1. Introduction

The building sector is the leading energy consumer by consuming about 40% of world's total energy and represents about 30% contributors of global Greenhouse Gas emission [1—3]. A larger proportion of the energy consumed in the building sector is used for the provision of thermal [4].

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 [5]. According to [5] and [6], the determination of building cooling load is a prerequisite for rightsizing a building cooling system. The researcher [7] stated that an inaccurate 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 [8].. According to [9], 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 [5], 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. Some studies stated that the use of simulation software for building cooling load prediction is costly [10-12].

The inverse models include linear and non-linear models [7]. The researcher [12] 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 [11]. According to [11], 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 [13-19]. The non-linear data-driven models include the Artificial Neural Network (ANN), support vector machine (SVM) etc [20], and are complex because of the difficulty of the models to converge to an optimal solution [11].

To this end, this paper therefore attempts to develop a cooling load prediction model for office buildings of Bayero University Kano (BUK) using Taguchi orthogonal array and multiple linear regression method.

2. Study Area Description

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

3. Development of the Cooling Load Prediction Model

3.1 *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.

Table 2: Selected Blocks with their Faculty

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

3.2 *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.

DOI: 10.46565/jreas.2022.v07i01.**009**

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.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

e) The sensible heat gain from occupants can be determined from equation 8 considering Q_s being 70W for an adult male [21]. This implies that:

$$\dot{Q}_{sen}^{ppl} = 70N_p \quad Watts \;\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Similarly, the latent heat gain from occupants can be determined from equation 9 considering Q_l being 45W for an adult male [21]. This implies that:

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

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.

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

$$\therefore \quad \dot{Q}_{total}^{ppl} = 80.5N_p \quad Watts \;\ldots\ldots\ldots\ldots (10)$$

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

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

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

$$\dot{Q}_{equip} = 1.143P_t \quad Watts \;\ldots\ldots (12)$$

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

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

$$\therefore \quad \dot{Q}_{equip}^{total} = 0.571P_t \quad Watts \;\ldots\ldots (13)$$

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

3.3 *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 [22], 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.

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

DOI: 10.46565/jreas.2022.v07i01.**009**

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

DOI: 10.46565/jreas.2022.v07i01.**009**

3.4 *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 therefore, they were not considered for the model development.

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 Fig. 1.

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

3.5 *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 determined 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.

3.6 Estimation of the Cooling Load of the Site Office Building

The cooling load model developed was used to estimate the cooling load of the site office building with the cooling load parameters presented in Table 9.

Table 9: Values of the Cooling Load Predictor Parameters

S/N	Cooling Load Parameter	Value
1	N_p	2.000
2	l_g	1.831m
3	h_g	1.222m
4	N_g	4.000
5	P_m	34.880m

Substituting the pertinent information aforementioned into the cooling load model given in equation 3.55 yields:

$$\begin{aligned} Y = -14486 - 1440(2) &+ 3150(1.831) \\ &+ 7455(1.222) + 2916(4) \\ &+ 38.2(34.88) \end{aligned}$$

$$\therefore \quad Y = 10477.52W \approx 10.48kW$$

3.7 Validation of the Cooling Load Prediction Model

The building model of the site office building was created using DesignBuilder software as shown n Fig. 1. The cooling load of the site office model was the determined using EnergyPlus thermal simulation

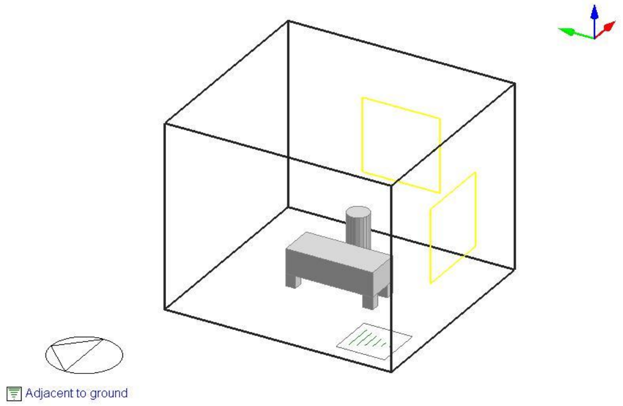

Figure 1. 3D Model of the Site Office Building

The cooling load determined using EnergyPlus was 10.29 kW as shown on the EnergyPlus output in Fig. 2.

