Case Studies in Construction Materials xxx (2018) e00185

Contents lists available at ScienceDirect

Case Studies in Construction Materials

journal homepage: www.elsevier.com/locate/cscm

Case study

Artificial neural network evaluation of cement-bonded particle board produced from red iron wood (*Lophira alata*) sawdust and palm kernel shell residues

Olumoyewa D. Atoyebi[a,*], Temitope F. Awolusi[b], Iyinoluwa E.E. Davies[a]

[a] Department of Civil Engineering, Landmark University, Omu-Aran, Nigeria
[b] Department of Civil Engineering, Ekiti State University, Ado Ekiti, Nigeria

ARTICLE INFO

Article history:
Received 12 March 2018
Received in revised form 13 July 2018
Accepted 13 July 2018

Keywords:
Particleboard
Palm kernel shell
Cement-bonded board
Waste
Construction material

ABSTRACT

As a way of promoting environmental sustainability, it becomes paramount to salvage the quantity of agricultural wastes being destroyed or disposed into the environment. A novel strategy to reduce these wastes is by reusing them. In the present study, the physical and mechanical properties of particleboards produced from red iron wood (*Lophira alata*) sawdust and palm kernel shell (PKS) was evaluated by artificial neural network (ANN). The production of this particle boards involved the synergistic combination of effective parameters such as percentage composition of cement, sawdust and palm kernel shell varied between 25–40, 20–50 and 20–50 respectively. The boards were tested for physical properties such as water absorption (WA), thickness swelling (TS), density and mechanical properties such as modulus of rupture (MOR) and modulus of elasticity (MOE). The networks was trained and tested by Multilayer Normal Feed Forward Perceptron (MNFFP), with a quick propagation learning algorithm. The performance of the ANN network shows it has a high potential for predicting the properties of cement bonded particle board.

1. Introduction

The high and rapid demand for forest products as a result of the ever-increasing industrialization and urbanization requires huge amounts of natural resources. This is considered as a major contributing factor to the high deforestation rate worldwide [1]. Deforestation has serious environmental impact and as well contributes to global warming of the earth. One of the ways that has been embraced to control the negative environmental impact of deforestation and bring about sustainability environmentally in the construction is by inculcating wastes in panel based products; this is also an alternative solution for preventing the excessive usage of raw materials [2]. The wide availability of agricultural wastes makes them a suitable and dependable alternative to use, wherever they are abundantly available. The enormous quantities of industrial and agricultural residues and waste are cheaper and abundant; their usages have been reported by different researchers [3–7]. Huge quantities of agricultural residues and wastes are produced annually and are vastly under-utilized in Nigeria [8]. The advantage of incorporating agricultural wastes in the production of panel based product will provide better handling and

Abbreviations: PKS, palm kernel shell; ANN, artificial neural network; WA, water absorption; TS, thickness swelling; MOR, modulus of rupture; MOE, modulus of elasticity; MNFFP, multilayer normal feed forward perceptron.

* Corresponding author.
E-mail address: atoyebi.olumoyewa@lmu.edu.ng (O.D. Atoyebi).

https://doi.org/10.1016/j.cscm.2018.e00185

management of waste generated. This will eliminate the common practice of agricultural waste being burnt in open fields or allowed to decompose. In recent times the possibility of utilizing non-wood ligno-cellulosic biomass in the production of composites including particleboard has arose the interest of researchers [2,9]. Several studies have revealed that processing of particleboard and cement bonded board can be achieved with various agricultural wastes and residues they include, cotton stalks [10], rice husk [11], hazelnut husk [12], kenaf stalks [13], almond shells [14], kenaf core [15], corncob [16] sunflower stalks [17], eggplant stalks [9], waste grass clippings [18] and bagasse [19].

In recent times, particleboard comes with different properties like maximum design flexibility for easy production lines, reliable quality, dimension variety, easy-to-use physical characteristics [20]. It can be used for a varieties of purpose such as office and residential furniture, soundproof, home decking, ceiling, roofing, and shuttering, cabinets, partitioning, cladding stair treads, underlaying floor, table, shelving, store fixtures, wall bracing, ceiling boarding, constructions in the home, sliding doors, kitchen shelves, interior signs, exam pad, photo lamination, low cost cabins peaker box, bulletin boards, packing boxes, thermal insulation and other industrial product. There are many factors affecting the characteristics of the particleboards and the most prominent among them are species of wood, fibre structure, density, hardness, compressibility, type and size of particles and technique of particle drying [3]. Other factors include particle screening and separation, particle size distribution, type and amount of binding agents, method of mat formation, structure of particleboard, moistening of particles prior to pressing, final moisture content of board, conditioning, curing conditions, thickness of board [21]. In 1993, the estimated quantity of sawn wood and wood based panel products consumed in Nigeria is 2.866 and 0.121 million m^3 respectively. This estimated quantity is expected to increase to 4.704 and 0.688 million m^3 by the year 2010 [22]. The oil palm industry is one of the most important agro-industries in countries, such as Malaysia, Indonesia, Thailand and Nigeria. Nigeria is the fourth largest producer of palm oil in the world and one of the major problems associate with the processing of palm fruit is the large amount of solid waste generated in the process. These solid wastes include oil palm bunches, palm fibre and palm kernel shells [22].

To date, there are two categories about the prediction of concrete compressive strength. The first category is traditional mathematics statistical forecasting methods which needs a huge amount of data and the second category, nonlinear prediction methods, lacks a unified mathematical theory. More attentions have been paid to models based on artificial intelligence. Machine learning techniques, such as artificial neural network (ANN) is increasingly used to simulate the strength of concrete materials and has become an important research area. Artificial Neural Network (ANN) is a computational method with a highly organized network structure that can be used to understand complex system. It is stirred by studying the brain and nervous system in biological organisms [23–25]. The network has the ability to learn from examples through iteration, without requiring a prior knowledge of relationships between variables under investigation. Each example contains the experimentally obtained inputs and response. ANN tries each example in turn using the inputs to calculate answers which it compares to experimentally obtained response. If it is wrong, ANN corrects the network by making changes in the internal connections (weights). The trial and error process continues until the network outputs are in good agreement with patterns to a certain specified level of accuracy [26–29]. Muthupriya et al. [30] explored a multilayered feed forward neural network of ANN in predicting the compressive strength and durability of concrete. The ANN was able to predict these properties with good level of accuracy [30]. This study focuses on reducing the excessive demand for timber product by providing an alternative material for producing particle board. The particleboards produced were investigated for physical and mechanical properties namely thickness swelling, water absorption, density, modulus of elasticity and modulus of rupture.

