DEVELOPMENT OF A COOLING LOAD PREDICTION MODEL FOR OFFICE BUILDINGS OF BAYERO UNIVERSITY KANO

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ABSTRACT

Overestimation of building cooling load results into an oversized cooling system with consequent waste of energy. Conversely, thermal comfort would be sacrificed if the building cooling load is underestimated because of the use of undersized cooling system. The computer-based methods for cooling load calculation are costly while most of the inverse models are complex and require enough time to train the models. In this paper, a simplified multiple linear regression model was developed using the concept of Taguchi orthogonal array. The model developed has high performance based on the computed R^2 and variance inflation factor. The prediction model developed was validated using resampling technique and the consistency in the root mean squared error (RMSE) in all the holdout samples indicates the high accuracy of the model developed. The proposed model has high inference and prediction powers and could be used for predicting cooling load of office buildings of Bayero University Kano (BUK) or any building with similar characteristics.

Keywords: Building Cooling Load; Prediction Model; Office Building; Regression Analysis, Taguchi Analysis

INTRODUCTION

Buildings consume about 40% of the global energy and represent about 30% contributors of carbon emissions (Kim et al, 2016; Ravat et al, 2017; Sun et al, 2018). A larger proportion of the energy consumed in the building sector is used for the provision of thermal (Koranteng et al, 2015).

The cooling load of a building is the amount of heat energy that must be removed from a space to maintain the parameters (temperature, relative humidity, and air velocity) within the acceptable comfort range (Hashim *et al.*, 2018). According to Hashim *et al.*, (2018) and Obuka *et al.*, (2015), the determination of building cooling load is a prerequisite for rightsizing a building cooling system. Yan *et al.* (2017) stated that an inappropriate estimation of building cooling load causes waste of energy due to the use of an oversize system or sacrificing thermal comfort due to the use of undersize cooling system.

The building cooling loads are determined using two different approaches, namely: the forward or classical approach and the inverse or data-driven approach (Simon, Richard, & Eric, 2011). According to *Cheng et al.* (2017), a forward or classical approach requires detailed building information and the use of physical principles to characterize building thermal performance. The classical approach of building cooling load estimation can be traditional or computer-based. According to Hashim *et al.* (2018), the traditional method includes the following: heat balance (HB) method, transfer function method (TFM), etc. The difficulty in solving unsteady equations with unsteady or dynamic boundary conditions rendered the traditional method unpopular which occurs as a result of unsteady thermal storage characteristics of the building mass. To overcome this set back of the traditional method, simulation software such as EnergyPlus, DOE-2, BLAST, ESP-r, Hongye etc used. Apart from the complications involved in using these software, most of them are very expensive. (Siyue *et al.*, 2013; Qiang *et al.*, 2015; Chengliang *et al.*, 2019).

The data-driven models include linear and non-linear models (Yan *et al.*, 2017). Chengliang *et al.* (2019) gave examples of linear models to include: multiple linear regression (MLR), autoregressive (AR), etc.The regression models predict building cooling load by determining the appropriate coefficients that are associated with the most influential inputs (Qiang *et al.*, 2015). According to Qiang *et al.* (2015), MLR is the most commonly used regression model for the prediction of building cooling load because of its direct and simplified nature. Numerous researchers had employed the MLR model to predict building cooling load and energy consumption (Joseph *et al*., 2010; Hae & Eon, 2014; Mohammad *et al*., 2015; Maged *et al.,* 2015; Chaoba, 2017; Devindi & Thanuja, 2018; Navid *et al.,* 2017). The non-linear data-driven models include the Artificial Neural Network (ANN), support vector machine (SVM) etc (Jing & Xiaojuan, 2018), and are complex because of the difficulty of the models to converge to an optimal solution (Qiang *et al.* 2015).

To this end, this paper therefore attempts to develop a cooling load prediction model for office buildings of Bayero University Kano using Taguchi orthogonal array and multiple linear regression method. The use of Taguchi method enables the experimenter to reduce the number of experiment while still obtaining valid and statistically sound results.

MATERIALS AND METHODS

Study Area

The characteristics of the study area are presented in Table 1.

