Prediction of the Compressive Strength of Palm Kernel Shell Ash Concrete Using Multilayer Feed Forward Neural Network

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Abstract
This paper developed a multilayer Feed-Forward Artificial Neural Network (MLFNN) model for predicting the compressive strength of concrete containing palm kernel shell ash (PKSA) as partial cement replacement. An experimental study was conducted to determine the 28-days compressive strength of the concrete and the result was used as the target for the MLFNN while five other data were used as the input. The inputs considered in the study are cement content (C), fine aggregate content (FA), coarse aggregate content (CA), palm kernel shell ash content (PKSA) and water-binder ratio (w/b). The correlation coefficient is used to judge the performance of the model while mean absolute error and root mean square error are adopted as the comparative measures against the experimental results obtained from the laboratory.
Keywords: Artificial Neural Network, concrete, palm kernel shell ash, compressive strength, partial cement replacement.

1. Introduction

Concrete is currently the most widely used building material in construction industry all over the world (Aitcin, 2008). It is almost impossible to imagine a construction activity without the use of concrete. Concrete achieves its universal pre-eminence and acceptance as a result of some unique reasons which pertain to high strength and durability. The factors responsible for these are: its constituents are available locally, it is versatile and adaptable, it requires low maintenance cost as it resists water, it does not rot, it does not rust, it does not burn, it is not susceptible to insect attack, it has good aesthetics and is easy to make using simple technology (Newman and Choo, 2003 and Mindess et al., 2003 and). Concrete is a composite material made by mixing a binder (cement), fine aggregates (sand), coarse aggregates (stone) and admixtures with water which makes it set through a process called hydration.

The potential applications of industry/agricultural by-products in concrete as partial replacement for its constituents (depends on their chemical composition and grain size) arises from the environmental constraints in the safe disposal of these products and the need to save the planet from the greenhouse gases associated with both the production and application of Portland Cement (Padmavathi and Preethika, 2016). There is need for safe and economic disposal of agricultural waste materials to produce environmental friendly and cost-effective construction materials.

In recent times, many waste materials like fly ash, periwinkle shell ash, and ashes produced from various agricultural wastes such as palm kernel shell, rice husk ash, corncob ash, millet husk ash, groundnut husk have been researched as pozzolans or supplementary cementitious materials (Arum et. al., 2013). These supplementary cementing materials play an important role when added to Portland cement because they usually alter the pore structure of concrete to reduce its permeability, thus increasing its resistance to water penetration and water related deterioration such as reinforcement corrosion, sulphate and acid attack. PKSA as a material has proven to be a highly effective pozzolanic material (Olulope and Adegbite, 2015). The performance of concrete can be determined by conducting a laboratory experiment to determine the compressive strength. However, to determine the compressive strength require a lot of trial mixing which is time consuming, material wasting and not precise. To avoid the time wastage and inaccurate results, an ANN model can be developed to predict the compressive strength from the laboratory results which can be used on site and does require repeated laborious laboratory work.

This study is envisioned to develop a relationship between the various input parameters (concrete constituents) and output parameter (i.e. 28-day compressive strength) using ANN technique. In the recent years, the use of Computational intelligence techniques which include swamp logic, fuzzy logic and artificial neural network are becoming popular for engineering application. The theory of probability has been established and applied successfully in the fields of engineering and technology.

2. Artificial Neural Network

Artificial neural network is a computational tool focused on artificial modeling the human brain (Kiran and Lal, 2016). ANNs are mathematical models of human neural systems, trying to mimic the intelligence of humans. They are said to have the same network structure as the human brain. The structure consists of many neurons (non-linear calculation units) connected to each other. ANNs bear a resemblance to the brain in two ways which are: a.) knowledge is acquired by the network through a learning process called learning algorithm, b.) Interneuron connection strength known as synaptic weights are used to store the knowledge and involve in the learning through update.

