NEURO-FUZZY MODEL FOR MODELLING THE EFFECTS OF PETROLEUM PRODUCT CONTAMINATED SAND ON THE COMPRESSIVE STRENGTH OF CONCRETES USING: A CASE STUDY OF DIESEL

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Abstract: In this study an adaptive neuro-fuzzy inference system (ANFIS) was used to predict the compressive strength of concrete produced with diesel contaminated sand. Concrete produced using sand contaminated with diesel at 0, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 5 and 10 percent were each cured for 7, 14, 28, 58, 90 and 118 days. The compressive strength of the concretes were measured for each percentage contamination and curing days. Subsequently, an ANFIS model was developed and used to predict the compressive strength of the concrete. The ANFIS model predictions with a correlation coefficient (R) of 0.9877 predicted better than a fuzzy logic (FL) model which predicted with R value of 0.9086. The results show that ANFIS model could be used to predict the compressive strength of concretes produced with diesel contaminated sand.

Keywords: Neural-Fuzzy; Concrete; Diesel; Compressive Strength; Modelling

1. INTRODUCTION

Petroleum products which are often transported from one point to another via pipelines and tankers often spill and pollute the environment. These spills which occur due to pipeline vandalization, from natural causes or accidents, often spill crude oil and petroleum products on the environment. Such spills are a frequent sight in several parts of Nigeria, most especially in the Niger delta Region. The spills not only pollute the environment but also affect the quality of building materials used in these regions. For quality assurance of building materials, it is often very necessary to model the effects of contaminants on the strength of concrete used in buildings.

The effects of Crude Oil Impacted Sand (COIS) on the compressive strength of concrete was investigated by Ajagbe et al. [1]. The result they obtained showed that an 18–90% compressive strength was lost due to 2.5–25% crude oil contamination, respectively. Diab [2] investigated the impact of used engine oil on the compressive strength of concrete. The result they obtained showed that for low and high strength concrete, the reduction in compressive strength is 17 and 11.8 percent respectively. Attom et al. [3] studied the effect of sand contaminated with kerosene and diesel on the compressive strength of conventional normal weight concrete. The test results they obtained showed a noticeable reduction up to 42% in the concrete compressive strength as the level of contamination increases. From the works above and the works of other researchers it is imperative to model the effect of petroleum products on the strength of concrete materials. This is ever more important in the light of frequent collapse of buildings in Nigeria and in several developing countries. Hence the need to model the effects of crude oil and petroleum product contaminants on concrete strength is very important because as a result of lax environmental regulations, spills are often not cleaned, and the discharge of petroleum products like engine oil often do not follow laid down environmental standards.

The quality of concrete is primarily determined by its strength. Traditionally, laboratory trial mixes have been used to determine the strengths of concrete [4, 5]. It would be time consuming and costly to use experiments to determine the effect of crude oil and petroleum product contaminants on concrete strength. Hence, it is imperative that mathematical models and computational techniques should be sought to reduce cost and time. The fact that the development of mathematical models is often tasking and complex, and sometimes do not predict material properties very well, necessitates the use of computational modelling techniques such as fuzzy logic, neuro-fuzzy and artificial neural networks for modelling material or concrete properties [4, 5, 6]. The literature is replete with several works on the application of ANNs and Fuzzy Logic to the prediction of strength of engineering materials.

Basyigit et al. [7] predicted the compressive strength of heavyweight concrete which is produced using baryte aggregates using artificial neural network (ANN) and fuzzy logic (FL) models. Their results showed that ANN and FL systems have strong potential for predicting compressive strength of concretes containing baryte ($BaSO_4$). Ajagbe et al. [8] used feedforward-type artificial neural networks (ANNs) to predict the compressive strength of concrete made from crude oil contaminated soil samples. The result of the research has shown that the use of neural networks is effective in the prediction of the compressive strength of concrete made from crude oil impacted sand. Topçu and Sarıdemir [9] used artificial neural networks and fuzzy logic models for predicting the 7, 28 and 90 days compressive strength of concretes containing high-lime and low-lime fly ashes. The results they obtained showed that artificial neural networks and fuzzy logic systems have strong potential for predicting 7, 28 and 90 days compressive strength of concretes containing fly ash. Sarıdemir [10] developed models for predicting compressive strength of mortars containing metakaolin at the age of 3, 7, 28, 60 and 90 days using artificial neural networks and fuzzy logic. His results in the multilayer feed-forward neural networks and Sugeno-type fuzzy inference models have shown that neural networks and fuzzy logic systems have strong potential for predicting compressive strength of mortars containing metakaolin. Mukherjee and Biswas [11] applied artificial neural networks to the prediction of the mechanical behaviour of concrete materials at high temperature and obtained a very promising result. Oreta and Kawashima [12] proposed an artificial neural network (ANN) based model, to predict the confined compressive strength and corresponding strain of circular concrete columns. Their research showed the importance of validating the