2. Experimental section

Cement, Calcium chloride, Red iron wood sawdust and Palm kernel shell (PKS) used in the study were locally sourced. The cement type was Grade 42.5, ordinary Portland cement produced by Dangote group of companies.

The chemical additive used was $CaCl_2$ with dosage administered 3.0% by weight of the cement. The PKS was properly cleaned to ensure the removal of all foreign materials before drying. Hammer mill was later used to grind the PKS to different particle sizes before carrying out hot water pre-treatment at a constant temperature of 80^oC for one hour. This was to ensure further breakdown of inhibitory sugar compounds capable of hindering cement hydration [31]. After one hour the water was drained off and the same treatment was carried out on saw dust. The same process was repeated for both samples using cold water for another one hour. The pretreated PKS and saw dust were then dried separately under the sun to a moisture content of about 12% before board formation. The particles of sawdust and PKS retained on sieve of aperture size 0.600mm were used for the production of the cement-bonded board. In previous researches, it has been established that increase in cement/wood ratios will have an adverse effect on bending stiffness (MOE) and strength (MOR) of the board [2], this work looks into cement quantity being less in three different cement/waste ratios of 1:1.5, 1:2 and 1:3. Nine (9) different board compositions were produced; the compositions for the boards which are presented in Table 1 were used to observe the relationship between the composite materials and the board strength.

2.1. Mat formation and processing

The wooden mould has a dimension of 350 mm x 350mm x 32 mm and a cover of 20mm. The cover was made to fit properly into the mould and as well ensure final thickness of 12mm for boards produced. Boards produced were covered with polythene sheets for easy removal of boards from mould. The required amount of additive (calcium chloride ($CaCl_2$)) for each

Table 1
Experimental Design.

Specimen	% Composition of Cement	% Composition of Sawdust	% Composition of Palm Kernel Shell
A	40	40	20
B	40	30	30
C	40	20	40
D	33.3	33.3	33.3
E	33.3	22.2	44.5
F	33.3	44.5	22.2
G	25	25	50
H	25	50	25
I	25	37.5	37.5

cement-bonded board was dissolved completely in the required quantity of water as presented in Eq. (1). The dry mix of the sawdust, palm kernel and cement was evenly mixed before the water solution was added to it (Fig. 1).

$$\text{Volume of water (litres)} = 0.35C + (0.30 - M)W \tag{1}$$

Where $C = \textit{Weight of Cement}\ (kg)$, $M = \textit{Sawdust Moisture content}\ (oven - dry\ basis)$ and $W = \textit{Sawdust weight}\ (oven - dry)$.

A wooden caul plate was used to pre-press the formed mat inside the mould to reduce the thickness before loading to the cold press. Polythene sheet was used to cover the top of the mould with the mixture before placing the metal plate; this was transferred to the hydraulic press and allows for cold pressing under a pressing pressure of about $1.23N/mm^2$ for a period of 24 h. After pressing, the demoulded boards were cured for another 28 days in polythene bags; the bags were sealed tightly to prevent loss of water. The test specimens were cut on a circular saw and trimming of the edges was done to ensure smooth board testing. The board was further cut into various test specimen sizes and subjected to tests in accordance with the procedures stipulated in ASTM D 1037-93 [32]. The percentage of water absorption (WA), thickness swelling (TS) and board density were determined manually while the modulus of elasticity (MOE) modulus of rupture (MOR) and of the boards was determined using the Testometric Tensile testing Machine (M500-50AT)

2.2. Experimental procedure

- **Water Absorption Test**
  The test specimens with dimension $50mm \times 50mm \times 12mm$ were immersed in water (at room temperature) for moisture uptake for 2 h and 24 h. Water absorbed was determined as the percentage increase in weight of the particleboard over the original or initial weight as given by Eq. (2).

$$\mathrm{WA} = \frac{\mathrm{W2} - \mathrm{W1}}{W1} \times 100 \tag{2}$$

  Where: $WA = \textit{water absorption}\ (\%)$, $W_1 = \textit{initial weight}$, $W_2 = \textit{final weight}$
- **Thickness Swelling Test**

(a)  (b) 

Fig. 1. (a) Sawdust particles (b) Palm Kernel Shell particles. [24].

The Thickness swelling of boards after immersion in water for 2 h and 24 h at room temperature was measured using a veneer caliper. Thickness swelling was determined as the percentage change in length (increase) over the initial thickness using Eq. (3).

$$TS = \frac{T2 - T1}{T1} \times 100 \tag{3}$$

Where: $TS = thickness\ swelling\ (\%);\ T2 = final\ thickness;\ T1 = initial\ thickness$

- **Density Test**

The cement-bonded boards were cut into $50\,mm \times 50\,mm$ to determine the density property of each board type. Density test was carried out on the cement bonded board to determine the density for each board type as given by Eq. (4) [33].

$$\delta = \frac{m}{v} \tag{4}$$

Where: $\delta = density\ of\ the\ sample\ test\ piece,\quad m = mass\ of\ each\ sample\ test\ piece\ (Kg),\quad v = volume\ of\ the\ sample\ test\ piece\ (m^3)$

- **Modulus of Rupture (MOR)**

Test specimens with dimension $290\,mm \times 50\,mm \times 12\,mm$ were subjected to a load on the universal testing machine. The specimens were gradually and continuously loaded to the point of failure and the failure load was recorded for each specimen. The Modulus of Rupture (MOR) of the test specimens was obtained using Eq. (5) [34];

$$MOR = \frac{3\rho L}{2bd^2} \tag{5}$$

Where:
$MOR = Modulus\ of\ Rupture;\ \rho = Failing\ load;\ L = Span\ between\ centers\ of\ support\ (mm) = 20 \times d;\ b = Width\ of\ test\ specimen\ (mm);\ d = mean\ thickness\ of\ the\ specimen\ (mm).$

- **Modulus of Elasticity (MOE)**

The panel's stiffness known as the Modulus of Elasticity (MOE) as given by Eq. (6), was determined from the bending test performed on each specimen [34];

$$MOE = \frac{\rho_1 L^3}{4bd^3 H} \tag{6}$$

Where; $MOE = Modulus\ of\ elasticity\ of\ panel\ stiffness,\ \rho_1 = Load\ at\ proportional\ limit,\ L = Span\ between\ center\ of\ support\ (mm) = 20d,\ b = Width\ of\ test\ specimen\ (mm),\ d = Mean\ thickness\ of\ the\ specimen\ (mm);\ H = Increment\ in\ deflection\ (mm)$