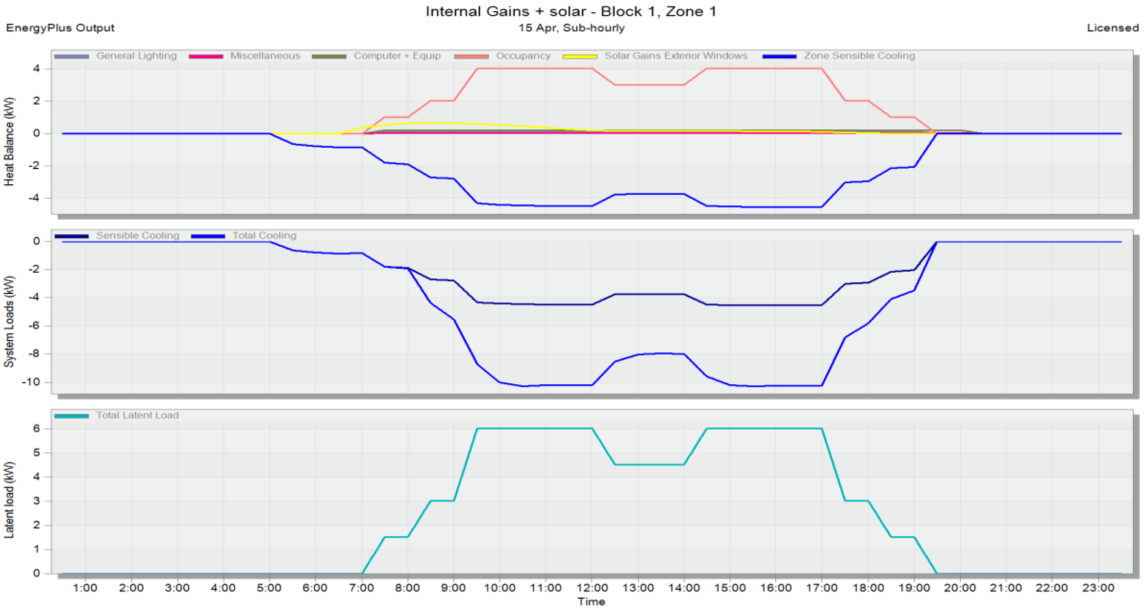

Figure 2: Computed Cooling Load using EnergyPlus

The RMSLE between the predicted and the simulated cooling loads is 0.017.

3. 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. Employing the cooling load model, the cooling load of the site office building was 10.48 Kw while the EnergyPlus simulated result was 10.29 Kw as displayed on the system load in Fig. 2. The RMSLE between the predicted and the EnergyPlus simulated result is 0.017 which indicates that the model developed has high predictive power.

3. CONCLUSION

In this study, a cooling load model was developed for the purpose of estimating the cooling load 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 low value of the RMSLE between the predicted and the simulated results portrays the high accuracy of the cooling load model developed. 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 attributes.

REFERENCES

[1] S. Kim, P. Zadeh, S. Staub-French, T. Froece, & B. Cavka, "Assessment of the Impact of Window Size, Position and Orientation of Building Energy Load using BIM", . International Conference on Sustainable Design, Engineering and Construction, 2016, 1324-1332.

[2] V. Ravat, S. Shivakar, D. Biplab, & B. Sel, "Effect of Orientation of Window on Building Heat Load: Perspective of N-E India", Material Science and Engineering. India: IOP Conference, 2017.

[3] Y. Sun, W. Yupeng, & R. Wilson, "A Review of Thermal and Optical Characteristics of Complex Window Systems and their Building Performance Prediction", Applied Energy, 2018, 729-742.

[4] C. Koranteng, C. Essel, & J. Nkrumah, "Paaive Analysis of the Effect of Window Size and Position on Indoor Comfort for Residential Rooms in Kumasi, Ghana", International Advanced Research Journal in Science, Engineering and Technology, 2(10), 2015, 114-120.

[5] H. Hashim, E. Sokolova, O. Derevianko, & D. Solovev, (2018). "Cooling Loads Calculations", International Multi-Conference on Industrial Engineering in Modern Technologies, 463, 2018, 1-6. doi:10.1088/1757-899x/463/3/032030

[6] N. Obuka, D. Utazi, P. Onyechi, N. Okoli, & C. Ene, "Determination of Nonresidential Space Cooling Load: Vb Program Application", International Journal of Scientific and Technology Research, 4(01), 2015.