ANN models in simulating physical processes especially when data are limited. The developed ANN model also performed well when compared to some analytical models. Nwobi-Okoye and Umeonyiagu have carried out extensive research on the use of artificial neural network to predict the compressive and flexural strength of concrete made with prevalent coarse and fine aggregate material from eastern Nigeria [4, 5, 13, 14, 15, 16]. The results they obtained showed that neural network is better than regression analysis in predicting the strength of concrete. Other works on the prediction of concrete strength using neural networks include: Lee [17], Kasperkiewicz et al. [18], Ahmet et al. [19] etc.

This research is therefore an attempt to further demonstrate the ability of Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict material strength as exemplified by concrete produced from sand contaminated with diesel.

2. PREPARATION, CURING AND TESTING OF CUBE SAMPLES

The method used to produce the concrete from diesel contaminated sand is hereby described. The coarse aggregate used was granite of 19mm maximum size; it was sourced from Abakiliki, Nigeria. Fine aggregate was fine sharp river sand of 5mm maximum size; it was sourced from Otamiri River, Nekede, Nigeria. The river sand stockpiled was air dried and divided into two parts. One part was used for casting 0% diesel contaminated concrete cubes, while the second was used for diesel oil contaminated cubes production. The sand was contaminated with 0, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 5 and 10% diesel relative to the sand. The concrete was allowed to set for 24 hours. After 24 hours, the cubes were put into the curing tank and cured for 7, 14, 28, 58, 90 and 118 days. The cubes were independently weighed and crushed using a compression testing machine. The cubes were loaded to failure in accordance with BS 1881: Part 116 [20].

3 THE ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The ANFIS is a multilayer feed-forward network consisting of nodes and directional links, which combines the learning capabilities of a neural network and reasoning capabilities of fuzzy logic [21]. According to Hosoz et al. [21] this hybrid structure of the network has the possibility of extending the prediction capabilities of ANFIS beyond ANN and fuzzy logic techniques when they are used alone. Analyzing the mapping relation between the input and output data, ANFIS can determine the optimal distribution of membership functions that would minimize the average absolute error, using either a backpropagation gradient descent algorithm alone, or in combination with a least squares method [21].

Figure 1 shows the architecture of the A first order Adaptive Neuro-Fuzzy Inference Systems (ANFIS). Sugeno Model was used for the inference system.

Assuming two rules for simplicity, the rule for the model is of this nature.

Rule 1

If x is A_1 and y is B_1 then

$$f_1 = p_1x + q_1y + u_1 \quad (10)$$

Rule 2

If x is A_2 and y is B_2 then

$$f_2 = p_2x + q_2y + u_2 \quad (11)$$

The details of the layers of the ANFIS architecture are explained herein.

Layer 1

$O_{n,i}$ is the output of the ith node of the layer n.

Every node i in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{A_i}(x) \ \ for\ i = 1,2 \quad (12)$$

Or

$$O_{1,i} = \mu_{B_{i-2}}(x) \ \ for\ i = 3,4$$

x (or y) is the input node i and A_i (or B_{i-2}) is a linguistic variable associated with this node.

Therefore $O_{1,i}$ is the membership grade of a fuzzy set (A_1, A2, B1, B2).