Table 1: Characteristics of the Case Study

Title	Characteristics
Building type and location	Office, Bayero University, Kano, Nigeria. Latitude: 12.05°N, Longitude: 8.53°E Elevation: 481m above sea level
Floor height	3.0m
Occupancy (person/m^2)	0.068
Office hours	8:00am – 4:00pm

Development of the Cooling Load Prediction Model

Sampling of office buildings for the study

A convenient non-probability sampling technique was adopted for sampling the office blocks in the New Campus of BUK. The sampled office blocks selected for the study are presented in Table 2.

Cooling Load Components Analysis of the Sampled Office Blocks

The architectural plans of the four selected blocks were obtained from the Physical Planning Unit (PPU) of BUK. The internal conditions of all the offices in all the four blocks selected were studied through physical inspections. Based on the pertinent information obtained from the architectural plans and physical inspection of the office blocks, the descriptive characteristics of the building were collected and presented in Table 3.

Table 2: Selected Blocks with their Faculty

S/N	Block Name	Faculty
1	Phase III	Agriculture
2	Dean's block	Computer Science and Information Technology
3	Economics block	Social Sciences
4	Departmental block	Law

Table 3: Descriptive Parameters of the Study Area

S/N	Item	Maximum	Minimum	Mean
1	Wall length (m)	8.60	3.40	5.60
2	Wall width (m)	9.45	2.95	5.00
3	Wall height (m)	3.45	3.45	3.45
4	Window width (m)	3.94	1.50	3.04
5	Window height (m)	1.50	1.00	1.10
6	Wall thickness (m)	0.27	0.27	0.27
7	Number of staff per office	3.00	1.00	2.00
8	Number of refrigerator per office	2.00	0.00	1.00
9	Number of lighting points per office	4.00	2.00	3.00
10	Number of ceiling fans per office	3.00	1.00	2.00

The performance levels of the pertinent building cooling load variables were determined using the information gotten from the study area and some pertinent standard factors. Based on the data obtained, three performance levels were considered for this study as shown in Table 4.

Table 4: Performance Levels of Cooling Load Variables

S/N	Variable	Unit	Performance Level		
			1	2	3
1	Gross floor area	m^2	10.03	28.00	81.27
2	Ventilation rate	ACH	0.35	0.425	0.50
3	Number of persons per office	-	1	2	3
4	Number of lighting points per office	-	2	3	4
5	Wattage of bulb	W	18	20	22
6	Number of ceiling fans per office	-	1	2	3
7	The wattage of the ceiling fan	W	60	65	70
8	Number of refrigerators per office	-	0	1	2
9	Wattage of refrigerator	W	200	275	350
10	Window area, A_g	m^2	1.5	3.34	5.91
11	The volume of office, V_b	m^3	34.6	96.6	280.38
12	Roof area, A_r	m^2	11.582	33.26	938.39
13	Wall area, A_w	m^2	11.73	19.32	32.60
14	Window-to-wall-ratio (WWR)	%	13	17	18

(a) Heat transfer through the window is the sum of the solar and conductive heat transmissions and can be determined from equation 1.

$$\dot{Q}_{win} = 877.51 l_g h_g \quad Watts \qquad (1)$$

The total heat transfer through N_g numbers of glazing windows can be determined from equation 2.

$$\Rightarrow \quad \dot{Q}_{win}^{total} = 877.51 l_g h_g N_g \quad Watts \qquad (2)$$

b) Heat transfer through the plane wall can be determined from equation 3.

$$\therefore \quad \dot{Q}_{wall} = 24.76\left[H_w\left(\frac{1}{2}P_m - H_w\right) - N_g l_g h_g\right] \quad Watts \qquad (3)$$

c) The heat transfer through the roof can then be determined from equation (4)

$$\therefore \quad \dot{Q}_{roof} = 0.232 A_z \quad Watts \qquad (4)$$

d) The sensible heat load of infiltration can be determined from equation 5.

$$\therefore \quad \dot{Q}_{sen}^{infil} = 1.293 L_w W_w H_w \quad Watts \qquad (5)$$

