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Development of Carbon-Emission Prediction Model for Halls of Residence in Nigeria

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ABSTRACT

This study identified carbon intensive element of building projects, evaluated the relationship between embodied carbon and cost of building elements and developed a carbon prediction model that could serve as a tool for estimating embodied carbon in the building industry. Relevant data were extracted from Bills of quantities and project drawings of thirty halls of residence of tertiary institution in Nigerian. The data collected were analyzed using percentage to identify the carbon intensive elements, Pearson correlation was used to rank the significance of the relationship between embodied carbon and life cycle cost. In addition, regression analysis was used to establish the predictive power of the independent variables on embodied carbon. Finishes, frames and upper floors were identified as the carbon intensive elements of building projects. The findings suggested that there was significant relationship between embodied carbon and life cycle cost. Floor area and gross internal wall area were found to be the significant predictors of the model. Based on the findings it was recommended that there is need for early design stage carbon estimation, prioritizing carbon intensive elements, and embracing low carbon alternative materials as these will go a long way to achieving carbon emission reduction in the industry.

Keywords: Embodied carbon, building design parameters, regression analysis and carbon intensive elements.

INTRODUCTION

Industrial activities such as manufacturing, mining and construction are responsible for adding over one hundred tons of carbon dioxide daily into the atmosphere, only forty percent of these emissions can be absorbed by nature. However, the remaining sixty percent persist over a longtime in the atmosphere thereby causing global warming, climate change and rise in sea level (Ashworth & Perera, 2015). Carbon dioxide is a naturally occurring gas that is fixed into organic matter by photosynthesis and can also be released as a byproduct of fossil fuel combustion (Boden et al., 2009). Carbon dioxide in the atmosphere hastens global warming, triggering man-made climate change such as storms, flashfloods, tornadoes, hurricanes and droughts, contributes to ocean acidification and disrupt earth thermal balance (Ahmed Ali et al., 2020). The building industry is responsible for thirty eight percent of global energy related carbon dioxide emissions. The processes involved in manufacturing its materials consumes non-renewable energy, materials such as cement and steel (Fernando et al., 2018). Cement emits about half a metric ton of carbon dioxide for every tonnage produced while steel emits nearly two tons of carbon dioxide for every tonnage of steel (Dixit & Singh, 2018). Cement and steel are used in high quantity in building institution halls of residence in Nigeria. Hence using academic buildings as a case study is of necessity considering the need for more of these buildings due to the growing population of students which calls for the need for sustainable construction.

Sustainable construction is the process of developing buildings that are environmentally responsible and efficient in conserving natural resources throughout the life cycle of the building (Ashworth & Perera, 2015). Carbon is an indicator of sustainability as carbon emissions is used as a benchmark for building performance in the construction industry (Matthew et al., 2019). Hence there is need to measure the carbon footprint of construction processes and materials. Carbon emission is classified into embodied and operational carbon. Embodied carbon emission poses a threat to sustainable environment as it accounts for close to eleven percent of total global carbon emissions, its reduction became imperative for both developed and developing countries. About fifty percent of a new development carbon footprint can be traced to its embodied carbon (Chapa, 2019). These created a gap for study on embodied carbon reduction.

M. Victoria et al., (2015) developed a decision support system to optimize the design in terms of cost and carbon during the early stages of design using sample data obtained from database of processed building data. The study found substructure, frames and upper floors to be the carbon hotspot. M. F. Victoria & Perera, (2018) developed a parametric embodied carbon prediction model using historical data collected from an online cost analysis database. Wall-floor ratio and numbers of basements were found to be the significant predictors. This however created a gap for this research as real life and detailed data from existing building projects were used as case study.

Ezema et al., (2016) estimated embodied and operational carbon dioxide emissions associated with a typical urban residential apartment building using the life cycle carbon dioxide assessment approach. Frame and upper floors, finishes were found to be the carbon hotspots. Fernando et al., (2018) compared embodied carbon of an office building and apartment building, the outcome of the study revealed Frame as the element with the best opportunity for carbon reduction. The researchers mentioned above have one thing in common, their knowledge of estimating techniques, which suggest that Quantity surveyors who are knowledgeable in the area of estimating are in the best position to estimate carbon emission. The researchers however encouraged early-stage project's carbon emission estimation as there is potential to cut back embodied carbon emissions through the utilization of building materials that emits less carbon during production (Ranathungage et al., 2018). This study identified elements with high carbon reduction potential, allowing for the most effective embodied carbon reduction possible. A model was developed that will serve as a tool for measuring the carbon dioxide emission of building projects.

METHODOLOGY

This work analyzed the embodied carbon of building elements of the case study projects. The case study projects were some of the halls of residence in Babcock University, Ilishan-remo, Ogun state, Nigeria. Babcock University Halls of residence was used as case study because they are high-rise, framed-structure built with cement and steel which are major contributors to carbon emissions. Also, because they are institutional buildings, institutional buildings accounts for higher embodied carbon emissions compared to domestic buildings (M. F. Victoria & Perera, 2018).

This study was limited to Cradle to Gate system boundary because of the embodied carbon inventory used. This study had limitations in measuring the embodied carbon of electrical, mechanical and plumbing services due to the fact that information on these elements is not available at the early phase of the building project. More so, embodied carbon coefficient on these elements is not readily available.

