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Heating Load of Residential Buildings Using Multiple Linear Regression Artificial Neural Network

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ABSTRACT

Global warming is one metric of climate change which is defined as an increase in the average global temperature. Residential buildings contribute significantly to the pollution that causes climate change. It is essential to have a comprehensive understanding of the functions of highly energy efficient buildings in view of projected climate projections, the quality of their heating systems, and the impact on human health and well-being. Thus, in this study, the effects of six input variables which are Overall Height, Glazing Area, Wall Area, Relative Compactness, Roof Area, and Glazing Area Distribution on one output variable, namely Heating Load (HL) of residential buildings was investigated using Multiple Linear Regression and Artificial Neural Network (MLR-ANN) approaches. Two-layer hyperbolic tangent-identity transfer functions with 6-3-1 configurations were employed as it was found as the best neural network model. A dataset of 768 residential buildings was used for secondary data. The Mean Square Error (MSE), determination coefficients R^2, as well as the percentage of normalized importance analysis were used to assess the statistical prediction capabilities of the MLR-ANN model. Based on the current findings, Wall Area is the most contributing factor towards HL, followed by Relative Compactness, Roof Area, Overall Height, Glazing Area, and Glazing Area Distribution. It can be suggested that HVAC (heating, ventilation, and air conditioning) systems should be implemented in residential buildings to reduce energy use. Natural ventilation is encouraged in buildings through vernacular design, and radiant heating and cooling systems as it is very effective and efficient way of providing thermal comfort within a structure.

1. Introduction

As the world facing global warming impact, architects are devising new ways to design buildings that load heat efficiently while mitigate environmental impact. It is critical to have a comprehensive overview of the functions of highly energy efficient buildings under climate projections, the quality of their heating systems, and the effect on human health and well-being of their residents [1]. In the United Kingdom, residential buildings accounted for almost 25% of greenhouse gas (GHG) final

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emissions in 2012, prompting the UK government to pledge to an 80% reduction in GHG emissions by 2050 [2]. According to the Dean *et al.,* [3], when upstream power generation is incorporated, buildings and construction contribute for 36% of total final energy use and 39% emission of carbon dioxide (CO2). Although progress toward more buildings and architecture that are environmentally sustainable are being developed the progress are still lagging behind with the booming construction industry and expanding demand for energy services.

Heating and cooling account for around 30-40% of the building's energy use. It is critical to initiate efforts to reduce surface temperatures in order to reduce total emission of greenhouse gases [4]. According to Tsanas and Xifara [5], the energy consumption of a structure varies depending on the climate, the building's purpose, design parameters, and operation conditions. Therefore, numerous new technique such as highly efficient equipment are being developed to improve building design based on a few factors including overall height, glazing area, wall area, relative compactness, roof area and glazing area distribution [6]. The calculation of the heating load (HL) and cooling load (CL) is essential in efficient building design to define the parameters for the heating and cooling equipment required to preserve a contented interior environment [4].

HL refers to the entire quantity of heat energy necessary to maintain a standard room temperature [7]. The HL prediction can assist heating operators in predicting heat demand and developing realistic operation plans [8]. At present, there are several research studies on the prediction of HL. Ding *et al.,* [9] found that the HL of a structure is mostly impacted by external elements; however, considering interior variables may aid in the development of more accurate HL prediction models. Although heating load prediction is important for building development, the application of a cooling predicting model provides additional benefits for the system stability. Predicting heating and cooling load is important for a number of reasons, including reducing electricity consumption based on occupancy patterns, managing energy demands through the building's energy performance, lowering operational costs, and reducing hazardous gas emissions [10].

Liu *et al.,* [11] stated that the prediction cycle for HL can be classified into three categories: immediate term, medium term, and longer - term. Forecasting the prospect in HL variations in the following 24 hours is referred to as short term prediction. Based on study by Ashouri *et al.,* [12], temporal, autoregressive, and exogenous variables, has forecasted heating and cooling energy consumption in office buildings through hourly short-term modeling. Another study by Bacher *et al.,* [13] forecasted the heat load during the following two days, as well as the hourly heat load for each house using this short term load prediction in sixteen houses located in Denmark. According to study by Dagdougui *et al.,* [14], the best performance may be reached for one hour ahead of time. In general, medium-term HL forecasting refers to predicting the HL pattern for the upcoming week. A study by Ahmad and Chen [15], in the case of 14 days' period, the forecast performance was excellent in 7 days' period with the forecasting performance of the data mining (DM) model nearly sustain identical pattern. The average long-term prediction period is one year. Referring to Koschwitz *et al.,* [16], when effects on long-term HL projections are taken into account, the analysis revealed that heat demand fluctuates over time according to different retrofit orders due to decreasing heat consumptions and building utilization interruptions throughout the retrofit process.