Similarly, the latent heat load of infiltration can be determined from equation 6.

$$\therefore \quad \dot{Q}_{lat}^{infil} = 1.448 L_w W_w H_w \quad Watts \qquad (6)$$

Therefore, the total infiltration load can be determined from equation 7.

$$\dot{Q}_{total}^{infil} = \dot{Q}_{sen}^{infil} + \dot{Q}_{lat}^{infil}$$

$$\therefore \quad \dot{Q}_{total}^{infil} = 2.741 L_w W_w H_w \quad Watts \qquad (7)$$

e) The sensible heat gain from occupants can be determined from equation 8 considering Q_s being 70W for an adult male (ASHRAE-55, 2010). This implies that:

$$\dot{Q}_{sen}^{ppl} = 70N_p \ \ Watts \quad \text{……..………………………………….} (8)$$

Similarly, the latent heat gain from occupants can be determined from equation 9 considering Q_l being 45W for an adult male (ASHRAE-55, 2010). This implies that:

$$\dot{Q}_{lat}^{ppl} = 45N_p \ \ Watts \quad \text{…………………………………………} (9)$$

To account for the fluctuation in occupancy, a factor of 0.7 was applied. Therefore, the total heat gain from the occupants $\dot{Q}_{total}^{ppl}$ can be determined from equation 10.

$$\dot{Q}_{total}^{ppl} = 0.7(70N_p + 45N_p)$$

$$\therefore \quad \dot{Q}_{total}^{ppl} = 80.5N_p \ \ Watts \quad \text{………………………..…………} (10)$$

f) Heat gain from lighting $\dot{Q}_{lighting}$ can be determined from equation 11.

$$\dot{Q}_{lighting} = 0.72W_l \ \ Watts \quad \text{……………………..……} (11)$$

g) Heat gain from equipment/appliance can be determined from equation 12 assuming the total heat gain from equipment is P_t.

$$\dot{Q}_{equip} = 1.143P_t \ \ Watts \quad \text{…………………..………} (12)$$

Because of the usage of the equipment, the total heat gain from the use of the equipment can be determined from equation 13.

$$\dot{Q}_{equip}^{total} = 0.5 \times \dot{Q}_{equip}$$

$$\therefore \quad \dot{Q}_{equip}^{total} = 0.571P_t \ \ Watts \quad \text{…………………………..….} (13)$$

Based on the architectural information and the physical inspection carried out, the cooling load parameters considered for the model development are presented in Table 5.

Table 5: Cooling Load Model Parameters

Level	N_p	W_b	P_e	A_r	l_g	h_g	N_g	L_w	H_w	W_w	P_m
1	1	18	60	11.58	1.5	1.5	2	3.40	2.8	2.95	25.1
2	2	20	340	33.26	3.34	3.34	3	5.60	3.0	5.0	38.4
3	3	22	770	938.39	5.91	5.91	4	8.60	3.45	9.45	60.2

Determination of Cooling Load Components using Taguchi Analysis

Taguchi method is a universally accepted method of conducting design of experiments by using a special set of arrays called orthogonal arrays. According to Taguchi and Yokoyama (1993), orthogonal array $L_{27}(3^{13})$ should be used for 3-level factors up to 13. In this study, there are 11 factors and therefore $L_{27}(3^{11})$ orthogonal array was used. The L_{27} orthogonal array of the cooling load model parameters are presented in Table 6.

Regression Analysis of the Cooling Load

In order to develop the cooling load model, from Table 3.10, the total cooling load (Y) was regressed against the cooling load model parameters N_p, W_b, P_e, A_r, l_g, h_g, N_g L_w, H_w, W_w, and P_m using multiple linear regression technique run on Minitab 19 software. The regression analysis output presented in Table 8 shows that the P-values of the parameters W_b, P_e, A_r, L_w, H_w, and W_w were greater than 0.05 and hence, will statistically have less impact on the cooling load of the occupied space. Therefore, they were not considered for the model development.