According to Olulope (2014), the specific characteristics of ANNs are

- They can automatically learn to recognize patterns in data from real system or from physical models, computer programs or other sources.
- They can handle many inputs to produce answers that suitable for designers
- They are robust they have high parallelism i.e fast processing and hard ware failure
- They can learn and adaptively allow the system to modify its internal structure in response to changing environment

Other unique features of ANNs are
Non- linearity
Input-output mapping
Adaptivity
Contextual information
Uniformity of analysis and design

The trial model is usually capable of predicting the output accurately even for unseen new data. The first stage of modeling is to partition the dataset into a training set, validation set and a test set. Training set is used to train (fit) the model, the validation set is used to validate the training process and to control over fitting while the test set is used for testing the performance of the model after the training has been performed.

Moreover, ANNs are useful for problems that cannot be easily solved with an algorithm or problems without any mathematical model and that are very complex to describe. Khademika et al. (2016) reported that in the last two decades, ANNs has been a reliable model for efficient monitoring, predicting performance and controlling the operation and variables of processes in the complicated nonlinear and multivariable processes like highway engineering, wastewater engineering, structural and material engineering. ANNs can generally be grouped into Feed-forward neural networks, recurrent neural networks, self-organizing map, and radial basis function.

A multi-layer perceptron (MLP) is made up of multiple layers of nodes in a directed graph, in which each layer is fully connected to the next one. MLP employs a supervised learning technique called back propagation with Levenberg Maerquardt (LM) algorithm for training the network. LM is network training function that update weight and bias.

ANN automatically manages the relationships between variables and adapt based on the data used for their training, thus it is essential to collect a large volume of experimental data to perform the modeling of the system. The accuracy of the predictions of a network can be quantified by the root of the mean squared error (RMSE) difference between the measured and the predicted values, mean absolute error (MAE). This is similar to the root mean square safe that it uses absolute differences instead of squared difference and the multiple coefficient of determination which compares the accuracy of the model with the accuracy of a superficial benchmark model wherein the prediction is the mean of all samples.

This study utilizes the multilayer perceptron (MLP), a feed forward artificial neural network model. A number of databases are collected and examined to establish the input vectors and the output vectors. A new model is proposed based on ANN and then verified against experimental data which are obtained from the laboratory.

3. Application of Multi-layer Feed Forward Artificial Neural Network Techniques (MLFNN)

The multilayer perceptron with back propagation approach has been used for the modeling in ANN technique. Multilayer Feed-Forward Neural Networks (MLFNNs) are the common type of artificial neural networks. Multilayer feed-forward neural networks are used for approximation of a non-linear relationship between input and output. It is the commonly used ANNs for pattern classification which is trained to produce a spatial output pattern in response to an input spatial pattern. The mapping is static and is not at all suitable for a temporal pattern. MLFNN consists of an input layer, an output layer and generally, one or more hidden layers in-between and passes information in one way only as shown in Fig 1. The output is produced when each unit sums it inputs, add the bias to the sum and non-linearly

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transforms the sum. The behavior of the network is determined by the activation function. Various activations functions have been used in literatures to train MLFNN such as: threshold, piece-wise linear, sigmoid, tangent hyperbolic, and the Gaussian function [53]. Linear activation functions are used in this paper because of its precision.

Back propagation is common method of training artificial neural networks so as to minimize the objective function. It is a supervised learning method and a generalization of the Delta rule.