Several studies have attempted to successfully forecast the quantity of energy used in buildings through machine learning-based systems [6,17,18]. Artificial Neural Network (ANN) is one of these computer models that attempts to simulate the human brain's enormous cognitive and sensory capacities in order to use patterns to express and manipulate information [19]. It was established that the ANN had a higher level of precision in its predictions, proving that it outperformed other models [20]. Escandón *et al.,* [21] concluded that the ANN has been successfully used to be a tool for assessing retrofitting techniques as it accurately forecasted thermal comfort using real-world data collected in-situ. Al-Habaibeh *et al.,* [22] found that the neural network's outputs indicate great accuracy in forecasting actual energy savings when compared to estimated values, with a success rate of around 82%. On the other hand, the Multiple Linear Regression (MLR) is one among the most extensively utilized machine learning methods in building energy load prediction [23].

Considering the most important elements is critical in developing an accurate HL forecast model [24]. Many external factors have an impact on district HL. It is critical to comprehend the various sorts of influence factors in order to eliminate redundancy or less relevant variables via several features in order to increase the model's explicability, computation speed, and accuracy, minimize noise, and avoid the risk of overfitting [25].

Controlling cooling and heating has always been seen as a component connected to both comfort and survival. Nevertheless, it is now regarded not as a luxury, but as a fact of modern living. Efforts to create cooling systems with the goal of preserving control of the environment in indoor areas of offices and residential buildings were visible in the worldwide setting at the beginning of the twentieth century. This first approach to achieving comfort levels in terms of cooling and heating results in what is today known as heating, ventilation, and air–conditioning (HVAC) [26].

Thus, a study on HL of residential buildings using Multiple Linear Regression and ANN (MLR-ANN) approaches is proposed. The remaining sections of the paper are organized as follows: The research method, as well as the data background and MLR-ANN structure, are detailed out in Section 2. In Section 3, we describe our results and discussions. Finally, we provide our conclusions and suggestions in Section 4.

2. Methodology

This research aims to establish a study for assessing the contributing factors of HL on residential buildings. A dataset of 768 residential buildings was downloaded from the study of Tsanas and Xifara [5]. Each of the 768 simulated buildings was characterized by six parameters which are Overall Height, Glazing Area, Wall Area, Relative Compactness, Roof Area, and Glazing Area Distribution. The data from descriptive statistics can be seen in Table 1.

Table 1
The descriptive statistics

		Overall Height	Glazing Area	Wall Area	Relative Compactness	Roof Area	Glazing Area Distribution	Heating Load
N	Statistic	768	768	768	768	768	768	768
Range	Statistic	3.5	0.4	171.5	0.36	110.25	5	37.09
Minimum	Statistic	3.5	0	245	0.62	110.25	0	6.01
Maximum	Statistic	7	0.4	416.5	0.98	220.5	5	43.1
Sum	Statistic	4032	180	244608	586.88	135632	2160	17131.93
Mean	Statistic	5.25	0.2344	318.5	0.7642	176.6042	2.81	22.3072
	Std. Error	0.06319	0.00481	1.57424	0.00382	1.62979	0.056	0.3641
Std. Deviation	Statistic	1.75114	0.13322	43.62648	0.10578	45.16595	1.551	10.0902
Variance	Statistic	3.066	0.018	1903.27	0.011	2039.963	2.405	101.812
Skewness	Statistic	0	-0.06	0.533	0.496	-0.163	-0.089	0.36
	Std. Error	0.088	0.088	0.088	0.088	0.088	0.088	0.088
Kurtosis	Statistic	-2.005	-1.328	0.117	-0.707	-1.777	-1.149	-1.246
	Std. Error	0.176	0.176	0.176	0.176	0.176	0.176	0.176

2.1 Multiple Linear Regression (MLR)

MLR is known as regression models with a dependent variable and two or more independent variables. It is based on least-squares and is commonly used to assess the variable effects in a model [27,28]. In this study, MLR was performed on the training data set using HL as the response variable and the six predictor variables of Overall Height, Glazing Area, Wall Area, Relative Compactness, Roof Area, and Glazing Area Distribution. The outcome was expressed as a function of the six parameters in all cases.