Table 6: L_{27} Orthogonal Array of the Cooling load Model Parameters

Runs	N_p	W_b	P_e	A_r	l_g	h_g	N_g	L_w	H_w	W_w	P_m
1	1	18	60	11.58	1.00	1.0	2	3.4	2.80	2.95	25.1
2	1	18	60	11.58	3.04	1.1	3	5.6	3.00	5.00	38.4
3	1	18	60	11.58	3.94	1.5	4	8.6	3.45	9.45	60.2
4	1	20	340	33.26	1.00	1.0	2	5.6	3.00	5.00	60.2
5	1	20	340	33.26	3.04	1.1	3	8.6	3.45	9.45	25.1
6	1	20	340	33.26	3.94	1.5	4	3.4	2.80	2.95	38.4
7	1	22	770	938.39	1.00	1.0	2	8.6	3.45	9.45	38.4
8	1	22	770	938.39	3.04	1.1	3	3.4	2.80	2.95	60.2
9	1	22	770	938.39	3.94	1.5	4	5.6	3.00	5.00	25.1
10	2	18	340	938.39	1.00	1.1	4	3.4	3.00	9.45	25.1
11	2	18	340	938.39	3.04	1.5	2	5.6	3.45	2.95	38.4
12	2	18	340	938.39	3.94	1.0	3	8.6	2.80	5.00	60.2
13	2	20	770	11.58	1.00	1.1	4	5.6	3.45	2.95	60.2
14	2	20	770	11.58	3.04	1.5	2	8.6	2.80	5.00	25.1
15	2	20	770	11.58	3.94	1.0	3	3.4	3.00	9.45	38.4
16	2	22	60	33.26	1.00	1.1	4	8.6	2.80	5.00	38.4
17	2	22	60	33.26	3.04	1.5	2	3.4	3.00	9.45	60.2
18	2	22	60	33.26	3.94	1.0	3	5.6	3.45	2.95	25.1
19	3	18	770	33.26	1.00	1.5	3	3.4	3.45	5.00	25.1
20	3	18	770	33.26	3.04	1.0	4	5.6	2.80	9.45	38.4
21	3	18	770	33.26	3.94	1.1	2	8.6	3.00	2.95	60.2
22	3	20	60	938.39	1.00	1.5	3	5.6	2.80	9.45	60.2
23	3	20	60	938.39	3.04	1.0	4	8.6	3.00	2.95	25.1
24	3	20	60	938.39	3.94	1.1	2	3.4	3.45	5.00	38.4
25	3	22	340	11.58	1.00	1.5	3	8.6	3.00	2.95	38.4
26	3	22	340	11.58	3.04	1.0	4	3.4	3.45	5.00	60.2
27	3	22	340	11.58	3.94	1.1	2	5.6	2.80	9.45	25.1

The L_{27} orthogonal array of the cooling load model parameters and the corresponding computed cooling load components are presented in Table 7.

Table 7: L_{27} Orthogonal Array of Cooling Load Model Parameters and Cooling Load Components