Learning forms the major aspect of the formation of artificial neural network machine. Learning is done based on an optimisation algorithm called gradient

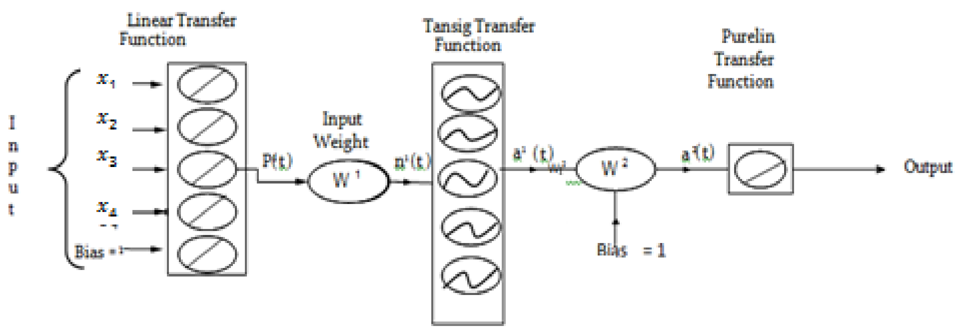

Fig1: Multilayer Feed-Forward Neural Networks

descent. The gradient descent back-propagation algorithm moves the weight along the negative of the gradient. This algorithm has problem such as; operating with fixed learning rate and convergence problem. Over time an improvement has been made by researchers that are based on advanced optimisation methods in order to improve the training time and reduce the memory space. The faster algorithms fall into two categories.

The first category is the heuristic optimisation which was developed from an analysis of performance of steepest gradient descent algorithm such as variable learning rate back propagation.

The second one is the numerical optimisation such as quasi-Newton, conjugate-descent algorithm and Levenberg-Marquardt (LM). LM is preferred and used in this paper because of its speed and accuracy

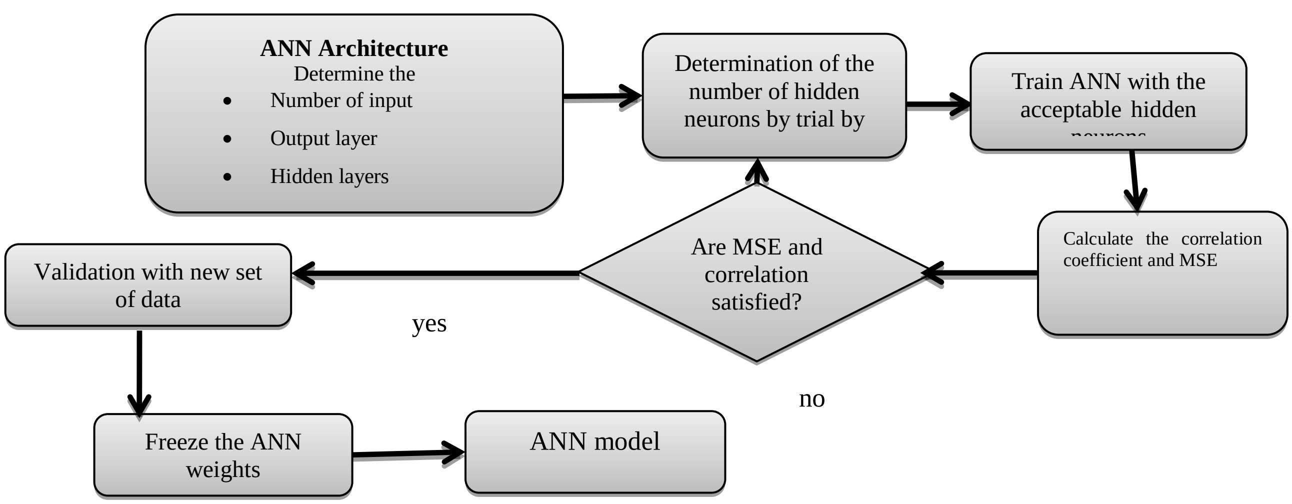

Fig 2: Flowchart for the Development of ANN

4. Data Collection

The data for the models were collected from series of laboratory experiments performed on concretes containing Palm Kernel Shell Ash as partial cement replacement from the department of Civil Engineering, Federal Polytechnic Ado. Table 1 presents a portion of the data used. The major parameters considered in the study are cement content (C), fine aggregate content (FA), coarse aggregate content (CA), palm kernel shell ash content (PKSA) and water-binder ratio (w/b). These five data were used as inputs to the ANN model. 28-days compressive strength was used as target of the ANN. The data were arranged in 2400 by 5 matrix format while the target is arranged in 2400 by 1 matrix format. From the arrangement, it indicates five inputs data and one target. The data were split into 70% for training, 15% for validation and 15% for testing. Matlab Toolbox containing ANN algorithm was used for the training, testing and the validation