2.3. ANN analysis

The most common type of ANN known as the Multilayer Normal Feed Forward Perceptron (MNFFP), which is a back propagation feed forward network available in CPC- X neural power software was used in this study. MNFFP network basically consists of three layers namely input, hidden and output layers. For this type of ANN, information will move in only one direction, forward from the input layer, through the hidden layer and to the output layer. The number of neurons in the input layer was determined by the number of independent variables and the number of neurons in the output layer corresponds to the number of dependent variables. The independent variables are the percentage composition of cement, sawdust and PKS the output variable are the water absorption (WA) for 2 and 24 h, thickness swelling (TS) for 2 and 24 h, density, modulus of elasticity (MOE) and modulus of rupture (MOR). The topology of the neural network to be used is presented in Fig. 2. The aim of every training algorithm is to decrease this global error by adjusting the weights and biases. The performance of the network was measured by the correlation coefficient (R) and coefficient of determination (R^2) using Eqs. (7a) and (7b).

$$R = \sqrt{1 - \frac{\sum_{i=i}^{n} (y_i - o_i)^2}{\sum_{i=i}^{n} (y_i - o_m)^2}} \tag{7a}$$

$$R^2 = 1 - \frac{\sum_{i=i}^{n} (y_i - o_i)^2}{\sum_{i=i}^{n} (y_i - o_m)^2} \tag{7b}$$

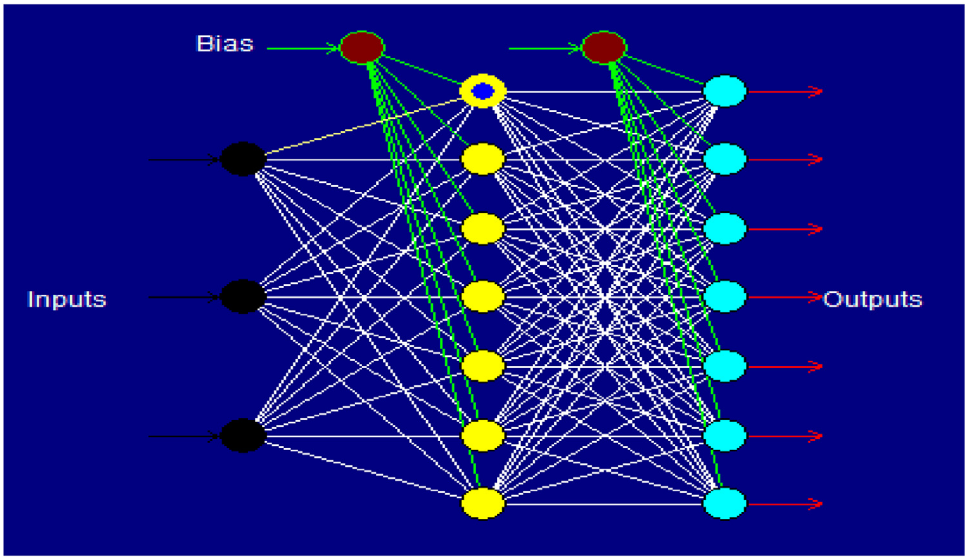

Fig. 2. The neural network topology.

Where Yi is the predicted value, Oi is the observed value, and n is the number of data set and o_m is the average of the observed value [28,35].

The quick propagation (QP) a form of back propagation algorithm was utilized in the study. Although the decision on the number of hidden layers may not be easy to decide, however according to Hush and Horne [36] most often times, not more than one hidden layer is used in a network [36]. The study utilized one hidden layer for the ANN analysis since there was no significant improvement in the generalization capacity of the ANN when the number of hidden layer was increased. In this a single hidden layer comprising of seven (7) nodes was selected for training. The selection of the number of nodes in the hidden layer is a try and error process and the study started training with five nodes and then gradually increased gradually to until a minimum RMSE is observed by the network for the test data set. A further increase in the node will lead to over fitting which reduces the generalization capacity of the network.

The ANN had three input nodes, a single hidden layer of seven nodes, three input nodes and seven output nodes (which can be designated as a 3:7:7 network) is presented in Fig. 2. The transfer function for the hidden and output layer was hyperbolic tangent (Tanh). This transfer function computes its output to the subsequent layer using Eq. (8). In Eq. (8), $\varepsilon(\mu_k)$ denotes the transfer function and Alpha (α) is called slope of transfer function Alpha (α) is a factor related to the shape of the hyperbolic tangent (Tanh) [37].

$$\varepsilon(\mu_k) = \frac{1 - exp(-\alpha\mu_k)}{1 + exp(-\alpha\mu_k)} \tag{8}$$

In addition to the selected transfer function two other parameters are required training the network. These parameters are the learning rate and momentum coefficient. The learning rate is an adjustable factor required to control the speed of the learning process. The momentum coefficient is updates the weight in order to avoid local minima and as well reduce oscillation of weight changes. In the case of QP back propagation algorithm the default learning rate is 0.8 while the momentum coefficient is not employed because the learning process for QP is heuristic in nature [38]. In evaluating the ANN, the data splitting of data into the training and testing subset was done. The following specimen numbers and their corresponding output were used for training (A, C, D, E, F and G) while B, H and I were used as testing data set. The network was trained using the training set. The level of generalization as well as monitoring of overtraining for the training set was kept in check by the test set. The epoch attained at the end of the training was 172 at time elapsed of 15 s.

3. Results and discussion

3.1. ANN analysis for the relative importance of input factors

The amount of contribution made by each of the independent variable (input) to the process is presented in Fig. 3. From Fig. 3 it could be observed that the change in % of sawdust has the most significant contribution to change in output followed by cement and lastly PKS.

