Agent	✕	✕	✓	✓
Dry Viscosifier	✕	✕	✓	✕
KCL	✕	✕	✕	✕
Accelerator	✕	✕	✕	✕

Preparing cup for the High Pressure High Temperature Consistometer.

1. Place the filled slurry container on the drive table in the pressure vessel, rotate the slurry container, and engage the paddle shaft drive bar with the potentiometer mechanism or other suitable device for measuring consistency.
2. Fill the vessel halfway with oil. The shaft of the paddle should not rotate.
3. Partially engage the threads by inserting the thermocouple through its fitting. Tighten the thermocouple threads when the pressure vessel is entirely filled with oil.
4. The test can commence after inputting the details in the equipment computer.

Programming and running the test on the High Pressure High Temperature Consistometer Computer.

After the consistometer cup has been placed in the Consistometer, the ramp time, temperature and pressure should be set up and the test should be monitored to ensure that it is going as planned.

Stopping the High Pressure High Temperature Consistometer.

When the desired tests results are achieved,

1. The High Pressure High Temperature Consistometer is turned off and cooled.
2. Pressure is released and oil is drained.
3. The consistometer cup is removed and cleaned of any set cement and debris.
4. The Consistometer cup is prepared and ready for another test.
5. Results generated would be analyzed to observe patterns and trends.

2.1.3.4 Transition time tests

The recommended API procedure for determining transition time would be followed:

1. Ensure Multiple Analysis Cement System (MACS II) slurry cup is clean and free from debris.

2. Prepare cement slurry to specification.
3. Fill Multiple Analysis Cement System (MACS II) cup with cement slurry, make sure no air is trapped in the cup.
4. Put Multiple Analysis Cement System (MACS II) cup in the Multiple Analysis Cement System.
5. Set the Desired Ramp up and End Time and Gel Strength and monitor the output on the attached computer system.

2.2 Mathematical Modelling of Transition Time as a Function of Temperature and Pressure

Regression models would be developed for transition time and thickening time as a function of Temperature and Pressure. Regression models provide flexibility when describing and testing hypothesis on relationships between explanatory variables and response variables [11].

For this study, regression analysis would be used for:

1. Modelling the relationship among the variables.
2. Prediction of target variables (Forecasting).
3. Validation of model

Multiple Linear Regression models development.

To develop a good linear regression, four main assumptions must be satisfied, and they are:

1. Lack of fit or using a mis-specified model.
2. Constant error variance (Homoscedasticity check).
3. The errors between the observed and predicted variables should be normally distributed.
4. There is no multi- collinearity in the data.

2.3 Artificial Neural Network – MATLAB

Artificial neural networks are basically made up of input, hidden, and output layers. Inputs for the network are fed into the system through the input layer, the bulk of the training/learning takes place in the hidden layer, and the results are brought out of the system through the output layer. Each of the layers usually consists of one or more neurons (also called nodes). The number of neurons in the input layer is the number of parameters which are to be used as inputs for the model. In this work, they are: temperature, pressure, density, and recipe identifier. The number of neurons in the output layer is similarly the number of parameters we are predicting (that is, outputs of the model). In this work, it is the transit time. Fig. 1 illustrates the architecture of the neural network used. The structure of this work already dictates that the architecture of the neural network to be used should have 4 input layer neurons and 1 output layer neuron.

What about the number of hidden layer neurons? Some procedure is usually required to decide an appropriate number of hidden layer neurons for a given neural network training. There are no specific rules for choosing the number of hidden layer neurons, but the following knowledge on behavior of neural networks helps. Using too few hidden layer neurons usually leads to a scenario known as under-training in which the neural networks do not learn adequately from the presented dataset, and so do not have the capability to make accurate predictions. On the other hand, using too many hidden layer neurons will lead to a contrary scenario known as over-training in which the neural networks learn so much from the presented dataset that they even memorize it. This is not good because such neural networks have capability to make accurate predictions of dataset which was used for their training, but they are not capable of accurately predicting dataset that is outside the training dataset. A good balance for the number of hidden layer neurons is therefore required to train neural networks that can generalize well. Such networks should not have too few or excessive number of hidden layer neurons, so that they can make accurate predictions for both data which are within and outside of the training dataset. What number is considered appropriate (not too few and not excessive)? This is usually a major question to answer during neural network trainings. The next paragraphs contain details of the processes which have been used in this work to answer this question.