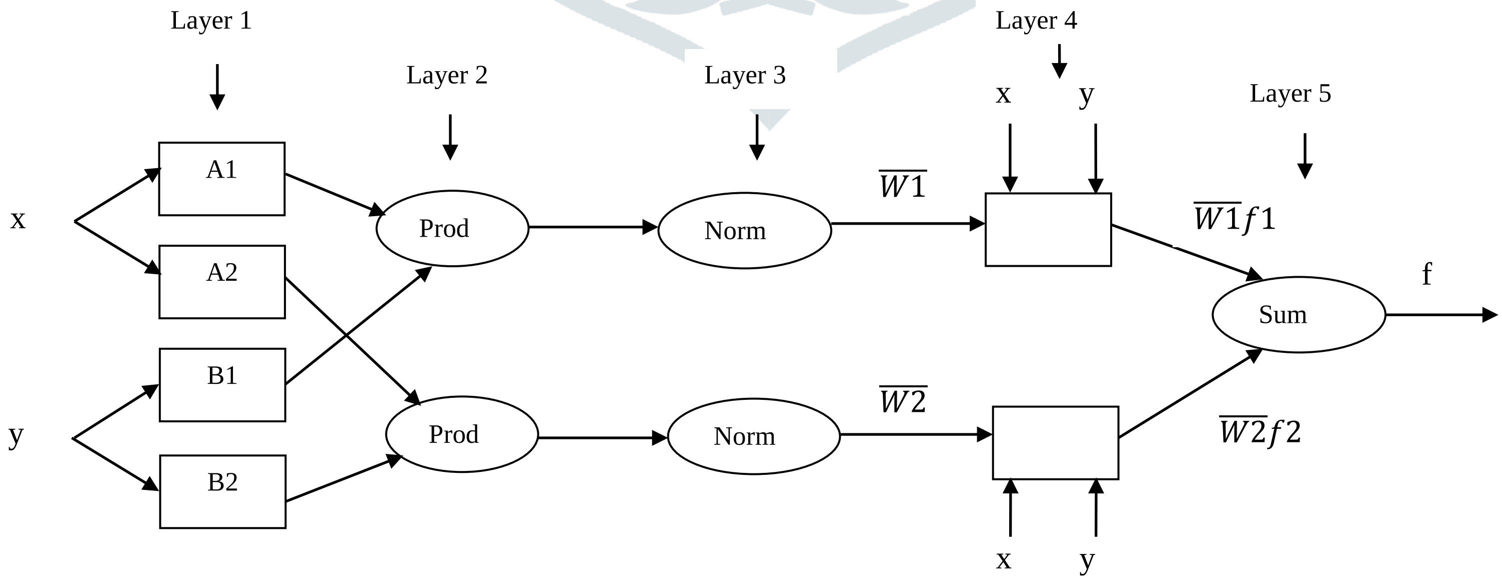

Figure 1: The ANFIS architecture

Layer 2
Every node in this layer is a fixed node labeled
Prod.
The output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y) \quad for\ i = 1,2 \qquad (13)$$

Each node represents the fire strength of the rule
Any other T-norm operator that perform the AND operator can be used.

Layer 3
Every node in this layer is a fixed node labeled Norm.
The ith node calculates the ratio of the ith rule's firing strength to the sum of all rule's firing strengths.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad for\ i = 1,2 \qquad (14)$$

Outputs are called normalized firing strengths.

Layer 4
Every node i in this layer is an adaptive node with a node function:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + u_i) \qquad (15)$$

$\overline{w}_i$ is the normalized firing strength from layer 3.
$\{p_i, q_i, u_i\}$ is the parameter set of this node.
These are referred to as consequent parameters.

Layer 5
The single node in this layer is a fixed node labeled sum, which computes the overall output as the summation of all incoming signals:

Overall output = $O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$ (16)

4 ANFIS FOR PREDICTING FLEXURAL STRENGTH OF CONCRETE

Recall that our application is for concrete strength prediction, and we used supervised learning. Hence, Seventy (70%) percent of the data (54 samples) was used for training, while thirty (30%) percent (23 samples) was used for testing and validation. The number of epoch was set to 100. The epoch was set to 100 not for any theoretical reasons but to ensure that there is sufficient number of iterations during the learning process. Also learning was fast at this level and the optimum performance was obtained in all cases when the epoch was less than 20.

Figure 2 shows the adaptive neuro-fuzzy inference system (ANFIS) for predicting the compressive strength of concrete. As shown in Figure 2, percentage diesel contamination and curing days are inputs to the fuzzy inference system, while the compressive strength derived from defuzzification is the output. The membership function for curing days is shown in Figure 3, while that of the percentage diesel contamination is shown in Figure 4. The membership function shown in Figure 7 consists of seven linguistic variables namely: Extremely short (Es), Very short (Vs), Short (S), Medium (M), Long (L), Very Long (VL) and Extremely Long (EL). The membership function shown in Figure 8 consists of five linguistic variables namely: Very low (VL), Low (L), Medium (M), High (H) and Very high (VH). The output has 35 membership functions.