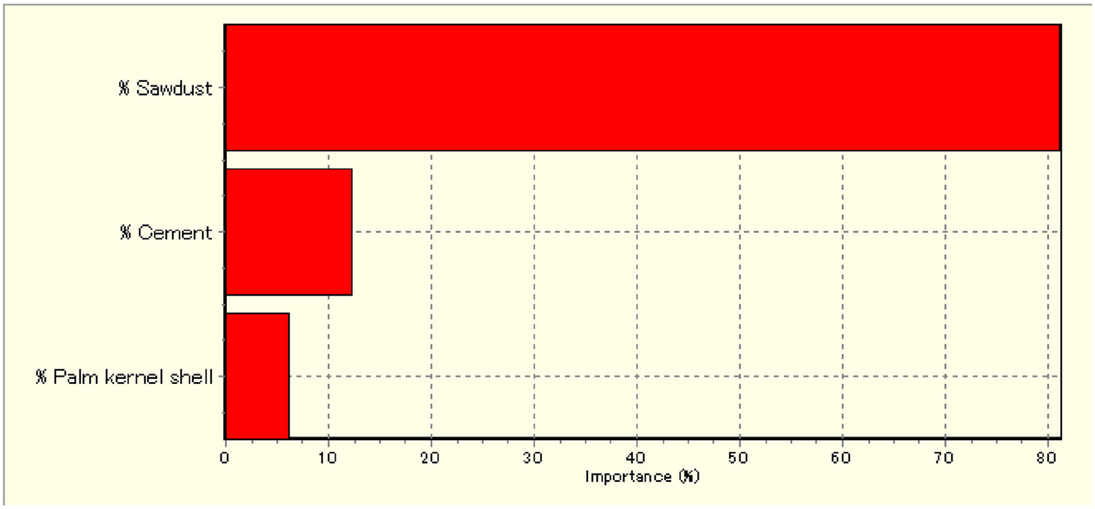

Fig. 3. Importance of effective parameters in the production of particle board.

3.2. ANN predicted values

The comparison of predicted and experimental values in training and testing sets, revealed the generalization capability of ANN in data prediction as presented in Table 2. This implies that the empirical model derived from ANN can be used to describe the relationship between the independent variables and all properties investigated. The correlation coefficient (R) and the coefficient of determination (R^2) were the statistical parameters used for measuring used the check the model performance of the model obtained. The correlation coefficient and coefficient of determination for 2 h WA, 24 h WA, 2 h TS, 24 h TS, density, MOR and MOE 0.87 and 0.76, 0.94 and 0.89, 0.86 and 0.73, 0.86 and 0.75, 0.82 and 0.67, 0.57 and 0.33 and 0.91 and 0.82 respectively. All experimental data presented in Table 2 is an average of four specimens.

The relationship between the predicted and observed values for all properties of the particle board investigated is further illustrated in Fig. 4(a–g). Fig. 4 presents the result of the regression analysis preformed on the data. From Fig. 4 a good relationship was observed between the predicted and the observed values given by the values of correlation coefficient obtained. For the coefficient of determination it could be observed only MOR had a coefficient of determination less than 0.5, however MOR had an absolute fraction of variance (AFV) value of 0.889 as presented in Fig. 4f and obtained through Eq. (9). According to Uygur et al. [47] values of AFV close to one imply better predicting ability of the model. The AFV value obtained for MOR shows a good level of prediction accuracy. The bias for MOR predicted by ANN was further evaluated by the mean prediction error (MPE) of the test data set given by Eq. (10). The value of MPE obtained for MOR was 1.12. The low value of MPE obtained for MOR has demonstrated that the error in predicting MOR is minimal and therefore prediction by ANN for

Table 2
Independent Variables and their corresponding experimental and predicted values.

Specimen	Obs. WA for 2 hours	Pred. WA for 2 hours	Obs. WA for 24 hours	Pred. WA for 24 hours	Obs. TS for 2 hours	Pred. TS for 2 hours	Obs. TS for 24 hours	Pred. TS for 24 hours	Obs. Density	Pred. Density	Obs. MOR	Pred. MOR	Obs. MOE	Pred. MOE
A	1.42	1.7	2.85	3.415	1.41	2.915	2.39	3.67	1639.2	1345.4	8.861	5.506	373.26	255.76
B	**1.14**	**1.14**	**1.93**	**1.9291**	**5.33**	**5.3289**	**6.84**	**6.8409**	**1552.5**	**1552.5**	**5.3**	**5.2999**	**321.43**	**321.43**
C	1.74	1.74	2.53	2.53	0.8	0.80003	1.19	1.19	1533.4	1533.3	4.853	4.8529	428.95	428.96
D	1.64	1.64	2.98	2.9801	0.88	0.88031	1.18	1.1798	1534	1534	4.743	4.743	228.75	228.75
E	1.93	1.7	3.46	3.415	2.52	2.915	3.36	3.67	1453.3	1345.4	4.925	5.506	218.07	255.76
F	1.63	1.63	2.62	2.6203	1.22	1.2204	2.73	2.7298	1520.6	1520.6	4.892	4.8919	153.79	153.8
G	2.06	2.06	3.97	3.97	1.67	1.6701	2.25	2.25	1387.2	1387.2	2.286	2.2858	82.569	82.576
H	**2.26**	**2.2601**	**4.9**	**4.8993**	**0.5**	**0.49908**	**0.5**	**0.50078**	**1051.6**	**1051.5**	**2.695**	**2.6949**	**113.95**	**113.95**
I	**2.04**	**1.7**	**4.06**	**3.415**	**0.72**	**2.915**	**0.72**	**3.67**	**1437.7**	**1345.4**	**2.151**	**5.506**	**185.49**	**255.76**
R	0.87		0.94		0.86		0.86		0.81		0.57		0.91	
R^2	0.76		0.89		0.73		0.75		0.67		0.33		0.82	

Bold characters present the test data set of the constructed ANN models.