Table 1; Halls of residence in Babcock University

S/N	Building Type	Quantity
1	Bungalow	16
2	Duplex	12
3	Halls standing at 3 floors height	18
4	Ditto 4 floors	12
	Total number of halls =	58

2.1 Data collection

Data was collected from the project drawings and bills of quantities of the projects understudy using Pro-forma. 30 out of the institution halls of residence that are standing three to four floors in height were chosen as it allowed good level of comparison for example concrete and steel quantities in a bungalow will be less than that of a three-storey building.

Table 2; Data from Project BOQ and Drawings

ID	Hall Name	No of floors	Building height(m)	Floor area(m2)	Gross internal floor area(m2)	Wall area(m2)
1	Adeleke	4	14.40	1597	8756	9888
2	Ameyo Adadevoh	3	12.30	1976	11216	8896
3	Bethel Splendor	3	12.90	1305	7466	8856
4	Courage court	3	12.00	917	7568	8241
5	Crystal	3	12.00	1863	16295	12700
6	Endeavour	4	15.80	1088	5821	7276
7	Endurance	4	15.60	899	3992	5877
8	Felicia Adebisi	3	13.40	4413	25476	24712
9	Gamaliel	3	12.90	908	4083	6053
10	Gideon Troopers	3	13.15	5213	23205	24412
11	Havillah Gold	3	13.15	4997	20394	25368
12	Justice Jeborah	4	15.60	2179	8665	16640
13	Neal Wilson	3	13.15	4618	12764	24428
14	Kings Delight	4	15.45	1479	10068	7536
15	Nelson Mandela	3	13.15	1863	16005	13205
16	Patience	3	12.00	1573	9093	9516
17	Royal	3	12.60	1892	10511	12571
18	Peace court	3	12.30	924	4120	6158
19	Platinum	4	16.40	2280	15196	10196
20	FSD block	4	15.60	360	12562	4966

21	BIG block	4	15.60	410	12586	4980
22	Queen Esther	4	16.40	2940	15742	14982
23	Samuel Akande	4	15.60	1894	16215	12735
24	Trust court	3	12.45	1313	9680	8416
25	Rehoboth	3	12.45	4458	25105	24268
26	Diamond	3	12.45	1505	9578	5883
27	Marigold	3	12.45	4670	15551	11608
28	Welch	4	13.45	1565	7462	13533
29	White hall	4	16.40	1906	18514	11618
30	Winslow	3	12.90	3566	20072	18527

2.2 Overview of the Method

The first step was to convert unit of the project elements to kilogram as the inventory of carbon and energy (ICE) presented embodied carbon coefficient of building components in kilogram. Elements with their respective carbon coefficient listed in kilogram were converted using equation 1;

$EUQ_N = \sum Q_N \text{ x } D_N$ ………………………………………………………equation 1

Where EUQ_N is the element unit quantity of element $_N$, Q_N is the quantity of material of element $_N$, D_N is the density of the material in kilogram. Table 3 presented the buildings elements in kilogram. Second step was to multiply elements quantities with their respective carbon coefficients using equation 2 to generate the embodied carbon for the building projects.

$ECT = \sum EUQ_N \text{ x } ECe_N$ ……………………………………………………. equation 2

Where ECT is the total embodied carbon for the entire building, EUQ_N is element unit quantity of material $_N$ in kilogram, ECe_N is the embodied carbon equivalent in $KgCO_2$ per KG. Table 4 presented the embodied carbon of building elements in $KgCO_2$. Third step was to use Percentage to determine the carbon intensive elements of each project, this was presented in Table 8. The fourth step was multiple regression analysis using embodied carbon data in Table 4 with building design parameters presented on Table 2 above as variables. The last step was validation of the regression model.

2.3 Regression assumptions

The dependent variable is the embodied carbon for the building projects listed on the last row on Table 4. The independent variables (which are Floor area, gross internal floor area, wall area, number of floors and average building height) are presented in Table 2 above. The first step to regression analysis is to test some assumptions to determine the following:

Normality of the variables; this was done by creating a Predicted probability (P-P) plot of the residuals. Residuals simply put are the error terms or differences between the observed values and predicted values. Figure 1 above showed the P-P plot, the residuals had normal distribution as they conformed to the diagonal line in the plot.

Linearity of the variables; this was done by creating a scatter plot to detect linear relationship between the variables. The dependent variable was plotted against the independent variables. Figure 2-6 below presented the scatter plot, there was linear relationship between Embodied carbon and Floor area, gross internal floor area and wall area.