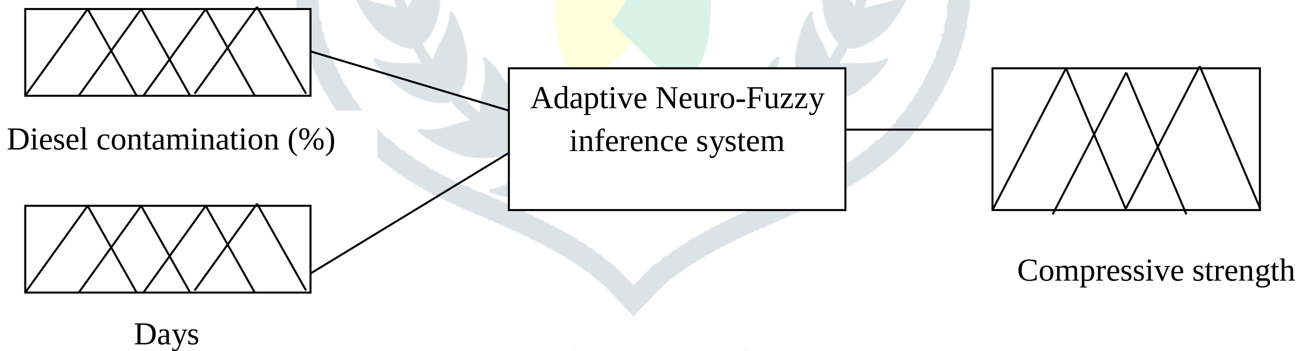

Figure 2: View of the developed fuzzy model

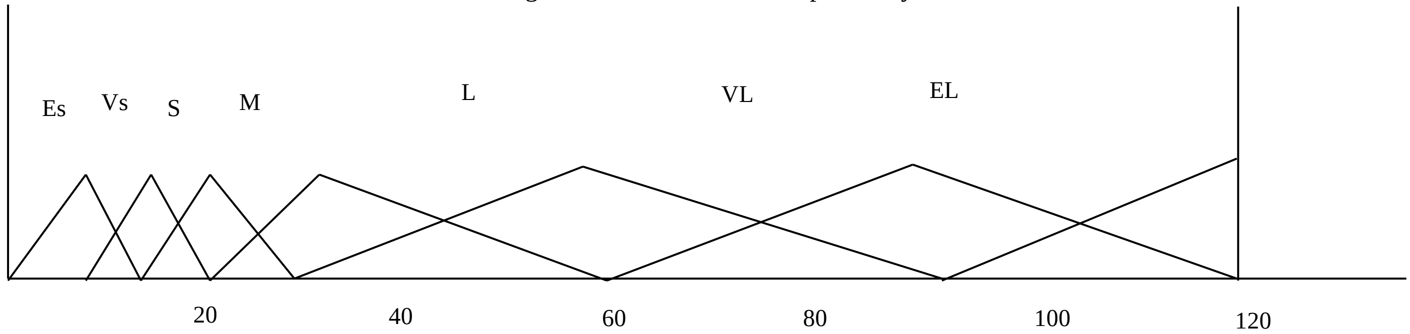

Figure 3: Membership function for days

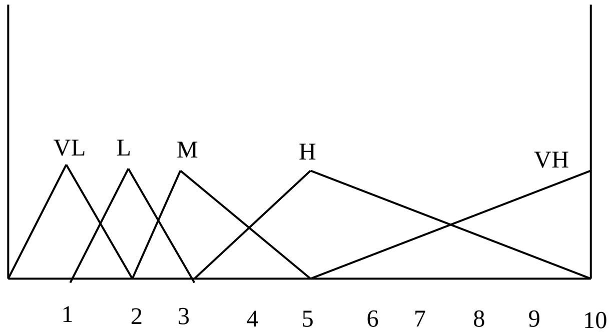

Figure 4: Membership function for percentage diesel contamination

After creating the input and output membership functions, the rules were established. Altogether 35 rules were created. Subsequently, the data was trained to identify the parameters of Sugeno-type fuzzy inference system based on the hybrid algorithm combining the least square method and the backpropagation gradient descent method. After training, fuzzy inference calculations of the developed model were performed. Then, the input variables from the test data set (Diesel contamination (%) and Curing days) were presented to the trained network and the predicted output variables (Concrete strength), were compared with the experimental ones for the performance measurement. The criteria used for measuring the network performance were the correlation coefficient (r) and average error (E).

5 ANFIS MODELLING RESULTS

Table 1 shows the data set for the comparison of the experimental results with the predicted result from ANFIS model and fuzzy model. Figure 3 shows the regression lines for the compressive strength predictions of the ANFIS Model. When compared with a fuzzy model based on MAMDANI fuzzy inference system shown in Figure 4, the ANFIS model with a correlation coefficient (R) of 0.9877 predicted better than the Fuzzy Model which has a correlation coefficient (R) of 0.9086.