Prior to the neural network training, the dataset was split systemically into 3 categories: first category for training (70% of the dataset), second category for validation (~15%), and third category for testing (~15%). The training dataset was used for actual training of the networks. The validation dataset was used to check and ensure that the trained networks generalize well, and to produce an optimal network. The testing dataset was used to test the prediction accuracy of the produced optimal network. The dataset in this work was systematically split into training, validation, and testing dataset based on the following criteria:

1. To constitute the validation dataset, 1 data point was first taken from each of the 11 recipes. In each recipe, the data point was randomly selected between the second and ninth cases. This gave 11 data points for the validation dataset. An additional data point was again taken from each of 5 recipes that were randomly selected from the 11 recipes. This gave another 5 data points, making a total of 16 data points for the validation dataset. The 5 additional data points were selected such that two of them are the first cases of their recipes, another two of them are the tenth cases, and the fifth one is randomly chosen from between the second and ninth cases of its recipe. The 16 data points chosen for the validation process therefore represents 14.55% of the entire dataset.
2. To constitute the testing dataset, 1 data point was first taken from each of the 11 recipes. In each recipe, the data point was randomly selected between the second and ninth cases (not including any data point that had been previously chosen for the validation dataset). This gave 11 data points for the testing dataset. An additional data point was again taken from each of the 6 remaining recipes (not including any of the 5 recipes in step 1 above). This gave another 6 data points, making a total of 17 data points for the testing dataset. The 6 additional data points were selected such that two of them are the first cases of their recipes, another two of them are the tenth cases, and the other two are randomly chosen from between the second and ninth cases of their recipes. The 17 data points chosen for the testing process therefore represents 15.45% of the entire dataset.
3. Steps 1 and 2 above leave us with 7 data points in each of the 11 recipes, giving a total of 77 data points for the training process, and this represents 70% of the entire dataset.

The above criteria for splitting the dataset was designed to ensure that there is a good spread of the data attributes/properties across each of the training, validation, and testing datasets. At least one data point was taken from each recipe to constitute each of the validation and testing datasets. Seven data points were consistently taken from each recipe to constitute the training dataset. Each of the training, validation and testing datasets were also ensured to contain some of the field data (first cases in each recipe), high temperature/pressure data (tenth cases in each recipe), and a random distribution of the rest of the laboratory data (second to ninth cases).

2.3.1 Deciding the number of hidden layer neurons

To decide the appropriate number of hidden layer neurons, 100 different neural networks were trained. The difference between the 100 neural networks was in the number of hidden layer neurons used for their training; the number of hidden layer neurons used was varied starting from 1 to 100 in steps of 1. After training the 100 neural networks, the performance of each network was evaluated using the root-mean-square error (RMSE) between the neural network predictions and the actual measurements. The following is how it was done:

1. Each of the 100 networks was used to predict the transit time corresponding to the validation dataset which was set apart from the training set.
2. The neural network predictions were compared to the actual measurements, and the errors of the predictions were computed as the differences between the neural network predictions and the actual measurements. That is: error = neural network prediction – actual measurement.
3. The RMSEs for each of the 100 neural networks were then computed using equation (1).

$$RMSE = \sqrt{\frac{\sum_i^n (error_i)^2}{n}} \qquad (1)$$

The results of the computed RMSE values are shown in Fig. 2. To study the behaviour of the neural networks in terms of over-training/under-training, the procedure of computing the RMSEs were repeated using the training and test datasets. Ideally, the best performing networks will predict transit times which are closest to the measured transit times, therefore their errors/RMSEs will be minimal.