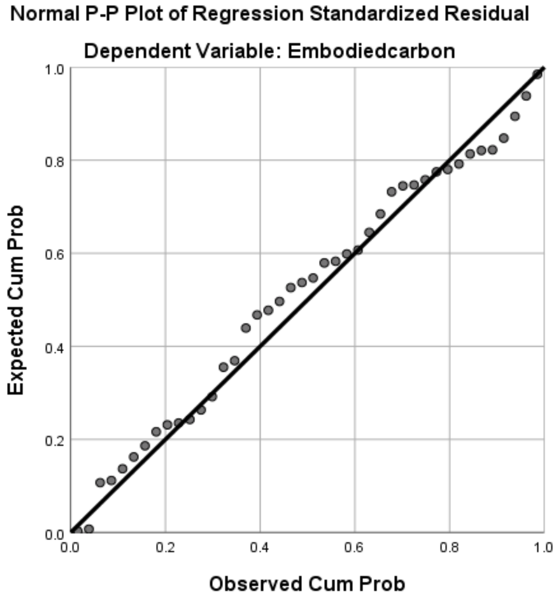


Figure 2; Embodied carbon and wall area scatter plot

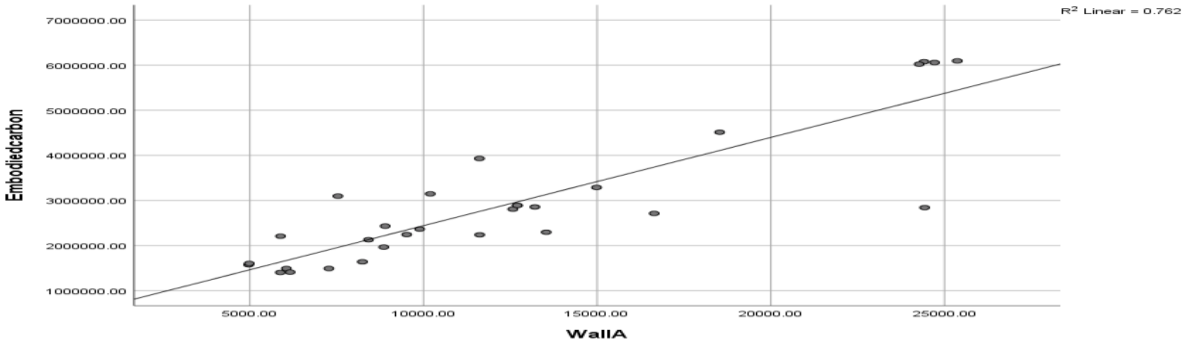


Figure 3; Embodied carbon and average height scatter plot

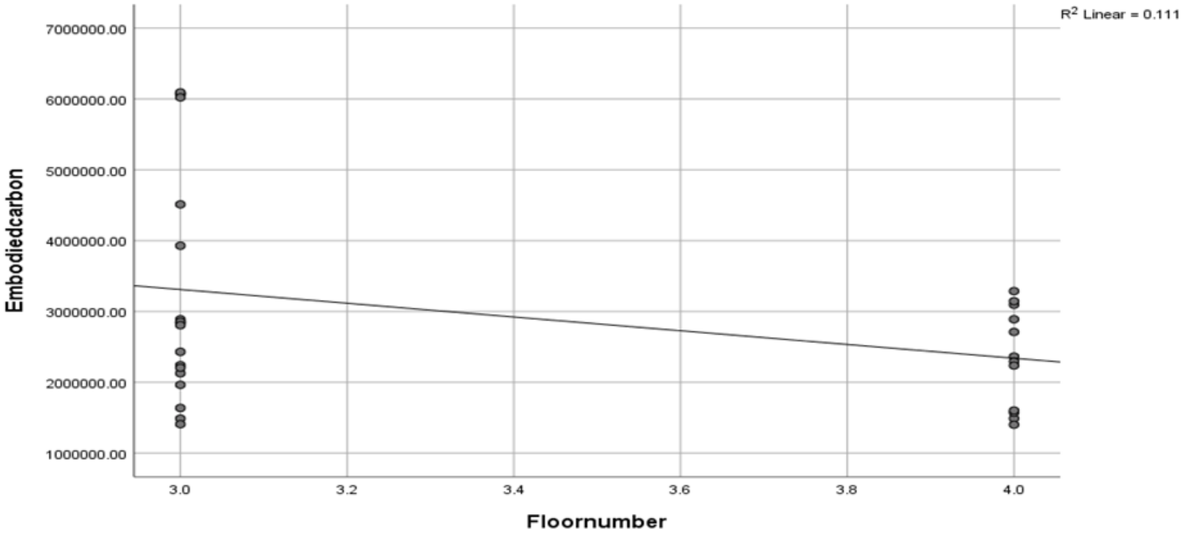


Figure 4; Embodied carbon and number of floors scatter plot

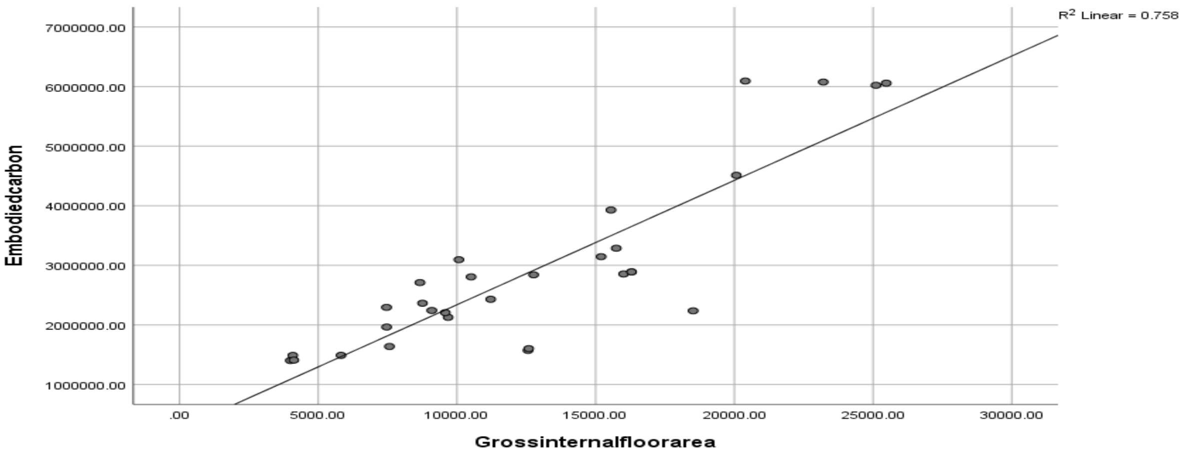
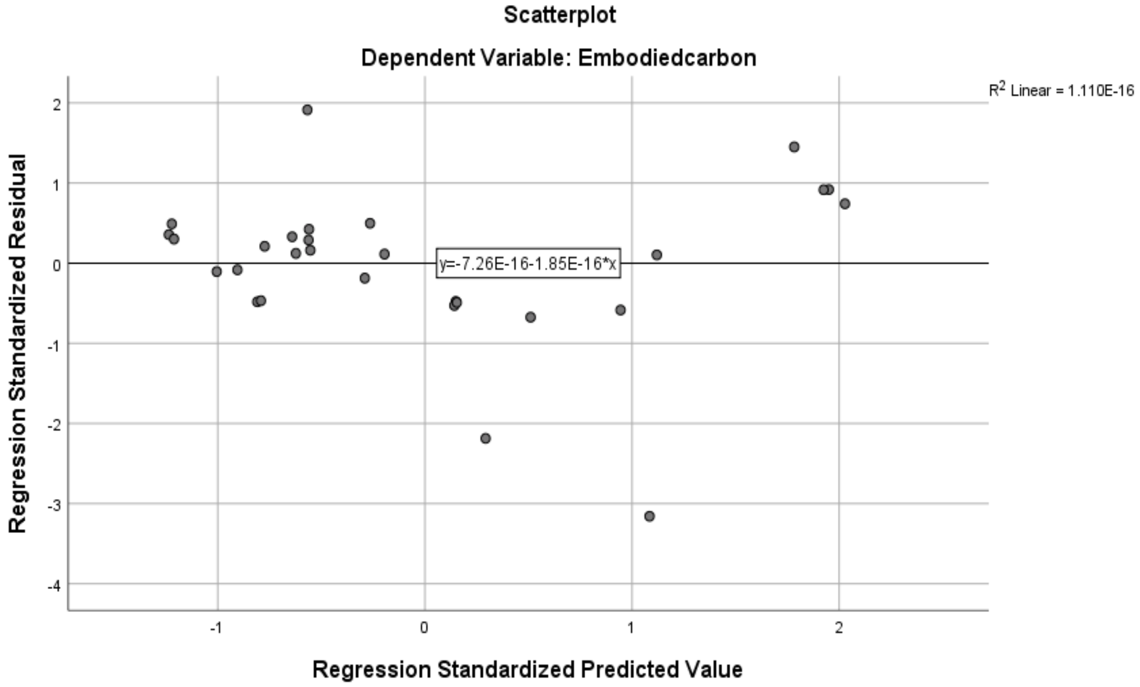


Figure 5; Embodied carbon and gross internal floor area scatter plot

Figure 6; Embodied carbon and floor area scatter plot


Scatterplot

Dependent Variable: Embodiedcarbon

Figure 7; Residual vs predicted value scatter plot.

Homoscedasticity of the variables; this was done by plotting the residual vs predicted values plot, presented in Figure 7 above. The data showed homoscedasticity as it did not have any visible pattern, there are points equally distributed above and below zero on the X and Y axis.

Multicollinearity; this refers to possible interactions between the independent variables. It occurs when two predictors are highly correlated, when this happens the regression coefficient might become insignificant due to large size of standard errors (Leech et al., 2014). Variance inflation factor (VIF) which is the inverse of tolerance value is the measure of multicollinearity. VIF values on Table 6 below which was less than ten showed this assumption was passed.

Durbin-Watson test; it was used to test the autocorrelation of the residuals (which means the residual difference has no pattern). The acceptable result is between 0 and 4 (Ziegel et al., 1999). The result at 2.375, shown on Table 7 below, indicates that there was no autocorrelation of the residuals which meant the model was sound.

Pearson correlation; this is a statistical tool for determining the degree and direction of a linear relationship between two variables. Each of the predictors (floor area, GIFA, wall area, average building height and number of floors) was ranked against the dependent variables that is the total embodied carbon for each project (shown on Table 4). The acceptable significance level is, α<0.050 at 95% confidence interval. From table 5 below, Floor area, Gross internal floor area and Wall area were the only significant predictors for this study with Sig value less than (.050) at (.000).

Table 5; Pearson correlation results

Independent Variables	Floor area	GIFA	Wall area	No of floors	Average height
Sig. level	.000	.000	.000	.072	.325
Pearson correlation	.898**	.871**	.873**	-.333**	-.186**

2.4 Regression analysis

The independent variables that passed the assumptions, floor area, Gross internal floor area and wall area were used to develop the prediction model for the embodied carbon (dependent variable) of the projects. The results were summarized in Table 6 and 7 below.