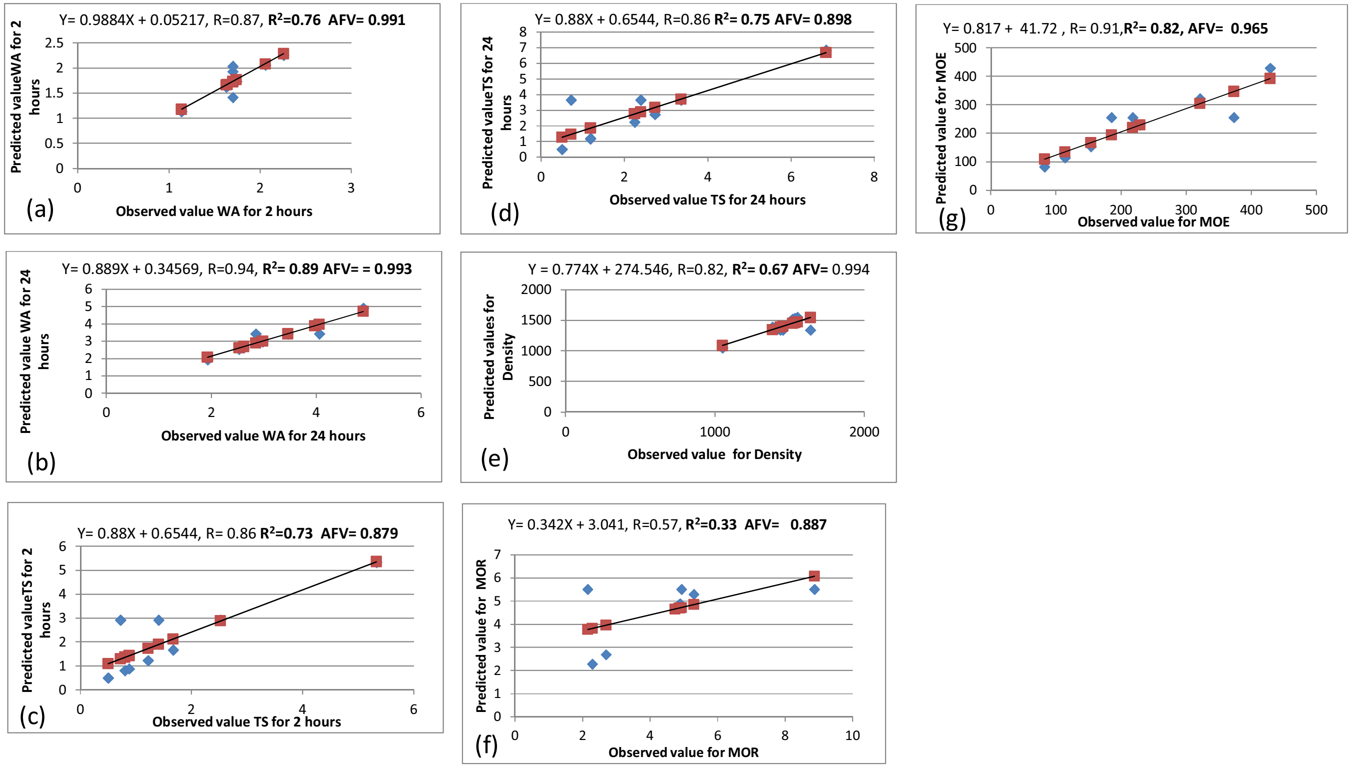

Fig. 4. (a–g): Scattered plot for observed response (in red) versus predicted response (in blue) by QP -ANN. Line represents the linear regression of the predicted and observed value.

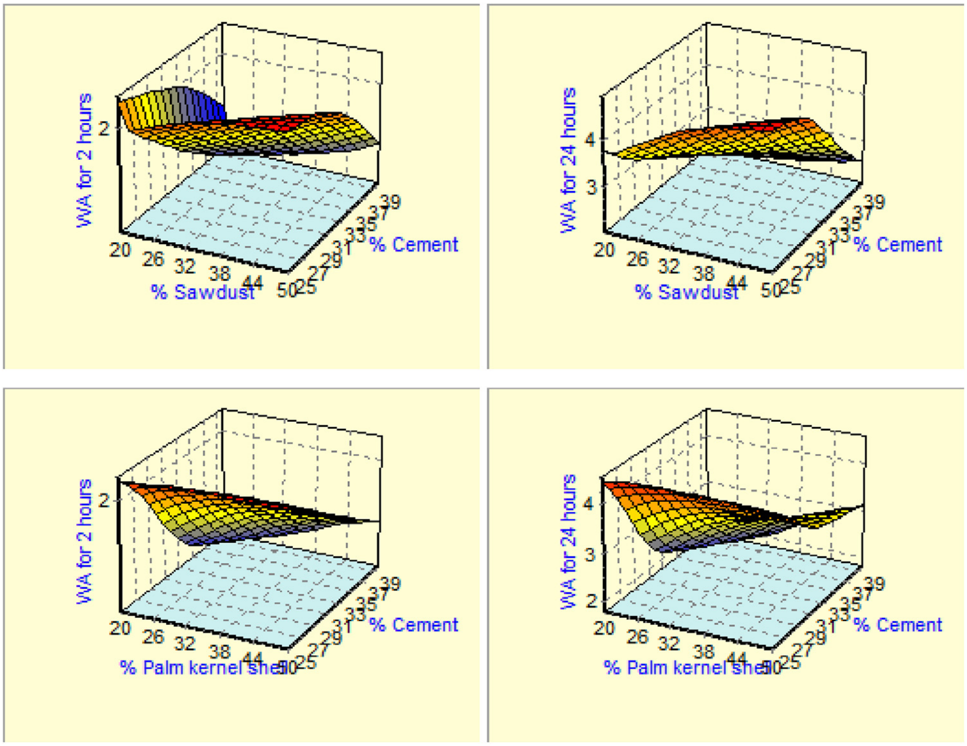

Fig. 5. Three dimensional plots showing the effect of cement, sawdust and PKS for water absorption.

MOR is acceptable.

$$\text{Absolute fraction of variance (AFV)} = 1 - \frac{\sum_{i=i}^{n} (o_i - yi)^2}{\sum_{i=i}^{n} (o_i)^2} \tag{9}$$

$$MPE = \frac{\sum (y_i - o_i)}{n} \tag{10}$$

where Yi is the predicted value, Oi observed value, and n is the number of data set [38,47].

3.3. Effect of production variables on WA, TS and density of the boards

The dimensional stability of the boards produced were measured using water absorption (WA) and thickness swelling (TS). It was observed for 2 and 24 h water absorption that board B had the least value of 1.14% and 1.93% respectively while board H had the highest value of 2.26% and 4.9% respectively. The three dimensional plots presented in Fig. 5 shows that increase in the quantity of % composition of cement and a reduction in the % composition of sawdust will reduce the quantity of water absorbed by the boards. However minimum water absorption can be achieved with % composition of PKS between 26 and 32. The % composition of PKS observed for reduced water absorption is within the range reported by [39], they observed water absorption decreases from 5%–1.06% with increase in PKS inclusion from 10 to 40% for the production of particulate composites. Indian Standard of cement bonded particle boards specification recommends maximum water absorption of 13% for 2 h and 25% for 24 h [40]. All the particle boards produced are within acceptable range for water absorption based on IS 14276: I995 specification.