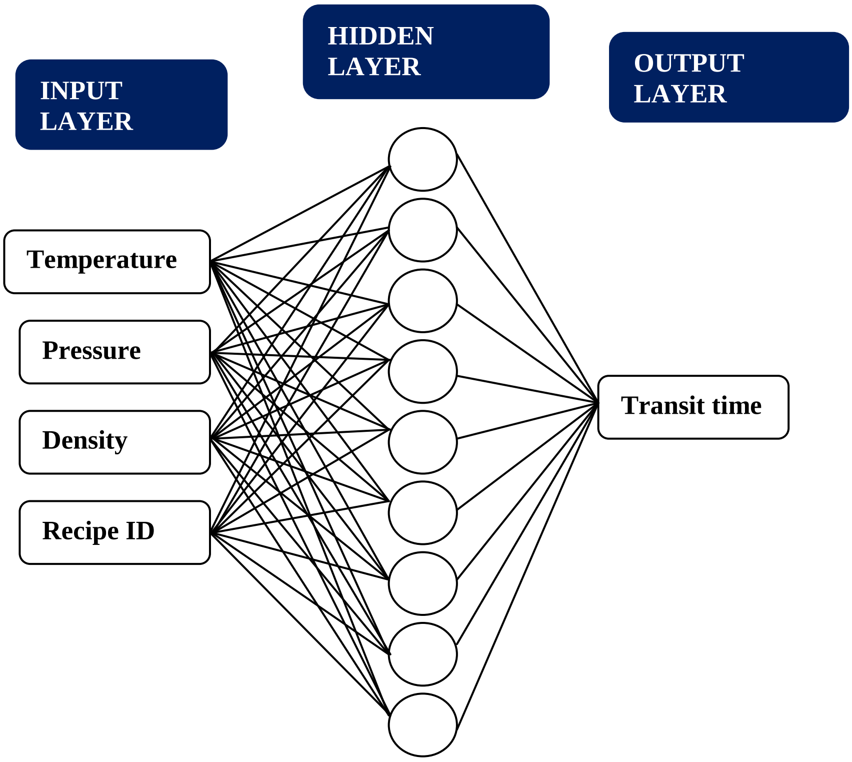

Fig. 1. Structure of the neural network used

The goal of the process is to choose the network that minimizes the prediction errors/RMSEs. There is however need to avoid an over-trained network. Over-trained networks memorize the training dataset, and so they predict the training dataset with high accuracy (the RMSEs are very small or close to zero). On the contrary, such over-trained networks are not capable of accurate predictions of other datasets outside of the training dataset (e.g., the validation and test datasets). This scenario is witnessed in Fig. 2 where the RMSEs associated with the training dataset become too small as the number of hidden layer neurons increase, but the RMSEs associated with the validation and testing datasets rather increase as the number of hidden layer neurons increase beyond ~9. The figure shows that over-training of the networks sets in around the scenario when the number of hidden layer neurons exceeds 9. Fig. 3 (showing RMSEs associated with only the validation dataset) demonstrates that the network with 9 hidden layer neurons gave the least RMSEs, and it is this network that has been adopted as the network for the final model development in this work.

From Table 3, Silica flour was in this slurry to check for strength retrogression, the first tests was used in a life field in Nigeria and the cement bond log showed good bonding in annulus also the cement slurry was batch mixed as well, hence it was a uniform slurry, over time studies have shown that batch mixing produces slurry with unvarying density and this is more desired than mixing on the fly but for the purpose of this research, the laboratory tests was the focus, the extender was reduced because it was acting as weighting agent with its initial concentration and also the presence of the silica flour and high amounts of extender would cause lumpy slurry.

Dispersants was increased to thin down the slurry and optimize the rheology at 3 and 6rpm respectively. Fluid loss concentration was increased to act secondarily as a Gas control agent as adding Gas control to this slurry was going to destabilize the cement slurry at this density not forgetting that the temperatures and pressures also affect the slurry down hole causing slurry to settle and since an anti-settling agent was not introduced here, hence the increase in fluid loss control. In the case of recipe 2 as seen in Table 4, anti-settling agent was introduced, and it helped in stabilizing the slurry. For recipe 3 as seen in Table 5, Silica flour present here helped with reduction of cement slurry strength retrogression and viscosifier helped stabilize the slurry while pumping and reduced disintegration. Gas control additive and fluid loss were optimized to obtain a working stable slurry. Retarder concentration was kept constant here. An Expanding agent was used to decrease possibility of set cement shrinkage after cement slurry placement due to the temperature in recipe 4 as shown in Table 6. A small quantity of expansion agent was blended with the dry cement and used in the slurry, if too much expansion agent is added, it would lead to cracks in the set cement. Gas control agent was optimized to avoid lumpiness of cement slurry and dispersant was optimized to obtain a pumpable slurry.

Table 3. Recipe 1 case 1-10

Recipes	Case/test carried out									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Class G BWOC	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Silica BWOC	35%	35%	35%	35%	35%	35%	35%	35%	35%	35%
antifoam (gal/sk)	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
extender (gal/sk)	2.03	2	1.8	1.5	1.2	1.1	1.1	1.1	1.1	1.1
fluid loss (gal/sk)	0.45	0.65	0.85	1	1.5	2	2.5	3	3	3
dispersant (gal/sk)	0.51	0.5	0.6	0.6	0.6	1	1	1	1	1.2
retarder (gal/sk)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 4. Recipe 2 case 1-10

Recipes	Case/test carried out									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Class G (BWOC)	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Silica (BWOC)	35%	35%	35%	35%	35%	35%	35%	35%	35%	35%
Antifoam (gal/sk)	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Anti-settling (gal/sk)	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Extender (gal/sk)	1.5	1	0.5	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Fluid loss (gal/sk)	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1	1	1
Dispersant (gal/sk)	0.13	0.15	0.15	0.15	0.16	0.16	0.16	0.16	0.16	0.16
Retarder (gal/sk)	0.085	0.085	0.085	0.085	0.085	0.07	0.07	0.07	0.07	0.07