Table 1: Data sets for comparison of experimental results with results predicted from the ANFIS model and fuzzy model

Testing Days	**Diesel (%)**	**Compressive Strength obtained from Experiment (KN/m2)**	**Compressive Strength Obtained from Fuzzy Model I (KN/m2)**	**Compressive Strength Obtained from ANFIS (KN/m2)**
7	0	14.3	15.00	14.00
7	0.5	14.1	15.00	14.00
7	1	13.8	15.00	14.00
7	1.5	13.6	15.00	14.00
7	2	13.3	15.00	13.30
7	2.5	13.2	15.00	13.20
7	3	13.01	15.00	13.00
7	3.5	12.9	12.00	13.40
7	4	12.6	10.60	12.90
7	5	12.2	8.33	12.20
7	10	11.1	8.33	11.10
14	0	22.6	15.00	22.00
14	0.5	22.4	25.00	23.00
14	1	21.8	25.00	22.00
14	1.5	21.2	22.50	21.20
14	2	20.1	20.00	20.10
14	2.5	19.8	20.00	19.80
14	3	19.4	20.00	19.40
14	3.5	18.2	18.60	18.20
14	4	17.5	17.50	17.00
14	5	16.2	15.00	16.00
14	10	11.5	8.33	12.00
21	0	24	15.00	24.00
21	0.5	23.8	25.00	24.00

21	1	23.2	25.00	23.20
21	1.5	22.5	22.50	22.50
21	2	21.9	20.00	22.00
21	2.5	21.4	20.00	21.00
21	3	20.5	20.00	20.00
21	3.5	19.6	20.00	19.40
21	4	19.1	20.00	19.00
21	5	18.9	20.00	18.00
21	10	13.7	15.00	14.00
28	0	24.8	15.00	24.80
28	0.5	24.5	25.00	24.00
28	1	24.3	25.00	24.00
28	1.5	24.1	25.00	24.00
28	2	24	25.00	24.00
28	2.5	23.9	25.00	24.00
28	3	23.6	25.00	24.00
28	3.5	23.4	25.00	23.40
28	4	23.2	25.00	23.00
28	5	23.1	25.00	23.10
28	10	19.2	20.00	20.00
58	0	26.5	15.00	20.00
58	0.5	26.2	25.00	26.00
58	1	26.01	25.00	26.00
58	1.5	25.9	25.00	26.00
58	2	25.8	25.00	26.00
58	2.5	25.71	25.00	26.00
58	3	25.64	25.00	26.00
58	3.5	25.6	25.00	25.60
58	4	25.55	25.00	25.50
58	5	25.4	25.00	25.40
58	10	22.5	20.00	22.00
90	0	27.4	15.00	27.40
90	0.5	26.1	25.00	26.10
90	1	24.9	25.00	24.90
90	1.5	23.5	25.00	23.50
90	2	22.8	25.00	22.80
90	2.5	21.6	22.50	21.60
90	3	20.2	20.00	20.00
90	3.5	19.45	20.00	19.40
90	4	18.2	20.00	18.20
90	5	17.6	20.00	17.60
90	10	16.3	15.00	16.30
118	0	28.4	15.00	28.40
118	0.5	26.1	28.10	26.10
118	1	23.4	28.40	23.40
118	1.5	21.8	19.50	21.80
118	2	13.7	15.00	13.70
118	2.5	13.7	10.60	13.70

118	3	12.2	8.33	12.00
118	3.5	12.4	8.25	12.40
118	4	12.6	8.05	12.60
118	5	12.8	8.33	12.80
118	10	11.1	8.33	11.10