Table 6; Regression analysis of Embodied carbon and Building design parameters

Variables	Coefficient	t-value	Sig	VIF
Constant	214827.053	.932		
Floor Area	.427	2.774	.010	5.848
GIFA	.415	4.079	.000	2.557
Wall area	.172	1.116	.274	5.825

Table 7; ANOVA and Model summary table

Model	R-value	R square	Adjusted R square	R square change	df	F-value change	Sig. value	Durbin Watson
1	.946a	.895	.883	.895	29	73.614	.000b	2.375

The model summary table reported the strength of the relationship between the model and the dependent variable (embodied carbon). From Table 7, the R-value of (0.946) indicated a strong relationship. R-square (coefficient of determination) represents the power of a model, the closer R square is to 1 the better the prediction, it showed that the model is effective enough to determine the relationship. A low R square means the model does not fit the data well. R-square showed the total variation for the dependent variable that could be expressed by the independent variable (Ziegel et al., 1999). The R square value of (0.895) is good, it implied that floor area and gross internal floor area predicted 89.5% of the variability of embodied carbon.

ANOVA table tested how acceptable the model was from a statistical perspective. The significance value of the F statistic, α<0.050 (5%) level of significance is acceptable for a 95% confidence interval. Sig. value of (0.000) meant the variation explained by the model was not by chance, hence the relationship is significant.

The regression coefficient table provided the impact or weight of a variable toward the entire model that is, it provides the amount of change in the dependent variable for a unit change in the independent variables. Unstandardized coefficients indicate the numbers of deviations that the outcome will change as a result of a change in the predictor variables (Brooks & Thompson, 2017). These tells the amounts of increase in embodied carbon that would be predicted by one unit increase in the predictors. They are referred to as unstandardized coefficients because they are measured in their natural units as such, they cannot be compared to identify which one is more influential in the model (Jain & Priya, 2019). The unstandardized coefficient (shown on Table 6 above) for the constant is the regression model constant which is 214827.053. The coefficient values for the predictors were positive at 0.427 and 0.415, it meant an increase in floor area and gross internal floor area will increase embodied carbon of the projects (Ziegel et al., 1999).

The significant value (α) for wall area predictor variable at 0.274 was greater than 0.050 which meant the predictor did not have a significant relationship with embodied carbon. Floor area α = 0.010, GIFA α = 0.000, indicated 95% confidence that the slope of the regression line is not zero. The significant values were less than 0.050, this meant that there was enough evidence to reject the null hypothesis. Therefore, there is significant relationship between embodied carbon, floor area and gross internal floor area.

3. RESULTS AND DISCUSSION OF FINDINGS

In this section, a detailed analysis of data and results were presented and discussed using tables.

3.1 Results

3.1.1 Regression output

The regression output is as follows;

Embodied carbon = $\beta 0 + \beta FA$ (Floor area) + $\beta GIFA$ (Gross internal floor area) …equation 3

where $\beta 0$ is the regression constant, βFA is the regression coefficient of floor area and $\beta GIFA$ is the regression coefficient of gross internal floor area.

3.1.2 Model Validation

Cross validation test was done for the model using decision trees, classification and regression trees method (CRT) in SPSS. 30 projects that falls within three to four number of floors was used to develop the model; the model developed was tested using 12 projects (within the duplex category) from the research population (shown on Table 1 above). Cross validation was done using the 30 case study projects as training samples and 12 projects as test samples. This was done because it is statistically wrong to test the regression model with the same data used to develop it. Mathematical method for validation was employed using average validity percentage (Alshamrani, 2017) computed using equation 4.

$$\text{AVP} = \frac{\sum^{n} 1-(A_1/C_1)}{n} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{ equation 4}$$

In this study, the total predicted embodied carbon value was 87671554 while the total actual EC value was 86028123. Where AVP is the average validity percentage, A_1 is the predicted value, C_1 is the actual value and n is the number of observations. AVP was 0.967, this meant the predicted model was 96.7% accurate when tested.

3.1.3 Carbon Intensive elements

The last row on Table 4 (Appendix B) presents the total embodied carbon for each project in KgCO2. These data were further analysed using percentage to determine the elements with the highest percentage of carbon emission. The result was presented in Table 8 below.

Table 8; Carbon Intensive elements analysis result

Building ID	Substructure	Frames & upper floors	External & Internal walls	Roof & Roof covering	Windows & Doors	Finishes
1	10.8%	31.0%	10.8%	14.0%	1.5%	31.9%
2	10.1%	33.5%	9.5%	9.3%	1.3%	36.3%
3	9.7%	34.1%	11.4%	8.7%	1.5%	34.7%
4	8.8%	34.5%	12.3%	4.8%	2.3%	37.4%
5	8.4%	29.3%	11.1%	6.1%	1.3%	43.7%
6	8.5%	37.0%	12.3%	5.6%	1.5%	35.1%
7	14.0%	36.5%	10.7%	9.1%	0.6%	29.1%
8	11.2%	28.6%	10.2%	14.7%	1.0%	34.3%
9	13.7%	37.6%	10.3%	8.9%	0.6%	28.9%
10	10.7%	28.4%	10.1%	14.6%	1.1%	35.1%
11	11.7%	29.2%	10.4%	15.1%	1.0%	32.7%
12	9.2%	29.5%	15.3%	17.3%	1.1%	27.7%