Table 5. Recipe 3 case 1-10

Recipes	Case/test carried out									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Class G (BWOC)	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Silica (BWOC)	35%	35%	35%	35%	35%	35%	35%	35%	35%	35%
Viscosifier (BWOW)	0.45%	0.45%	0.45%	0.45%	0.45%	0.45%	0.45%	0.45%	0.45%	0.45%
Gas Control (gal/sk)	1.50	1.5	1.55	1.55	1.58	1.6	1.6	1.65	1.66	1.66
Antifoam (gal/sk)	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Fluid loss (gal/sk)	0.3	0.3	0.3	0.4	0.4	0.4	0.45	0.45	0.45	0.45
Retarder (gal/sk)	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
Dispersant (gal/sk)	0.1	0.1	0.11	0.12	0.13	0.14	0.14	0.14	0.11	0.11

Table 6. Recipe 4 case 1-10

Recipes	Case/test carried out									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Class G (BWOC)	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%
Silica (BWOC)	35%	35%	35%	35%	35%	35%	35%	35%	35%	35%
Weighting Agent (BWOC)	50.00%	50.00%	50.00 %	50.00 %	50.00 %	50.00 %	50.00 %	50.00 %	50.00 %	50.00 %
Expanding agent (BWOC)	2.00%	2.00%	2.00%	2.00%	2.00%	2.00%	2.00%	2.00%	2.00%	2.00%
Gas Control (gal/sk)	2.80	3.00	3.10	3.10	3.20	3.15	3.10	3.00	3.00	2.80
Antifoam (gal/sk)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Retarder (gal/sk)	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
Retarder (BWOC)	0.30%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Dispersant (gal/sk)	0.2	0.2	0.2	0.25	0.3	0.3	0.3	0.2	0.2	0.2

3. RESULTS AND DISCUSSION

Recipe 1 started failing in case 2 as seen in Table 7 as the transit time kept on increasing a lot and almost became constant from case 7 with a transit time of 45 minutes which is just the exact transit time according to API, this slurry should not even be recommended for use except the strength retrogression reduction is achieved as at the given temperature and pressure which is quite doubtful. The thickening time for this slurry would be quite long because of the low concentrations of retarders used and would adversely affect the performance when set. In Table 8, recipe 2 showed a decreasing transit time with increasing temperatures and pressures which fits the reason for this research in further analysis, regression would be done using the temperature, pressure, and transit time to check if this is the convenient and desired slurry to achieve the objective of designing a tailored slurry to cater for long zero gel time and short transition time thereby solving gas migration issues.

From Table 9, the slurry formed from recipe 3 has transit time below 45 minutes at all times making a desired slurry, considering the density, temperature and pressures used, the case 1 shows that even if the temperature is lower, there is tendency for cement slurry to have lower transit time which is desired for the purpose of this research. Viscosifiers' are not generally desired in cement slurry because they are present in drilling mud and if the volume of spacer pumped ahead is not enough to clean the annulus, there is tendency of not having a clean sweep before cement slurry placement and the drilling fluid coming in contact with this kind of cement slurry recipe would lead to contamination which would cause cement not to have a good bond with formation, this could lead to formation fluid channeling and could lead to the need of a remedial cement job or even a blow-out. This cement slurry formed from recipe 4 as shown in Table 9, has a very high density meaning more materials would be used thereby increased cost for customers, even though it is a desirable slurry also the use of expanding agent requires carefulness while adding it to the cement while blending in the bulk plant and would require little to no contamination from previous cement meaning the silos have to be very clean. The time to reach 100 $lbf/100ft^2$ is fair enough and could mean time to reach thickening time is also good, gel strength and rheology would be good as well. The regression analysis and line of best fit equation would be discussed later.

Table 7. Recipe 1 case 1-10

Recipes	Case	SGSA (hr:mn)	Transit time (mins)	Density (ppg)	Temp (degF)	Pressure (psi)
1	1	8:13-8:44	31	15.02	230	9000
	2	8:40-9:40	60	15.02	250	9000
	3	8:40-9:35	55	15.02	270	10000
	4	8:40-9:45	65	15.02	280	12000
	5	8:34-9:35	61	15.02	290	14000
	6	8:35-9:30	55	15.02	300	16000
	7	8:39-9:25	46	15.02	310	18000
	8	8:42-9:28	46	15.02	320	20000
	9	8:40-9:25	45	15.02	330	22000
	10	8:39-9:25	46	15.02	350	24000

Table 8. Recipe 2 case 1-10

Recipes	Case	SGSA (hr:mn)	Transit time (mins)	Density (ppg)	Temp (degF)	Pressure (psi)
2	1	11:56-12:07	11	15.02	238	10000
	2	11:56-12:08	12	15.02	250	10000
	3	11:55-12:09	14	15.02	260	12000
	4	11:52-12:05	13	15.02	270	14000
	5	11:43-11:55	12	15.02	280	16000
	6	11:33-11:46	12	15.02	290	18000
	7	11:23-11:31	8	15.02	300	20000
	8	11:15-11:24	9	15.02	310	22000
	9	11:14-11:21	7	15.02	320	24000
	10	11:14-11:16	2	15.02	350	26000