Runs	Cooling load model parameters											Cooling load components							Total cooling load (Y) (W)
	N_p	W_b (W)	P_e (W)	A_r (m^2)	l_g (m)	h_g (m)	N_g	L_w (m)	H_w (m)	W_w (m)	P_m $(m$	Q_p (W)	Q_l (W)	Q_e (W)	Q_r (W)	Q_w (W)	Q_{win} (W)	Q_{in} (W)	
1	1	18	60	11.58	1.00	1.0	2	3.4	2.80	2.95	25.1	80.5	12.96	34.26	2.68	626.43	1350.36	76.99	2184.17
2	1	18	60	11.58	3.04	1.1	3	5.6	3.00	5.00	38.4	80.5	12.96	34.26	2.68	954.94	6773.41	230.24	8089
3	1	18	60	11.58	3.94	1.5	4	8.6	3.45	9.45	60.2	80.5	12.96	34.26	2.68	1691.17	15961.26	768.53	18551.36
4	1	20	340	33.26	1.00	1.0	2	5.6	3.00	5.00	60.2	80.5	14.4	194.14	7.72	1963.47	1350.36	230.24	3840.83
5	1	20	340	33.26	3.04	1.1	3	8.6	3.45	9.45	25.1	80.5	14.4	194.14	7.72	528.95	6773.41	768.53	8367.64
6	1	20	340	33.26	3.94	1.5	4	3.4	2.80	2.95	38.4	80.5	14.4	194.14	7.72	551.65	15961.26	76.98	16886.64
7	1	22	770	938.39	1.00	1.0	2	8.6	3.45	9.45	38.4	80.5	15.84	439.67	217.71	1295.88	1350.36	768.53	4168.48
8	1	22	770	938.39	3.04	1.1	3	3.4	2.80	2.95	60.2	80.5	15.84	439.67	217.71	1644.26	6773.41	76.98	9248.36
9	1	22	770	938.39	3.94	1.5	4	5.6	3.00	5.00	25.1	80.5	15.84	439.67	217.71	124.05	15961.26	230.24	17069.26
10	2	18	340	938.39	1.00	1.1	4	3.4	3.00	9.45	25.1	161	12.96	194.14	217.71	600.43	2970.79	264.21	4421.23
11	2	18	340	938.39	3.04	1.5	2	5.6	3.45	2.95	38.4	161	12.96	194.14	217.71	1119.59	6157.64	156.22	8019.25
12	2	18	340	938.39	3.94	1.0	3	8.6	2.80	5.00	60.2	161	12.96	194.14	217.71	1599.99	7980.63	330.02	10496.44
13	2	20	770	11.58	1.00	1.1	4	5.6	3.45	2.95	60.2	161	14.4	439.67	2.69	2167.55	2970.79	156.22	5912.32
14	2	20	770	11.58	3.04	1.5	2	8.6	2.80	5.00	25.1	161	14.4	439.67	2.69	450.14	6157.64	330.02	7555.55
15	2	20	770	11.58	3.94	1.0	3	3.4	3.00	9.45	38.4	161	14.4	439.67	2.69	910.67	7980.63	264.21	9773.26
16	2	22	60	33.26	1.00	1.1	4	8.6	2.80	5.00	38.4	161	15.84	34.26	7.72	1028.04	2970.79	330.02	4547.66
17	2	22	60	33.26	3.04	1.5	2	3.4	3.00	9.45	60.2	161	15.84	34.26	7.72	1787.18	6157.64	264.21	8427.84
18	2	22	60	33.26	3.94	1.0	3	5.6	3.45	2.95	25.1	161	15.84	34.26	7.72	484.68	7980.63	156.22	8840.34
19	3	18	770	33.26	1.00	1.5	3	3.4	3.45	5.00	25.1	241.5	12.96	439.67	7.72	665.92	3038.31	160.76	4566.84
20	3	18	770	33.26	3.04	1.0	4	5.6	2.80	9.45	38.4	241.5	12.96	439.67	7.72	835.89	8210.19	406.15	10154.08
21	3	18	770	33.26	3.94	1.1	2	8.6	3.00	2.95	60.2	241.5	12.96	439.67	7.72	1798.37	5852.46	208.62	8561.29
22	3	20	60	938.39	1.00	1.5	3	5.6	2.80	9.45	60.2	241.5	14.4	34.26	217.71	1781.23	3038.31	406.15	5733.56
23	3	20	60	938.39	3.04	1.0	4	8.6	3.00	2.95	25.1	241.5	14.4	34.26	217.71	408.29	8210.19	208.62	9334.97
24	3	20	60	938.39	3.94	1.1	2	3.4	3.45	5.00	38.4	241.5	14.4	34.26	217.71	1130.78	5852.46	160.76	7651.86
25	3	22	340	11.58	1.00	1.5	3	8.6	3.00	2.95	38.4	241.5	15.84	194.14	2.69	1091.92	3038.31	208.62	4793.01
26	3	22	340	11.58	3.04	1.0	4	3.4	3.45	5.00	60.2	241.5	15.84	194.14	2.69	1975.42	8210.19	160.76	10800.53
27	3	22	340	11.58	3.94	1.1	2	5.6	2.80	9.45	25.1	241.5	15.84	194.14	2.69	461.33	5852.46	406.15	7174.11