The thickness swelling (TS) of the boards followed a different trend from %WA (Table 2). It was observed that after immersion in water, for both 2 and 24 h boards H had the lowest value of 0.50% all through while board B had the highest value of 5.33% and 6.84% for 2 and 24 h respectively. The three dimensional plots presented in Fig. 6 shows a reduction in the % composition of cement, sawdust and PKS will give low values of TS. However minimum TS can be achieved with % composition of cement between 29 and 35. From this study, it was observed that Particle boards C, D, H and I had swelling thickness within the acceptable range of 2.0% specified by the International Standard Organization (ISO) [41]

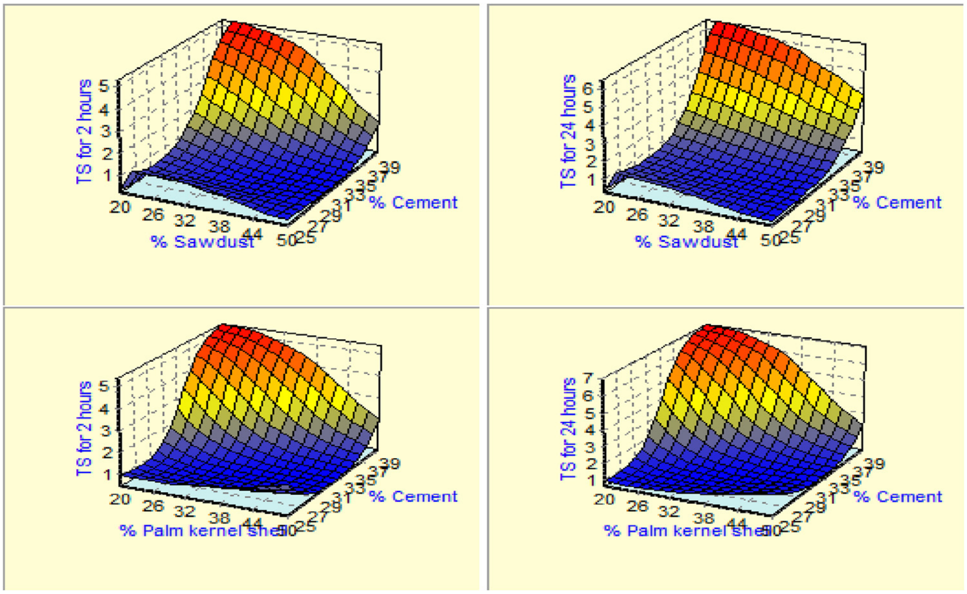

Fig. 6. Three dimensional plots showing the effect of cement, sawdust and PKS for thickness swelling.

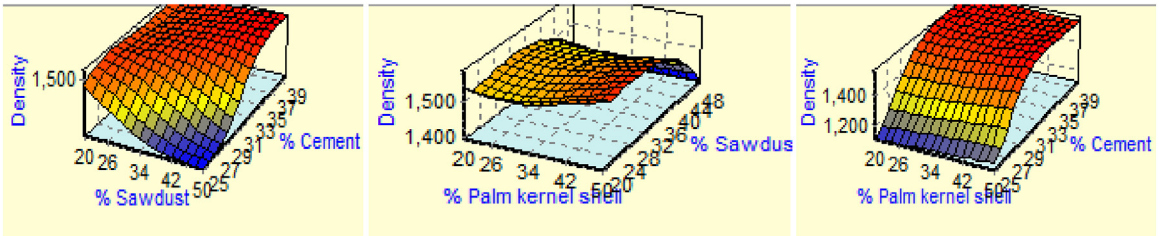

Fig. 7. Three dimensional plots showing the effect of cement, sawdust and PKS for density.

The board H had the lowest density value of 1051.592 Kg/m^3 while board A had the highest density value of 1639.223 Kg/m^3. From the three dimensional plots shown in Fig. 7 the increase in % composition of cement and a reduction in the % composition of sawdust will increase the density while an increase in the % composition of PKS had little or no effect on the density of the particle board. The densities of all the boards produced met the minimum requirement of 1000Kg/m^3 specified by the International Organization for Standardization [41]. The Indian Standard of cement bonded particle boards specification recommends minimum density of 1250 Kg/m^3 [40], all particle boards produced with the exception of board H met this recommended minimum standard. According to the Japanese Industrial standard [42] which recommended a minimum acceptable density value of 800Kg/m^3 and all boards met this requirement.

3.4. Effect of production variables on mechanical properties

The modulus of rupture (MOR) and modulus of elasticity (MOE) was used to measure the mechanical properties of the board. For modulus of rupture (MOR) board A had the highest value of 8.86 N/mm^2, while board I had the lowest value of 2.151 N/mm^2. From the three dimensional surface plot presented in Fig. 8 increase in the % composition of cement will increase the MOR while PKS and sawdust had no significant effect on MOR. Research by Zhou and Kamdem [43] reported MOR values between 5.09 N/mm^2 and 9.52 $N/mm^2$for cement bonded particleboard. In another research by Aladejana and Oluyege [44] MOR values ranging between 0.76 and 10.22 N/mm^2 for boards produced from the wood species was reported. Ajayi and Badejo [45] also reported modulus of rupture ranged from 7.68 N/mm^2 to 9.75 N/mm^2, 5.00 N/mm^2 to 8.67 N/mm^2 and 5.49 N/mm^2 to 8.93 $N/mm^2$for boards made from *G. arborea*, *L. leucocephala* and a combination of both species respectively. MOR values obtained for cement bonded particleboard in the study, were within the range of values reported by the aforementioned researchers. However the American National Standard Institute [46] specifies MOR values ranging

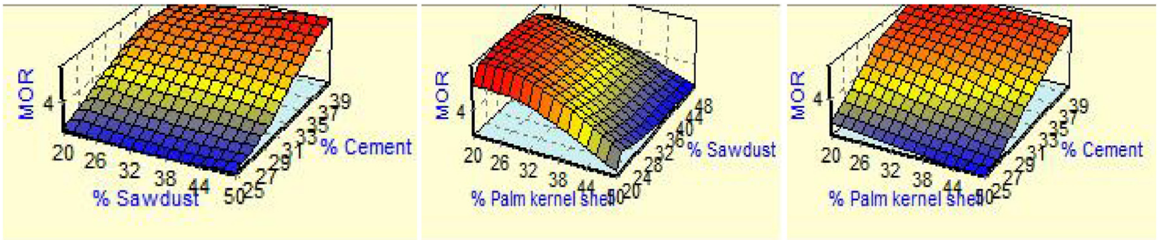

Fig. 8. Three dimensional plots showing the effect of cement, sawdust and PKS for modulus of rupture.