Table 9. Recipe 3 case 1-10

Recipes	Case	SGSA (hr:mn)	Transit time (mins)	Density (ppg)	Temp (degF)	Pressure (psi)
3	1	3:36-3:54	18	16.19	392	17700
	2	3:33-3:53	20	16.19	400	18000
	3	3:31-3:54	23	16.19	400	19000
	4	3:31-3:58	27	16.19	400	20000
	5	3:26-3:55	29	16.19	400	21000
	6	3:26-3:56	30	16.19	400	22000
	7	3:23-3:56	33	16.19	400	23000
	8	3:22-3:53	31	16.19	400	24000
	9	3:18-3:49	31	16.19	400	24500
	10	3:18-3:50	32	16.19	400	25000

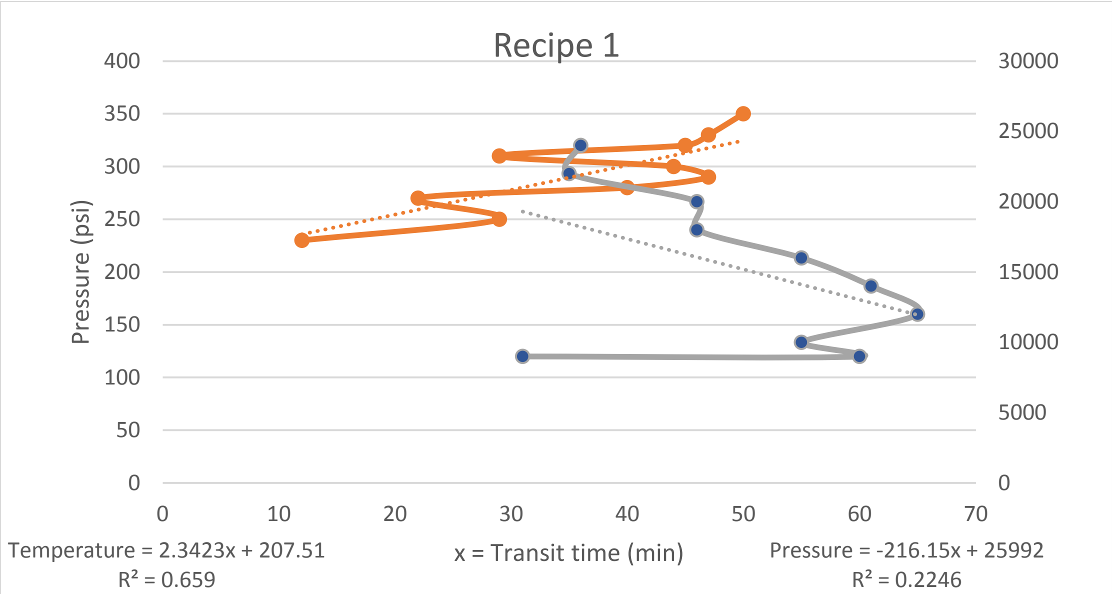

Fig. 2. Recipe 1 temperature and pressure vs transit time

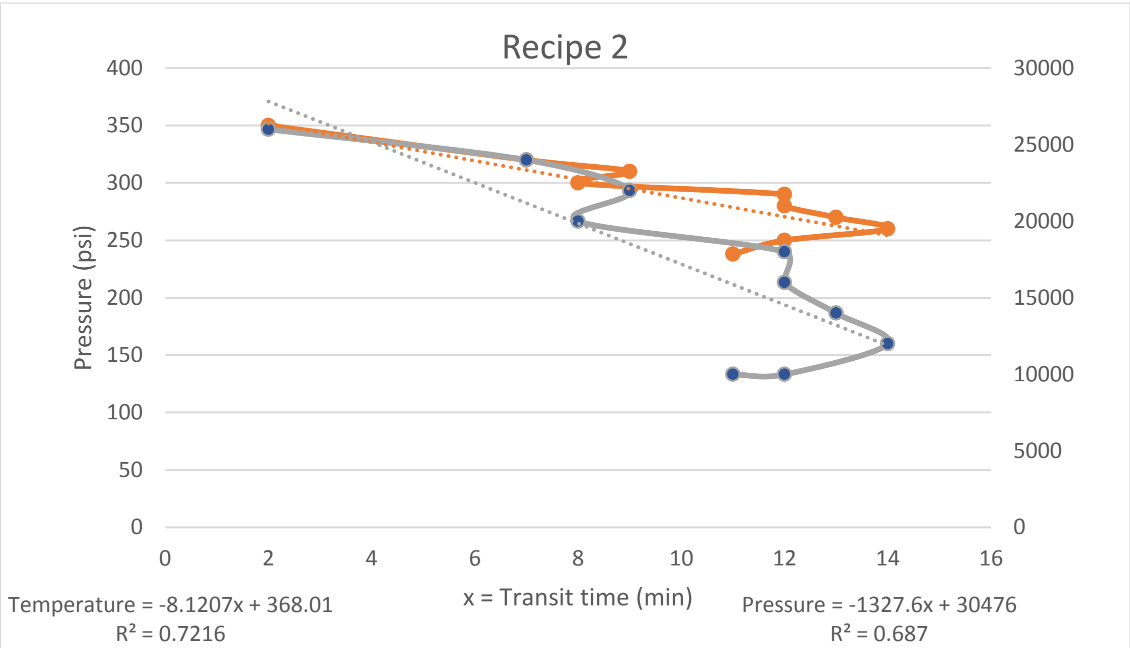

Fig. 3. Recipe 2 temperature and pressure vs transit time

Table 10. Recipe 4 case 1-10

Recipes	Case	SGSA (hr:mn)	Transit time (mins)	Density (ppg)	Temp (degF)	Pressure (psi)
4	1	6:07-6:46	39	18	224	3000
	2	5:57-6:17	20	18	230	5000
	3	5:57-6:18	16	18	240	9000
	4	5:57-6:19	13	18	250	13000
	5	5:57-6:20	13	18	260	17000
	6	5:57-6:21	11	18	270	21000
	7	5:57-6:22	9	18	280	25000
	8	5:57-6:23	6	18	300	25000
	9	5:57-6:24	5	18	330	25000
	10	5:57-6:25	4	18	350	25000