13	9.2%	25.3%	21.3%	10.9%	1.0%	32.3%
14	10.1%	29.6%	6.1%	18.8%	1.8%	33.7%
15	8.8%	28.4%	11.7%	6.1%	1.3%	43.7%
16	11.2%	30.9%	11.4%	13.4%	1.2%	31.9%
17	15.5%	29.9%	11.6%	12.5%	1.1%	29.4%
18	10.1%	39.8%	11.1%	9.1%	0.6%	29.3%
19	10.6%	31.0%	8.0%	9.0%	1.4%	40.0%
20	6.9%	28.2%	8.1%	6.5%	0.8%	49.5%
21	7.1%	28.3%	8.0%	6.4%	0.8%	49.5%
22	12.4%	29.7%	11.3%	7.6%	1.4%	37.7%
23	8.6%	29.2%	11.1%	6.1%	1.3%	43.7%
24	8.3%	36.4%	10.1%	9.2%	1.0%	35.1%
25	11.8%	28.6%	9.5%	14.5%	1.0%	34.7%
26	10.4%	35.4%	6.8%	10.0%	2.0%	35.5%
27	12.3%	31.8%	7.1%	16.0%	1.4%	31.4%
28	10.4%	32.1%	14.8%	11.4%	1.9%	29.4%
29	10.4%	26.7%	13.1%	5.6%	1.2%	43.1%
30	10.1%	22.2%	10.3%	13.6%	1.2%	42.6%
Average	10.4%	31.1%	10.9%	10.5%	1.2%	36.0%

From table 8 above, finishes with average of 36.0%, Frames and upper floors with average of 31.1% were the carbon intensive elements of the building projects as they account for over 65% of the gross embodied carbon emission of the projects.

3.2 Discussion of findings

3.2.1 Carbon intensive elements

Table 8 implied that, Finishes, Frames and upper floors have very high reduction potential and the material constituents of these elements should be exchanged with low carbon alternatives in order to maximize carbon reduction potential. This implied that on the average 67.1% of the buildings embodied carbon were caused by 33% of the building's elements. As such, substituting the material constituents of these elements will allow for the most effective embodied carbon reduction possible. The carbon footprint of a structure can be reduced by utilizing alternative building materials with lower embodied carbon levels. Mud bricks, thatched roofs, stone walling, bamboo, and other materials with minimum processing are examples (Ashworth & Perera, 2015). This will be a positive step towards reducing the building industry carbon emission and develop buildings that are environmentally safe. In line with this study, M. Victoria et al., (2015) found substructure, frame, upper floors, external walls and finishes as the carbon hotspot in their study.

Royal Institution of Chartered Surveyors, (2012) identified substructure, frame, upper floors, roof, external and internal walls, external windows and doors and finishes as carbon intensive elements for most building types. According to (Fernando et al., 2018) the hierarchy of carbon intensive elements varies between types of buildings (due to difference in specifications) as they found frames as the carbon intensive element in their study. Taking into account the carbon intensive elements at the early design stage of projects will make a significant difference in managing building's embodied carbon. Therefore, it is vital to estimate carbon at the early design stage of building projects to maximize carbon reduction potential on building projects thereby encouraging the construction of environmental-friendly and sustainable buildings.

3.2.2 Carbon Prediction Model

The model is as follows;

Embodied carbon = 214827.053 + 0.427 (Floor area) + 0.415(Gross internal floor area).

Positive regression coefficient for floor area (βFA) meant as floor area increases, embodied carbon will increase by 42.7% on the average while holding gross internal floor area constant. Meanwhile, positive regression coefficient for gross internal floor area ($\beta GIFA$) meant as GIFA increases, embodied carbon will increase by 41.5% on the average while holding floor area constant. Sig. value that is less than 0.050 (5%) means the null hypothesis was rejected, therefore there is a significant relationship between embodied carbon, floor area and gross internal floor area building design parameters. The model developed was validated using average validity percentage method, (Alshamrani, 2017) also agreed with this validation method. Result of the AVP was (0.967) which meant the model was 96.7% accurate when tested. The model is easy to use (users need to input the floor area and gross internal floor area of their proposed project in the appropriate section of the equation to get the embodied carbon of their project). The information required is such that will be available at design phase of a project. It will facilitate easier and faster prediction of carbon at the early stages of design and encourages comparison between alternative design solutions.

4. CONCLUSIONS

A direct and well-constructed regression model was developed to predict embodied carbon of building projects using building design parameters. The building design parameters are floor area, gross internal floor area, wall area, numbers of floors and average building height. However only two of these parameters were significant predictor variables of the model which are, floor area and gross internal floor area (GIFA). The embodied carbon model accounted for 42.7% of the variability in embodied carbon per floor area and 41.5% of variability in embodied carbon per GIFA. The model was validated at 96.7% accuracy by comparing the predicted values with actual values using mathematical equation. This model will facilitate carbon estimation of projects at the early design phase where insufficient information is available. Also, the model would improve on the level of exposure of Nigerian Quantity surveyors to carbon estimation with the aim of reducing the emission of their projects.

References

Ahmed Ali, K., Ahmad, M. I., & Yusup, Y. (2020). Issues, Impacts, and Mitigations of Carbon Dioxide Emissions in the Building Sector. Sustainability, 12(18). https://doi.org/10.3390/su12187427

Alshamrani, O. S. (2017). Construction cost prediction model for conventional and sustainable college buildings in North America. Journal of Taibah University for Science, 11(2). https://doi.org/10.1016/j.jtusci.2016.01.004

Ashworth, A., & Perera, S. (2015). Cost studies of Buildings. Routledge.

Boden, T., Marland, G., & Andres, R. (2009). Global, regional, and national fossil-fuel CO2 emissions. Carbon Dioxide Information Analysis Center, 10.

Brooks, C., & Thompson, C. (2017). Predictive modelling in teaching and learning. Handbook of Learning Analytics , 61–68.