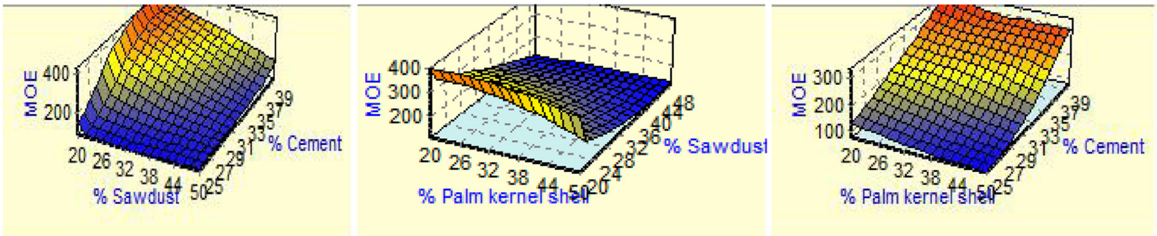

Fig. 9. Three dimensional plots showing the effect of cement, sawdust and PKS for modulus of elasticity.

between 11 N/mm^2 and 16.5 N/mm^2 for Commercial and Industrial purpose particle boards, judging by this specification particle boards produced could be used for non-structural purpose (Fig. 8).

For modulus of rupture (MOR) board C had the highest value of 428.952 N/mm^2, while board G had the lowest value of 82.952 N/mm^2. From Fig. 9 it was observed that increase in % composition cement, reduction in the % composition of sawdust will increase the modulus of elasticity while % composition of PKS had little or no effect on the modulus of elasticity.

4. Conclusion

The physical and mechanical properties of cement-bonded particleboards produced from red iron wood (*lophira alata*) sawdust and palm kernel shell residues was evaluated by artificial neural network. This was done by varying the percentage composition of cement, sawdust and PKS. At the end of the investigation, the following conclusions were drawn.

- Minimum water absorption can be achieved with percentage composition of PKS between 26% and 32%.
- Minimum thickness swelling can be achieved with percentage composition of cement between 29% and 35%.
- The density, MOR and MOE increases with increase in cement content of the boards
- ANN can be a powerful tool for predicting the investigated physical and mechanical properties of cement-bonded particleboards.
- The parameter which majorly influences the particleboards properties is sawdust followed by cement and lastly PKS.

Conflict of interest

This research work is part of a BSc Thesis of Davies Iyinoluwa E.E. and there is no specific grant from funding agencies in the public, commercial, or non profiting sectors.

Acknowledgement

The Authors will like to thank the Management of Landmark University, Omu Aran, Kwara State Nigeria for the laboratory facilities provided to carry out this research work.

References

[1] O. Sotannde, A. Oluyege, P. Adeogun, S. Maina, Variation in wood density, grain orientation and anisotropic shrinkage of plantation grown Azadirachtaindica, J. Appl. Sci. Res. 6 (11) (2010) 1855–1861.
[2] O. Sotannde, A. Oluwadare, O. Ogedoh, P. Adeogun, Evaluation of cement-bonded particle board produced from Afzelia africana wood residues, J. Eng. Sci. Technol. 6 (7) (2012) 732–743.