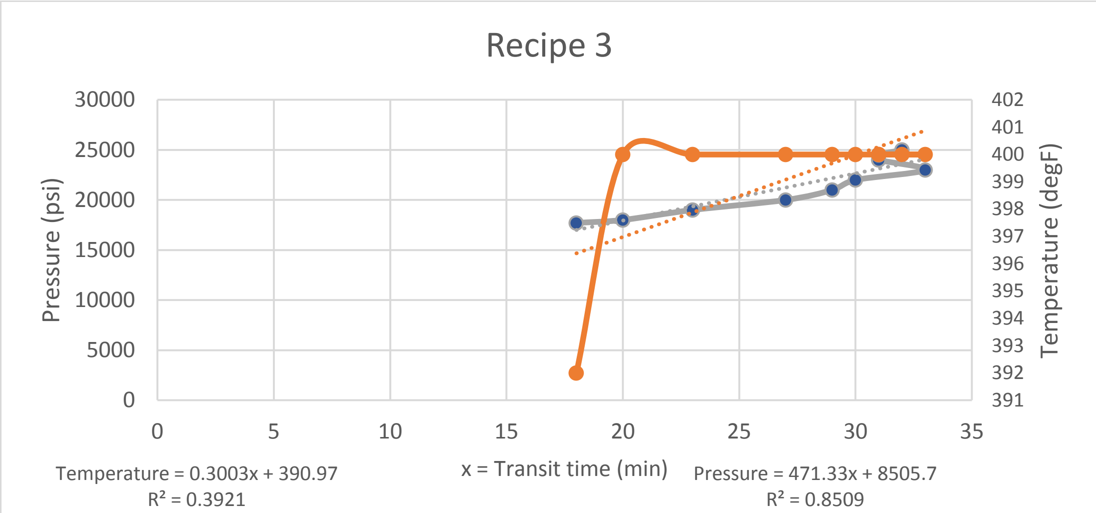

Fig. 4. Recipe 3 temperature and pressure vs transit time

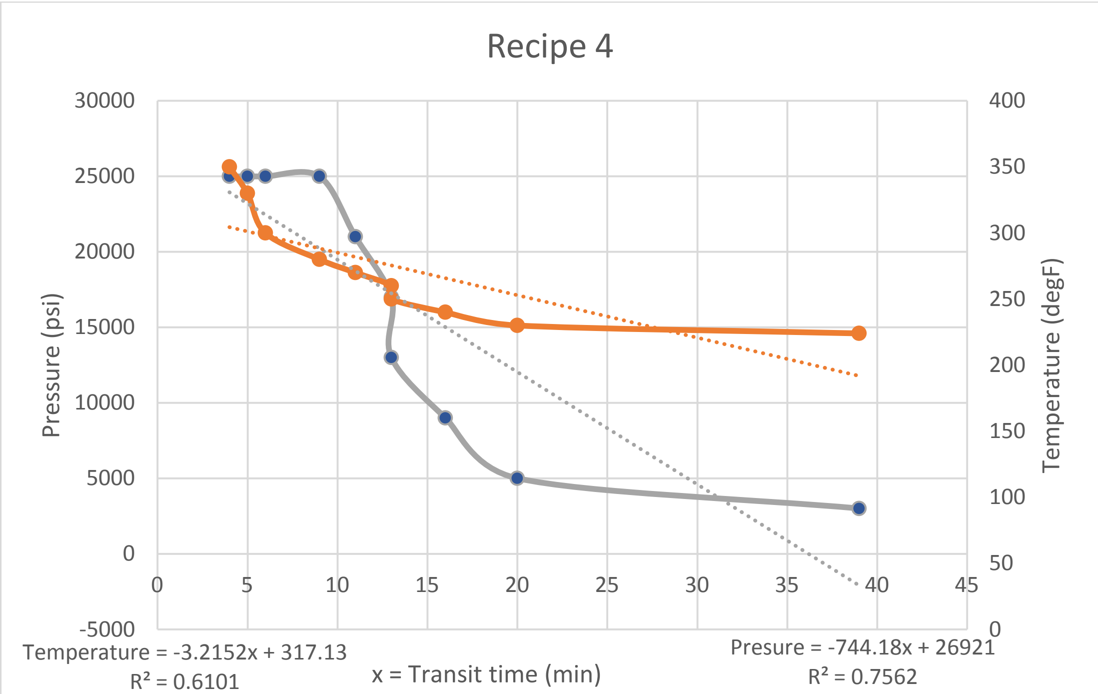

Fig. 5. Recipe 4 temperature and pressure vs transit time

From Fig. 2, The linear relationship between temperature and transit time is given as 2.3423x+207.51, while the regression analysis shows 65.9% correctness, the linear relationship equation for pressure vs transit time gave -216.15x + 25992 and a regression analysis value of 22.46%. The regression values are very low and the linear relationship for pressure gave a negative value which is unacceptable. The linear relationship between temperature and transit time is given as -8.1207x+368.01 in Fig. 3, while the regression analysis shows 72.16% correctness, the linear relationship equation for pressure vs transit time gave -1327.6x + 30476 and a regression analysis value of 68.7%. The desired regression value should ten towards 1 or should be close to 100% depending on what is being used but the closer the better, these values for this recipe are not close both for temperature and pressure and they also have negative linear relationships which indicates reduction in transit time as temperature and pressures increase, very necessary for the success of achieving the objectives of this research.

The linear relationship between temperature and transit time is given as 0.3003x+390.97, while the regression analysis shows 39.21% correctness, the linear relationship equation for pressure vs transit time gave 471.33x + 8505.7 and a regression analysis value of 85.09% as seen in Fig. 4.

The linear relationship between pressure and transit time as well as the regression values are quite high and promising but the corresponding values for temperature vs transit time, makes this recipe to fail to achieve the objectives of this project. The linear relationship between temperature and transit time is given as -3.2152x+317.13, while the regression analysis shows 61.01% correctness, the linear relationship equation for pressure vs transit time gave -744.18x + 26921 and a regression analysis value of 75.62% as seen in Fig. 5.

This recipe has a good regression value of 75.62% for pressure vs transit time and not so good for temperature vs transit time.

Recipe 2 has regression values that could be acceptable since it tends towards or 100% and since the transit time gets smaller with increasing temperature and pressure which is good for this research as one of the objectives is get a very low transit time with increasing temperatures and pressures.

Recipe 4 showed decreasing transit time with increasing temperature and pressure, but relatively low regression values. The use of expanding agent in this slurry simply shows that this slurry would shrink under increasing temperature and pressure, the expanding agent would cure this issue but of concern is if the blending process in the bulk plant would be factored in as the cement blend needs to as accurate as possible also, the use of weighting agent to achieve cement slurry density could mean that slurry density may be unstable.