Table 8: Regression Analysis Output for Cooling Load Model

Training	**Cooling Load Parameter**	***p*-Value**	**VIF**	**R^2 Value** (%)
First Model Training	N_p	0.001	1.00	94.95
	W_b	0.997	1.00	
	P_e	0.584	1.00	
	A_r	0.780	1.00	
	l_g	0.000	1.00	
	h_g	0.000	1.00	
	N_g	0.000	1.00	
	L_w	0.715	1.00	
	H_w	0.643	1.00	
	W_w	0.645	1.00	
	P_m	0.084	1.00	
Second Model Training	N_p	0.000	1.00	94.62
	l_g	0.000	1.00	
	h_g	0.000	1.00	
	N_g	0.000	1.00	
	P_m	0.046	1.00	

The cooling load was again regressed against the remaining parameters and the improved cooling load model developed is given in equation 3.48 and the Pareto chart of the standardized effects of the parameters in the improved model is shown in Figure 1.

$$Y =- 14486 - 1440N_p + 3150l_g + 7455h_g + 2916N_g + 38.2P_m \text{ .... (14)}$$

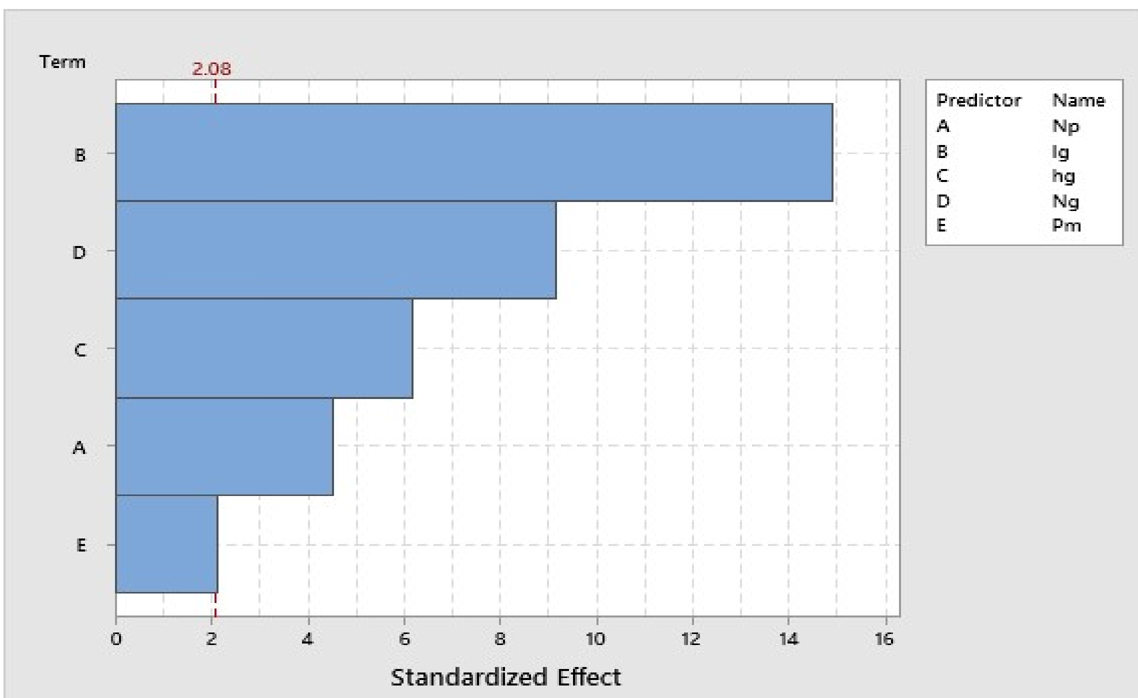


Figure 1: Pareto Chart of the Improved Parameters

Performance of the Cooling Load Prediction Model

ANOVA was employed to determine the performance of the model developed. Therefore, coefficient of determination R^2 was used to determine the association between the dependent variable (cooling load) and the independent variables (cooling load parameters). The R^2 value was found to be 94.62% as shown in Table 8. This implies that 94.62% variation in the cooling load (Y) could be explained by the cooling load parameters N_p, l_g, h_g, N_g, and P_m.