Chapa, J. (2019). Bringing embodied carbon upfront. Built Environment Economist: Australia and New Zealand, 38.

Dixit, M. K., & Singh, S. (2018). Embodied energy analysis of higher education buildings using an input-output-based hybrid method. Energy and Buildings, 161. https://doi.org/10.1016/j.enbuild.2017.12.022

Ezema, I., Opoko, P., & Oluwatayo, A. (2016). De-carbonizing the Nigerian housing sector: the role of life cycle CO2 assessment. International Journal of Applied Environmental Sciences, 11(1), 325–349.

Fernando, N., Victoria, M., & Ekundayo, D. (2018). Embodied carbon emissions of buildings: a case study of an apartment building in the UK. 7th World Construction Symposium 2018: Built Asset Sustainability.

Jain, R., & Priya, C. (2019). How to interpret the results of the linear regression test in SPSS? Knowledge Tank; Project Guru.

Leech, N., Barrett, K., & Morgan, G. (2014). IBM SPSS for intermediate statistics: Use and interpretation. Routledge.

Matthew, O., Osabohien, R., Olawande, T., & Urhie, E. (2019). Manufacturing industries and construction emissions in Nigeria: Examining the effects on health conditions. International Journal of Civil Engineering and Technology, 10(1), 2401–2414.

Ranathungage, A., Alwan, Z., Fernando, N., & Gledson, B. (2018). Estimating embodied carbon emissions of buildings in developing countries: a case study from Sri Lanka.

Royal Institution of Chartered Surveyors. (2012). Methodology to calculate Embodied Carbon of materials: RICS Information paper.

Victoria, M. F., & Perera, S. (2018). Parametric embodied carbon prediction model for early stage estimating. Energy and Buildings, 168. https://doi.org/10.1016/j.enbuild.2018.02.044

Victoria, M., Perera, S., & Davies, A. (2015). Developing an early design stage embodied carbon prediction model: a case study. 267–276.

Ziegel, E. R., Rawlings, J. O., Pantula, S. G., & Dickey, D. A. (1999). Applied Regression Analysis: A Research Tool. Technometrics, 41(1). https://doi.org/10.2307/1271013.

APPENDIX A; Table 3 Conversion of Data units in the BOQ to KG

ITEM	**DESCRIPTION**	**UNIT**	**QUANTITIES**									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	SUBSTRUCTURE											
1.11.2	1:4:8 Blinding	kg	123,760	78,540	45,220	71,400	59,500	28,560	99,960	333,200	107,100	10
1.11.2	1:3:6 to foundation footing	kg	249,900	183,260	216,580	278,460	326,060	180,880	209,440	1,042,440	204,680	1,0
1.11.2	1:2:4 to columns bases and starter	kg	1,187,620	1,349,460	868,700	495,040	1,190,000	566,440	756,840	2,872,660	813,960	2,7
1.11.13	Formwork (Plywood)	kg	5,850	3,939	4,407	2,808	17,316	3,666	7,540	17,043	7,696	23,
1.11.34	Reinforcement	kg	24,190	14,660	11,000	18,890	17,650	9,670	25,420	50,070	25,500	41,
1.14.1	Hollow blockwall 225mm	sq.m	920	820	1,305	472	533	607	753	3,489	765	3,9
1.14.1	Mortar 1:6	kg	28,980	25,830	41,108	14,868	16,790	19,121	23,720	109,904	24,098	12
	FRAMES & UPPER FLOORS											
1.11.2	1:2:4 to columns beams, slab	kg	2,720,340	2,913,120	2,463,300	1,746,920	3,272,500	1,973,020	1,953,980	6,430,760	2,089,640	6,3
1.11.21	Formwork (Plywood)	kg	120,159	138,775	109,447	100,815	137,332	87,464	75,855	284,648	80,821	34
1.11.34	Reinforcement	kg	156,370	178,850	144,000	139,310	172,880	122,690	108,660	369,150	122,500	34
1.14	**EXTERNAL & INTERNAL WALLS**											
1.14.1	Hollow blockwall 225mm	sq.m	6,381	7,272	8,321	6,405	12,058	6,830	5,742	15,504	5,898	15,
1.14.1	Hollow blockwall 150mm	sq.m	3,507	1,624	535	1,836	642	446	135	9,208	155	8,9
1.14.1	Mortar 1:6	kg	311,472	280,224	278,964	259,592	400,050	229,194	185,126	778,428	190,670	76
1.14.1	Clay facing bricks	sq.m	1,079	584	0	0	0	0	0	1,812	0	1,3
1.17	**ROOF TRUSSES & COVERING**											
1.17.1	Aluminium sheet	kg	3,167	3,715	2,068	1,187	3,580	1,591	1,702	9,737	1,827	9,4
1.16.1	Hardwood truss	kg	952,090	591,981	471,704	209,275	432,465	207,438	347,920	2,524,102	358,161	2,5
1.23	**WINDOWS & DOORS**											
1.23.8	Glass	kg	2,171	2,020	1,892	2,317	2,433	1,430	510	3,658	536	4,3
1.23.8	Aluminium profile	kg	2,388	2,222	2,081	2,548	2,676	1,573	561	4,023	590	4,8
1.28	**FINISHES**											
1.28.7	Mortar 1:3	kg	275,814	353,304	235,179	238,392	513,293	183,362	125,748	802,494	128,615	73
1.28.1	Mortar 1:4	kg	1,652,818	1,804,916	1,546,763	1,296,910	2,571,236	1,172,501	978,268	4,381,658	1,045,939	4,8
1.28.1	Tiles	kg	332,728	426,208	283,708	287,584	619,210	221,198	151,696	968,088	155,154	88
1.28.9	PVC ceiling sheets	kg	2,904	3,248	2,798	0	700	2,292	0	1,850	0	1,8
1.29.1	Paint	kg	134,628	147,017	125,990	105,638	209,437	95,505	79,684	356,902	85,196	39
1.28.9	Ceiling board	kg				1,051	2,234		2,598	4,525	2,644	4,4