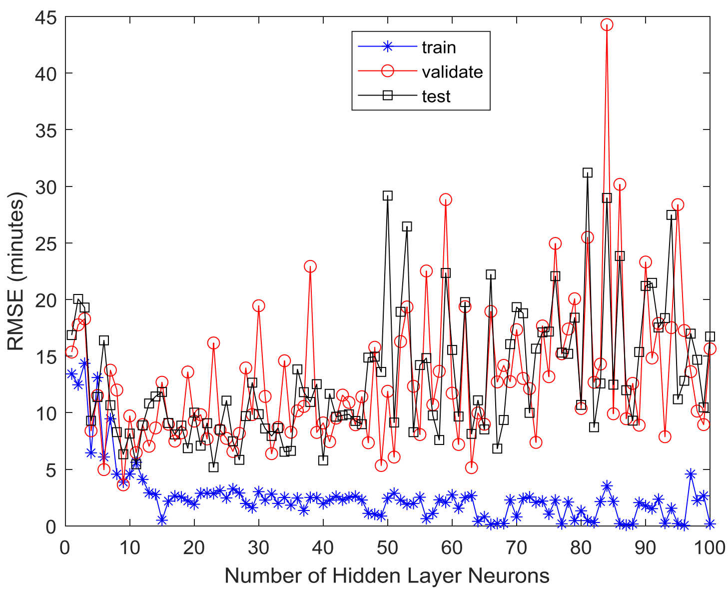

Fig. 6. RMSEs associated with the training dataset

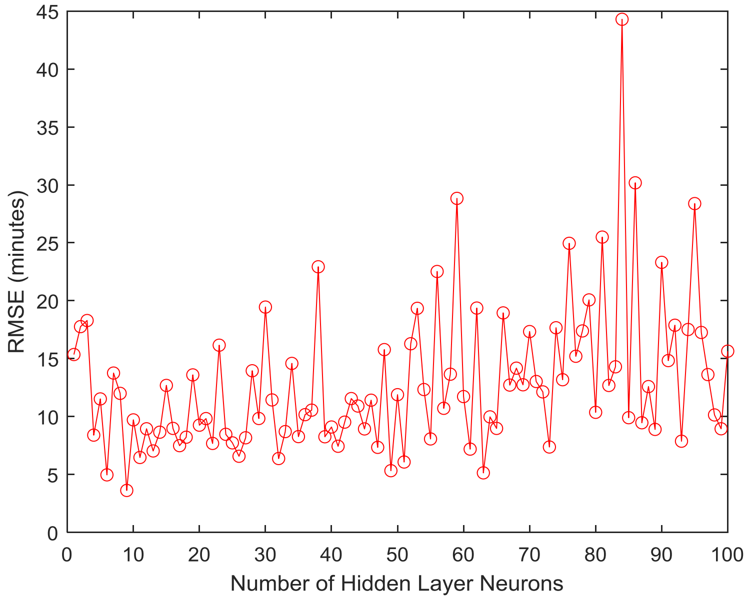

Fig. 7. RMSEs associated with only the validation dataset

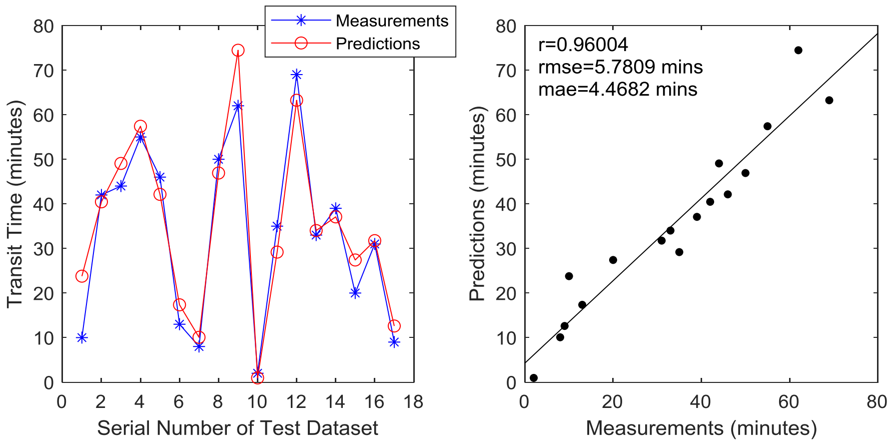

Fig. 8. Neural Network testing based on the satisfactory performance of the developed ANN models

Based on the satisfactory performance of the developed ANN models in predicting the shear stress of gas well cement slurries, the down flow curve for a particular mixture was predicted by changing the shear rate and keeping the admixture dosage and temperature unchanged. Subsequently, stress-shear rate curve corresponding to a zero shear rate, and the plastic viscosity was the slope of the curve. One slurry mixture for each of the admixtures was randomly selected from the testing data and used to develop the down flow curve at different temperatures (23°C, 45°C, and 60°C). These gas well cement mixtures were made with 0.5% of each additives.

4. CONCLUSION

In this study, the relationships amongst the pressure, density, temperature, recipe type and dosage for gas well cement slurries have been analyzed. The rheological properties of gas well cement slurries were modeled using a feed-forward back-propagation artificial neural network. The results obtained here are similar to the results obtained by Anjuman Shahriar and Moncef Nehdi, [12]. The models were then used to develop flow curves, which were used to calculate the yield stress and plastic viscosity values for gas well cement slurries with different recipes and at different test temperatures. Based on this study, the following conclusions can be drawn:

- The flow curves developed using the ANN based models allowed predicting the Bingham parameters (yield stress and plastic viscosity) of gas well cement slurries with an acceptable accuracy and were found to be in good agreement with experimental results.
- The models proposed by the approach was found to be sensitive to the effects of temperature
  increase and admixture dosage on the rheological properties of gas well cement slurries.
- The ANN-based model performed relatively better in predicting the rheological properties of gas well cement slurries.
- The proposed ANN based models can be extended and used to limit the number of laboratory trial mixtures and develop gas well cement slurries with suitable rheological properties, thus saving time and reducing the cost of gas well cement slurry design for specific applications.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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