[7] D. Yan, Z. Qiang, Y. Tianhao, & Y. Fan, "Effect of Input Variables on Cooling Load Prediction Accuracy of an Office Building", Applied Thermal Engineering, 2017. Retrieved from http://dx.doi.org/10.1016/j.applthermaleng.2017.09.007

[8] S. Simon, K. Richard, & W. Eric, "An Intelligent Approach to Assessing the Effect of Building Occupancy on Building Cooling Load Prediction", Building and Environment, 46, 2011, 1681-1690. doi:10.1016/j.buildenv.2011.02.008

[9] H. Chen, C. Jiao, L. Zheifen, Z. Qianru, & C. Yezan, "Solving Model of Temperature and Humidity Profiles in Spray Cooling", Building and Environment, 123, 2017, 189-199. http://dx.doi.org/10.1016/j.buildenv.2017.06.043

[10] K. Siyue, G. Guangeai, H. Tianhe, & and W. Rong, "A Simplified Method for Building Cooling Load Calculations", ICSDEC, 2013

[11] G. Qiang, T. Zhe, D. Yan, & Z. Neng, "An Improved Office Building Cooling Load Prediction Model based on Multivariable Linear Regression", Energy and Buildings, 107, 2015, 445-455. http://dx.doi.org/10.1016/j.enbuild.2015.08.041

[12] F. Chengliang, I. Yundan, & Yunfei, D. "Development of a Cooling Load Prediction Model for Air Conditioning System Control of Office Buildings", International Low-carbon Technologies, 14(1), 2019, 70-75. http://doi.org/10.1093/ijlct/cty057

[13] C. Joseph, K. Kevia, L. Dalong, & C. Tsang, "Multiple Linear Regression Models for Energy Use in Air Conditioned Office Buildings in different Climates", Energy Conversion and Management, 2010, 2692-2697. doi:10.1016/j.proeng.2015.08.495

[14] J. Hae, & K. Eon, "Development of Heating and Cooling Loads Equations for Office Buildings in Korea", Journal of Asian Architecture and Building Engineering, 13(2), 2014, 437-445.

[15] A. Mohammad, "Assessment of Passive Downdraft Evaporative Cooling Technique for Environmental Sustainability in Buildings", International Journal of Research in Chemical, Metallurgical and Civil Engineering, 3, 2016, 326-330. http://doi.org/10.15242/IJRCMCE.U1016309

[16] A. Maged, F., Joseph, & R. Ranji, (2015). "An Enhanced Linear Regression-based Building Energy Model (LRBEM+) for Early Design", Journal of Building Performance Simulation, 2015. http://dx.doi.org/10.1080/19401473.2015.1004108

[17] Z. Chaoba, Z. Yang, Z. Xuejun, F. Cheng, & L. Tingting, (2017). "An Improved Cooling Load Prediction Method for Buildings with the Estimation of Prediction Interval", 10th International Symposium on Heating, Ventilation and Air Conditioning. 205,2017, 2422-2428. Jinan, China.. doi:10.1016/j.proeng.2017.09.967

[18] G. Devindi, & R. Thanuja, "A Model for Estimating Cooling Energy Demand at Early Design Stage of Condominiums in Sri Lanka", Journal of Building Engineering. https://doi.org/10.1016/j.jobe.2018.01.011

[19] A. Navid, K. Georgios, D. Daniel, & M. Timothy, "Linear Regression Models for Prediction of Annual Heating and Cooling Demand in Representative Australian Residential Dwellings", International Conference on Improving Residential Energy Efficiency, 121, 2017, 79-86. doi:10.1016/j.egypro.2017.07.482

[20] J. Zhao, & X. Liu, "A Hybrid Method of dynamic Cooling and Heating Load Forecasting for Office Buildings based on Artificial Intelligence and Regression Analysis", Energy and Building, 2018, Doi: 10.1016/j.ebuild.2018.06.050

[21] ASHRAE-55, Thermal Environmental Condition for Human Occupancy. Atlanta: American Society of Heating, Refrigeration and Air Conditioning Engineers, 2010

[22] G. Taguchi, & Y. Yokoyama, Taguchi Method: design of experiment. Amer Supplier Inst., 1993

[23] A. Kaushik, A. Mohammed, P., Tumula, & J. Ebohon, "Effect of Thermal Comfort on Occupant Productivity in Office Buildings: Response Surface Analysis", Building and Environment, 2020, https://doi.org/10.1016/j.buildenv.2020.107021