APPENDIX B; Table 4 Embodied Carbon emission of the projects in KgCO2

ITEM	**DESCRIPTION**	**UNIT**	**PROJECT ID**									
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	SUBSTRUCTURE											
1.11.2	1:4:8 Blinding	kg	9,158	5,812	3,346	5,284	4,403	2,113	7,397	24,657	7,925	7,9
1.11.2	1:3:6 to foundation footing	kg	22,991	16,860	19,925	25,618	29,998	16,641	19,268	95,904	18,831	95,
1.11.2	1:2:4 to columns bases and starter	kg	148,453	168,683	108,588	61,880	148,750	70,805	94,605	359,083	101,745	34
1.11.13	Formwork (Plywood)	kg	3,990	2,686	3,006	1,915	11,810	2,500	5,142	11,623	5,249	15,
1.11.34	Reinforcement	kg	48,138	29,173	21,890	37,591	35,124	19,243	50,586	99,639	50,745	83,

1.14.1	Hollow blockwall 225mm	kg	20,056	17,876	28,449	10,290	11,619	13,233	16,415	76,060	16,677	86,
1.14.1	Mortar 1:6	kg	3,478	3,100	4,933	1,784	2,015	2,294	2,846	13,188	2,892	14,
	subtotal substructure		256,263	244,190	190,137	144,362	243,718	126,830	196,260	680,155	204,063	64
	FRAMES & UPPER FLOORS											
1.11.2	1:2:4 to columns beams, slab	kg	340,043	364,140	307,913	218,365	409,063	246,628	244,248	803,845	261,205	79
1.11.21	Formwork (Plywood)	kg	81,948	94,645	74,643	68,756	93,660	59,650	51,733	194,130	55,120	23
1.11.34	Reinforcement	kg	311,176	355,912	286,560	277,227	344,031	244,153	216,233	734,609	243,775	69
	Subtotal frames&upper floors		733,167	814,696	669,115	564,348	846,754	550,431	512,214	1,732,583	560,100	1,
1.14	**EXTERNAL&INTERNAL WALLS**											
1.14.1	Hollow blockwall 225mm	kg	139,106	158,530	181,398	139,629	262,864	148,894	125,176	337,987	128,576	33
1.14.1	Hollow blockwall 150mm	kg	57,515	26,634	8,774	30,110	10,529	7,314	2,214	151,011	2,542	14
1.14.1	Mortar 1:6	kg	37,377	33,627	33,476	31,151	48,006	27,503	22,215	93,411	22,880	92,
1.14.1	Clay facing bricks	kg	20,717	11,213	0	0	0	0	0	34,790	0	34,
	subtotal external&internal walls		254,714	230,003	223,647	200,890	321,399	183,712	149,605	617,200	153,999	61
1.17	**ROOF TRUSSES & COVERING**											
1.17.1	Aluminium sheet	kg	39,273	46,062	25,638	14,723	44,393	19,730	21,099	120,745	22,656	11
1.16.1	Hardwood truss	kg	291,340	181,146	144,341	64,038	132,334	63,476	106,463	772,375	109,597	77
	subtotal roof trusses&covering		330,613	227,209	169,979	78,761	176,727	83,206	127,563	893,120	132,253	88
1.23	**WINDOWS & DOORS**											
1.23.8	Glass	kg	3,126	2,909	2,725	3,336	3,503	2,059	734	5,267	772	6,
1.23.8	Aluminium profile	kg	31,475	29,286	27,431	33,586	35,269	20,734	7,389	53,026	7,772	63,
	subtotal windows&doors		34,601	32,195	30,155	36,922	38,772	22,793	8,122	58,293	8,544	69,
1.28	**FINISHES**											
1.28.7	Mortar 1:3	kg	55,163	70,661	47,036	47,678	102,659	36,672	25,150	160,499	25,723	14
1.28.1	Mortar 1:4	kg	264,451	288,787	247,482	207,506	411,398	187,600	156,523	701,065	167,350	78
1.28.1	Tiles	kg	249,546	319,656	212,781	215,688	464,408	165,899	113,772	726,066	116,366	66
1.28.9	PVC ceiling sheets	kg	9,380	10,491	9,038	0	2,261	7,403	0	5,976	0	5,
1.29.1	Paint	kg	176,363	192,592	165,046	138,386	274,362	125,111	104,385	467,542	111,606	52
1.28.9	Ceiling board	kg				3,395	7,217	0	8,392	14,616	8,539	14,
	subtotal finishings		754,902	882,187	681,383	612,653	1,262,304	522,685	408,221	2,075,764	429,584	2,
	total kgco2		2,364,260	2,430,479	1,964,417	1,637,936	2,889,674	1,489,657	1,401,986	6,057,115	1,488,543	6,