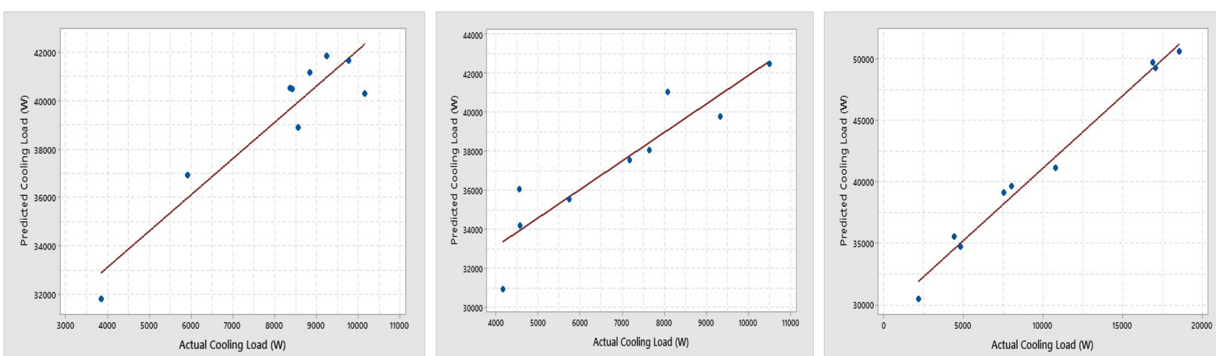
Variance Inflation Factor (VIF) was used to check the severity of multicollinearity. VIF less than 5 as shown in Table 8 for all the independent parameters shows that there is no multicollinearity. The ANOVA results summarized and presented in Table 8 show that the mathematical correlation of the building cooling load is statistically significant at 95% confidence level.

Validation of the Cooling Load Prediction Model

Resampling validation technique was employed for the validation of the cooling load prediction model. The 27 full dataset was randomly divided into three holdout samples or sub-samples and the model developed in the full dataset was validated across the sub-samples. The performance metrics: root means squared log error (RMSLE) and the correlation coefficient of the sub-samples in this validation technique are presented in Table 9 and the lines of best fit at 95% confidence level are shown in Figure 2.

Table 9: Resampling Validation of the Cooling Load Prediction Model

Sub-sample	RMSLE	Coefficient of correlation
1	1.62	0.937
2	1.75	0.920
3	1.68	0.992



Sub-sample 1 Sub-sample 2 Sub-sample 3

Figure 2: Line of Best Fits of the Sub-samples of the Resampling Validation

DISCUSSION

The cooling load prediction model parameters were statistically significant for predicting the building cooling loads since their P-values are less than 0.05 as presented in Table 4. The VIF for the model parameters are all less than 5.0 as shown in Table 8. This indicates that there is complete absence of the effect of multicollinearity in the model developed. This is in concordance with the work of Kaushik et al. (2020) who stated that VIF of less than 5.0 does not indicate high correlation among the independent variables and hence, no measure is required to remove the collinearity. The value of R^2 of 94.62% as shown in Table 8 implies that the developed prediction model has high inference power, meaning that

94.62% variation of the predicted cooling load could be explained by the cooling load model parameters. RMSLE and the correlation coefficients across the sub-samples in Table 9 as well as the line of best fits shown in Figure 2 indicate the high prediction accuracy of the model developed.

CONCLUSION

This paper proposed a cooling load prediction model for the prediction of cooling loads of office buildings in the New Campus of Bayero University Kano, Nigeria. The performance of the model developed is high with respect to the P-value and the VIF of the cooling load model parameters. The consistencies in the performance metrics: root mean square log error and the coefficient of correlation across the sub-samples indicate that the accuracy of the building cooling load prediction model developed is high. Therefore, this proposed model could reliably be used to predict the cooling load of office buildings in the New Campus of Bayero University Kano and, also, in any other building with similar characteristics.

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