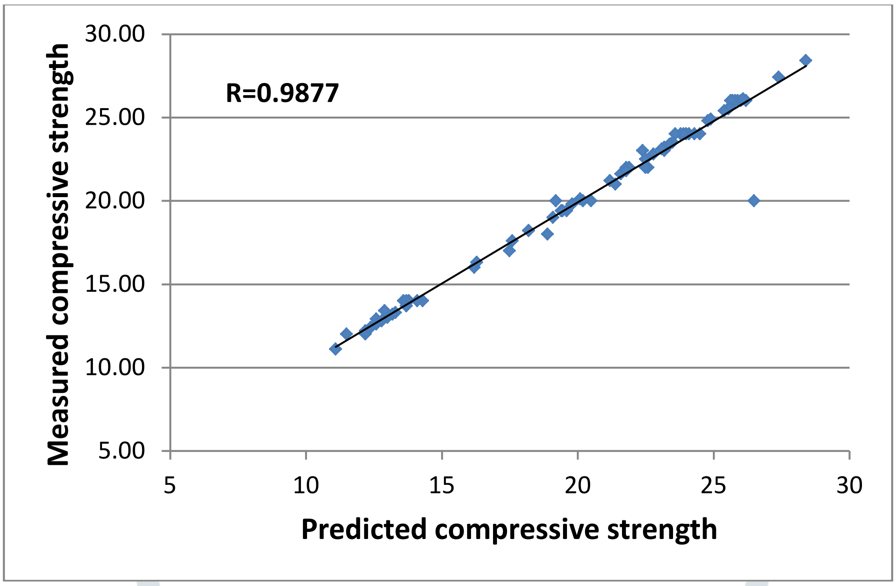

Figure 5: Measured compressive strength vs predicted (ANFIS)

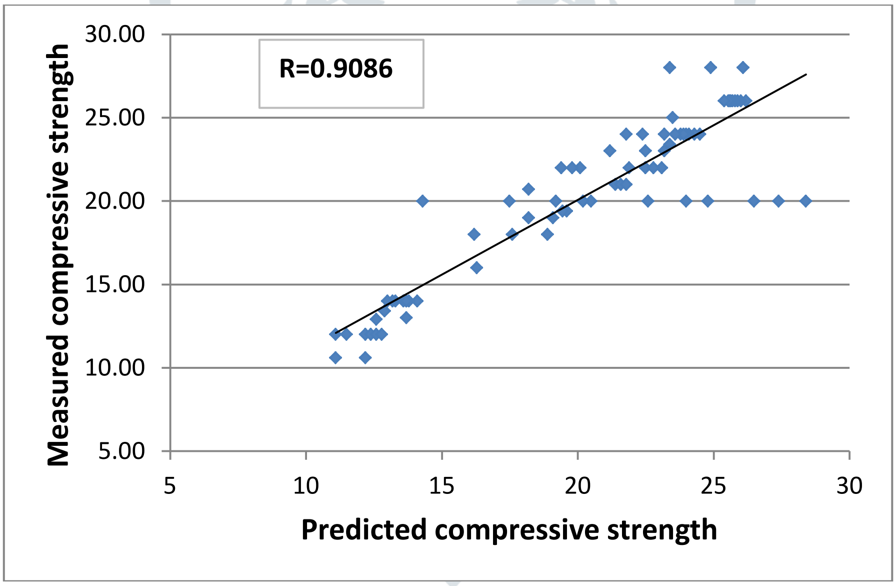

Figure 6: Measured compressive strength vs predicted (Fuzzy Model)

6. DISCUSSION

The analysis in this work show that ANFIS model is excellent in predicting the compressive strength of concrete produced with diesel contaminated sand. ANFIS had better prediction than fuzzy logic model. Generally, the compressive strength of concrete decreases with increasing diesel contamination of the sand used to produce. The ANFIS model prediction with an R value of 0.9877 was better than the FL model prediction of Basyigit et al. [7] which had a value of 0.8264. Hence, it appears that ANFIS is much better in predicting concrete strength than ordinary fuzzy logic (FL) models. Generally, the experimental result showed that the strength of the concrete decreased with increase in diesel contamination for all curing days, confirming experimental results from other researchers such as Ajagbe et al. [1], Attom et al. [3], Diab [2] etc.

7. CONCLUSION

The construction industry is a major component of the economy of any nation. Buildings and structures are indispensable in any modern society. Concrete is the primary building material in Nigeria and other African countries. This study is very expedient because cases of collapsed buildings and structures are endemic in Nigeria and other African countries. These have resulted in the loss of lives and properties. In addition to these, the economy is impacted negatively. Often poor concrete mixtures and inadequate knowledge of the role of concrete mixture properties to its strength are to blame.

As shown in this study, computational models using ANFIS offer a very promising solution to the problem of concrete strength prediction. Computational models are simple because it does not involve complex mathematical analysis. Hence, what the engineer needs is good and reliable computer software and a matching hardware to do his analysis. The ubiquity of various computing platforms ranging from desktop PCs, laptops, palmtops, tablets etc means that such analysis is made even easier. Finally, ANFIS models for other contaminants to building materials used in construction in Nigeria should be developed by engineers and scientists. This will further boost the quality of construction of buildings and other structures.

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