[3] A. Olorunnisola, O. Adejisan, Trial production and testing of cement-bonded particleboard from rattan furniture waste, Wood Fibre Sci. 34 (1) (2002) 116–124.
[4] F. Aisien, A. Amenaghawon, K. Bienose, Particle boards produced from cassava stalks: evaluation of physical and mechanical properties, S. Afr. J. Sci. 111 (5/6) (2015) 1–4.
[5] S. Odeyemi, M. Akinpelu, O. Atoyebi, R. Yahaya, Determination of load carrying capacity of clay bricks reinforced with straw, Int. J. Sustain. Constr. Eng. Technol. 8 (2017) 2180–3242.
[6] O. Atoyebi, O. Sadiq, Experimental data on flexural strength of reinforced concrete elements with waste glass particles as partial replacement for fine aggregate, Data Brief 18 (2018) 846–859, doi:http://dx.doi.org/10.1016/j.dib.2018.03.104.
[7] O.M. Sadiq, O.D. Atoyebi, Flexural strength determination of reinforced concrete elements with waste glass aspartialreplacementfor fine aggregate, NSE Tech. Trans. J. Niger. Soc. Eng. 49 (2015) 74–81.
[8] A. Ogunwusi, M. Jolaoso, Forest products industry in Nigeria, Afr. Res. Rev. 6 (4) (2012) 191–205.
[9] E. Guntekin, B. Karakus, Feasibility of using eggplant (Solanum melongena) stalks in the production of experimental particleboard, Ind. Crops Prod. 27 (2008) 354–358.
[10] X.-y. Zhou, F. Zheng, H.-g. Li, C.-l. Lu, An environment friendly thermal insulation material from cotton stalks fibres, Energy Build. 42 (2010) 1070–1074.
[11] J. Bamisaye, Cement bonded particle board production from rice husk in southwestern Nigeria, Niger. J. Eng. Appl. Sci. 2 (1) (2007) 183–185.
[12] Y. Copur, C. Guler, M. Akgul, C. Tascioglu, Some chemical properties of hazelnut husk and its suitability for particle board production, Build. Environ. 42 (7) (2007) 2568–2572, doi:http://dx.doi.org/10.1016/j.buildenv.2006.07.011.
[13] H. Kalaycioglu, G. Nemli, Producing composite particleboard from kenaf (Hibiscus cannabinus L) stalks, Ind. Crops Prod. 28 (2006) 177–180.
[14] M. Guru, S. Tekeli, I. Bilici, Manufacturing of urea formaldehyde based composite particleboard from almond shell, Mater. Des. 27 (2006) 1148–1151.
[15] J. Xu, R. Sugawara, R. Widyorini, G. Han, S. Kawai, Manufacture and properties of low-density binderless particleboard from kenaf core, J. Wood Sci. 50 (2004) 62–67.
[16] A.A. Raheem, A.P. Adewuyi, L.O. Azeez, O.D. Atoyebi, O.M. Akanbi, An Investigation of the use of Corncob and sawdust in Ceiling production, Lautech J. Eng. Technol. (LAUJET) 6 (1) (2010) 149–155.
[17] I. Bektas, C. Guler, H. Kalaycioğlu, F. Mengeloglu, M. Nacar, The manufacture of particleboards using sunflower stalks (Helianthus annuus I) and poplar wood (Populus alba L.), J. Compos. Mater. 39 (5) (2005) 467–473, doi:http://dx.doi.org/10.1177/0021998305047098.
[18] G.S. Nemli, E. SametDemirel, A. Gümüşkaya, A. Aslan, C. Acar, Feasibility of incorporating waste grass clippings (Loliumperennel) in particleboard composites, Waste Manag. 29 (3) (2009) 1129–1131.
[19] X. Xu, F. Yao, Q. Wu, D. Zhou, The influence of wax-sizing on dimension stability and mechanical properties of bagasse particleboard, Ind. Crops Prod. 9 (2009) 80–85.
[20] A. Erakhrumen, S. Areghan, M. Ogunleye, S. Larinde, O. Odeyale, Selected physico-mechanical properties of cement-bonded particleboard made from pine (Pinus caribaea M.) sawdust-coir (Cocos nucifera L.) mixture, Sci. Resour. Essays 3 (5) (2008) 197–203.
[21] G. Nemli, Factors affecting the production of e type particleboard, Turk. J. Agric. For. 26 (1) (2002) 31–36.
[22] P. Shafigh, H.B. Mahmuda, M.Z. Jumaat, M. Zargar, Agricultural wastes as aggregate in concrete mixtures – a review, Constr. Build. Mater. 53 (2014) 110–117.
[23] A. Sarkar, P. Pandey, River water quality modeling usin g artifiacl neural network technique, Aquat. Procedia 4 (2015) 1070–1077.
[24] F. Khademi, S.M. Jamal, N. Deshpande, S. Londhe, Predicting strength of recycled aggregate concrete using artificial neural network, adaptive neuro-fuzzy inference system and multiple linear regression, Int. J. Sustain. Built Environ. 5 (2) (2016) 355–369.
[25] O. Gencel, The application of artificial neural networks technique to estimate mass attenuation coefficient of shielding barrier, Int. J. Phys. Sci. 4 (12) (2009) 743–751.
[26] K. Behfarnia, F. Khademi, A comprehensive study on the concrete compressive strength estimation using artificial neural network and adaptive neuro-fuzzy inference system, Iran Univ. Sci. Technol. 7 (1) (2017) 71–80.
[27] N. Shihani, B.K. Kumbhar, M. Kulshreshtha, Modeling of extrusion process using response surface methodology and artificial neural networks, J. Eng. Sci. Technol. 1 (1) (2006) 31–40.
[28] e. Afshin, N.Z. Raja, H.E. Diana, M.B. Ch'ngI, B.S. Abu, A modeling study by response surface methodology and artificial neural network on culture parameters optimization for thermostable lipase production from a newly isolated thermophilic Geobacillus sp. strain ARM, BMC Biotechnol. 8 (1) (2012) 96.
[29] O. Gencel, F. Kocabas, M. Gok, F. Koksal, Comparison of artificial neural networks and general linear model approaches for the analysis of abrasive wear of concrete, Constr. Build. Mater. 25 (8) (2011) 3486–3494.
[30] P. Muthupriya, K. Subramanian, B. Vishnuram, Prediction of compressive strength and durability of high performance concrete by artificial neural networks, Int. J. Optim. Civil Eng. 1 (2011) 189–209.
[31] I. Davies, O. Davies, Agro-waste-cement particleboards: a review, MAYFEB J. Environ. Sci. 2 (2017) 10–26.
[32] ASTM (1995). ASTM D 1037-93, Standard Methods for Evaluating Properties of Wood-based Fiber and Particle Panel Materials, American Society for Testing and Material, Philadelphia, PA, 1995.
[33] BS EN 323, British Standard Institution. Wood-based Panels—Determination of Density, European Committee for Standardization (CEN), London, 1993.
[34] R.S. Fono-Tamo, O. Idowu, F.O. Koya, Development of pulverized palm kernel shells based particleboard, Int. J. Mater. Mech. Eng. (IJMME) 3 (3) (2014) 54–61.
[35] G. Moghaddam, M. Khajeh, Comparison of response surface methodology and artificial neural network in predicting the microwave-assisted extraction procedure to determine zinc in fish muscles, J. Food Nutr. Sci. 2 (2011) 803–808.
[36] D. Hush, B. Horne, Progress in supervised neural networks, IEEE Signal Process. Mag. 10 (1993) 8–39.
[37] CPC-X Software, Neural Power User Guide Retrieved from, (2003) . http://www.geocities.com/neuralpower.
[38] A. Ghaffari, H. Abdollahi, M. Khoshayand, I. Soltani, A. Dadgar, M. Rafiee-Tehrani, Performance comparison of neural network training algorithms in modeling of bimodal drug delivery, Int. J. Pharm. 327 (2006) 126–138.
[39] U. Shehu, O. Aponbiede, T. Ause, E. Obiodunukwe, Effect of particle size on the properties/palm kernel shell particulate composites, J. Mater. Environ. Sci. 5 (2) (2014) 366–373.
[40] IS 14276, Indian Standard. Cement Bonded Particle Boards Specification, Bureau of Indian Standards (BIS) Division, New Delhi, 1995.
[41] ISO 8335, Cement Bonded Particle Board: Board Of Portland Or Equivalent Cement Reinforced With Fibrous Wood Particles, International Organization for Standardization, Stockhom, 1987.
[42] JIS.A.5908, Japanese Industrial standard. Particleboards, Japanese Standard Association, Japan, 2003.
[43] Y. Zhou, D. Kamdem, Effect of cement/wood ratio on the properties of cement-bonded particleboard using CCA-treated wood removed from service, For. Prod. J. 52 (1) (2002) 77–78.
[44] J. Aladejana, A. Oluyege, Assessment of selected physical and mechanical properties of cement Bonded Board Produced from Gliricidia sepium (Agunmaniye), PRO LIGNO 12 (1) (2016) 39–50.
[45] B. Ajayi, S.O. Badejo, Effects of board density on bending strength and internal bond of cement-bonded flakeboards, J. Trop. For. Sci. 17 (2) (2005) 228–234.
[46] A. A208-1-1999, American National Standard Institute. American National Standard -Particleboard, Composite Panel Association, Gaithersburg, 1999.
[47] I. Uygur, A. Cicek, E. Toklu, R. Kara, S. Saridemir, Fatigue Life Predictions of Metal Matrix Composites Using Artificial Neural Networks, Arch. Metall. Mater. 59 (1) (2014) 10–97, doi:http://dx.doi.org/10.2478/amm-2014-0016.