Training: Ten (10) hidden neurons were used for the training

Performance Index: Mean square error and regression analysis were used as the performance index. A good training will have one (1) and the maximum value of the regression and zero (0) as the mean square error while a poor training will have zero (0) as the regression results and wide margin from the target as the MSE.

5. Results of the Training and Testing

The training and testing were conducted to show the validity and accuracy of the ANN model. After the training, the regression analysis give a good results which h is 0.997, the regression analysis for the validation is 0.997 while that of the testing is 0.998. The result indicates a good training as well as the testing. The ANN model can be used to predict the compressive strength of the concrete with high precision, accuracy and time. Due to the high speed of data procession and the ANN, it training and testing took 1.36 minutes. This is fast and solves the challenge of waiting for 28 days before obtaining results. The result is shown in figure 3.

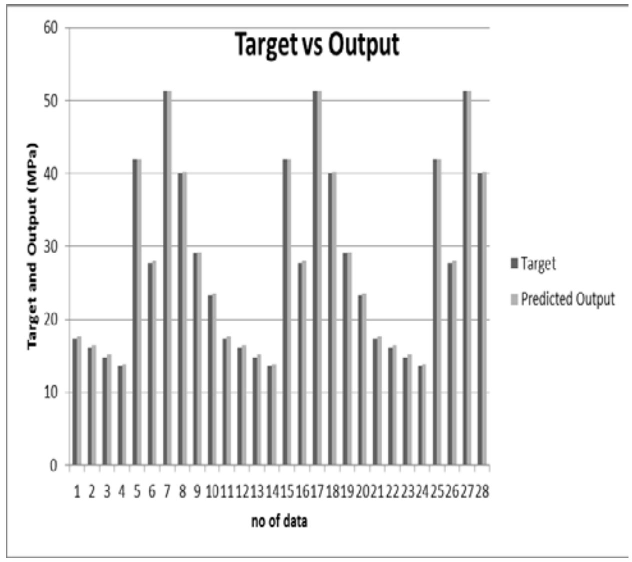

Fig 3: Comparison of Target and ANN predicted output

6. Conclusions

In this paper, prediction of 28 day compressive strength for concretes incorporating palm kernel shell ash has been done. The results show the accuracy of ANN prediction as well as the speed of operation. The results can be relied upon as seen from the performance analysis. The error rate is quite small and the regression result is close to one (1) which is the maximum for an accurate results. ANN is a good computational intelligence technique for prediction.

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Table 1: Presentation of Data, target and the ANN Predicted Output

Cement content kg/m^3	Fine aggregate content kg/m^3	Coarse aggregate content kg/m^3 (CA)	Palm kernel shell ash content kg/m^3 (PKSA)	Water-binder ratio (w/b).	Target (actual comp. strength (MPa)	ANN predicted strength (MPa)	error
6.6	13.9	27.78	0.35	0.5	17.38	17.6762	-0.2962
6.25	13.9	27.78	0.7	0.5	16.13	16.4387	-0.3087
5.9	13.9	27.78	1.04	0.5	14.79	15.1121	-0.3221
5.55	13.9	27.78	1.4	0.5	13.56	13.8944	-0.3344
2.31	749	1040	231	0.4	41.9	41.951	-0.051
168	855	1040	168	0.55	27.8	27.992	-0.192
416	662	1144	22	0.4	51.4	51.356	0.044
315	738	1144	35	0.5	40.1	40.169	-0.069
248	788	1144	44	0.6	29	29.18	-0.18
200	826	1144	50	0.7	23.3	23.537	-0.237
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