2.2 Artificial Neural Network (ANN)

The ANN is one of the widely-known computational methods in Artificial Intelligence. It is a revolutionary computing system and approach that processes data or information and is inspired by the human nervous system [29]. The information processors, known as neurons, are the most important aspect of this computing system. A huge number of interconnected neurons made up the ANN system, which works collectively to solve a problem. The input layer, hidden layer, and output layer are the three layers that connect the input units to the outputs in most ANNs [30]. Different neural networks can be formed based on the arrangement of neurons and layer connection patterns. Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks are two of the most established neural networks, having a broad range of problem-solving applications [31].

In this study, the MLR-ANN approaches were implemented for the analysis. Table 2 summarizes the dependent and the independent variables in this study.

Table 2
The dependent and independent variables

Variable	Description	Notation	Type
Dependent	Heating Load	HeatingLoad	Continuous
Independent	Overall Height	OverallHeight	Continuous
	Glazing Area	GlazingArea	Continuous
	Wall Area	WallArea	Continuous
	Relative Compactness	RelativeCompactness	Continuous
	Roof Area	RoofArea	Continuous
	Glazing Area Distribution	GlazingAreaDistribution	Continuous

The SPSS 23 was used to conduct the MLR-ANN analysis. A related approach can be seen in the studies by Ibrahim *et al.,* [32], Mangshor *et al.,* [33], and Ibrahim *et al.,* [34]. The two-layer neural network is adapted using the hyperbolic tangent transfer function (Eq. (1)) in the first layer and the *purelin* transfer function (Eq. (2)) in the second layer as in the study by López-Aguilar *et al.,* [35]. In Eq. (3), the general model of HL is depicted.

$$Hyperbolic\ tangent\ transfer, Y_i = \frac{e^{X_i} - e^{-X_i}}{e^{X_i} + e^{-X_i}} \tag{1}$$

$$and\ purelin, Y_j = \sum_{i=1}^{m} W_{ij} Y_i + b_j \tag{2}$$

where,
m = number of neurons in output layer,
W_{ij} = connections weight between layers i and j,
Y_i = outputs of neurons in layer i,
X_i = inputs of neurons in layer i,
b_j = bias of neurons in layer j.

$$HeatingLoad(HL) = purelin\left[LW^{2,1}\left[\tanh\left\{\begin{matrix}(IW_1)^{1,1} * OverallHeight + \\ (IW_2)^{1,2} * GlazingArea + \\ (IW_3)^{1,3} * WallArea + \\ (IW_4)^{1,4} * RelativeCompactness + \\ (IW_5)^{1,5} * RoofArea + \\ (IW_6)^{1,6} * GlazingAreaDistribution\end{matrix}\right\}\right]\right] \tag{3}$$

The data was separated into two sets during preprocessing which are training and testing. The total data, N is 768, and no excluded data is reported. The training set contains 68.5 % (526/768) of the total data, whereas, the test set contains 31.5 % (242/768) of the total data. Six input variables of Overall Height, Glazing Area, Wall Area, Relative Compactness, Roof Area, and Glazing Area Distribution were included as covariates of the MLR-ANN network. The network has one hidden layer of three nodes of H(1:1), H(1:2), and H(1:3). To simplify, the network's configuration was 6-3-1. The implemented network architecture is depicted in Figure 1.

The validation of the MLR-ANN in this study made use of the Mean Square Error (MSE) and the determination coefficient (R^2) as presented in Eq. (4) and Eq. (5) respectively.

$$MSE = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{ij} - y_{ij})^2}{nP} \tag{4}$$

where
P = number of output neurons,
n = sample size,
y_{ij} and d_{ij} = network output and desired output between layers i and j.

$$R^2 = \left(\frac{\sum_j (X_j - \bar{X})(d_j - \bar{d})}{n}\right)^2 / \frac{\sum_j (d_j - \bar{d})^2}{n}\sqrt{\frac{\sum_j (X_j - \bar{X})^2}{n}} \tag{5}$$

where
X_j = network outputs,
$\bar{X}$ = mean of the network outputs,
d_j = desired outputs,
d = mean of the desired outputs,
n = sample size.

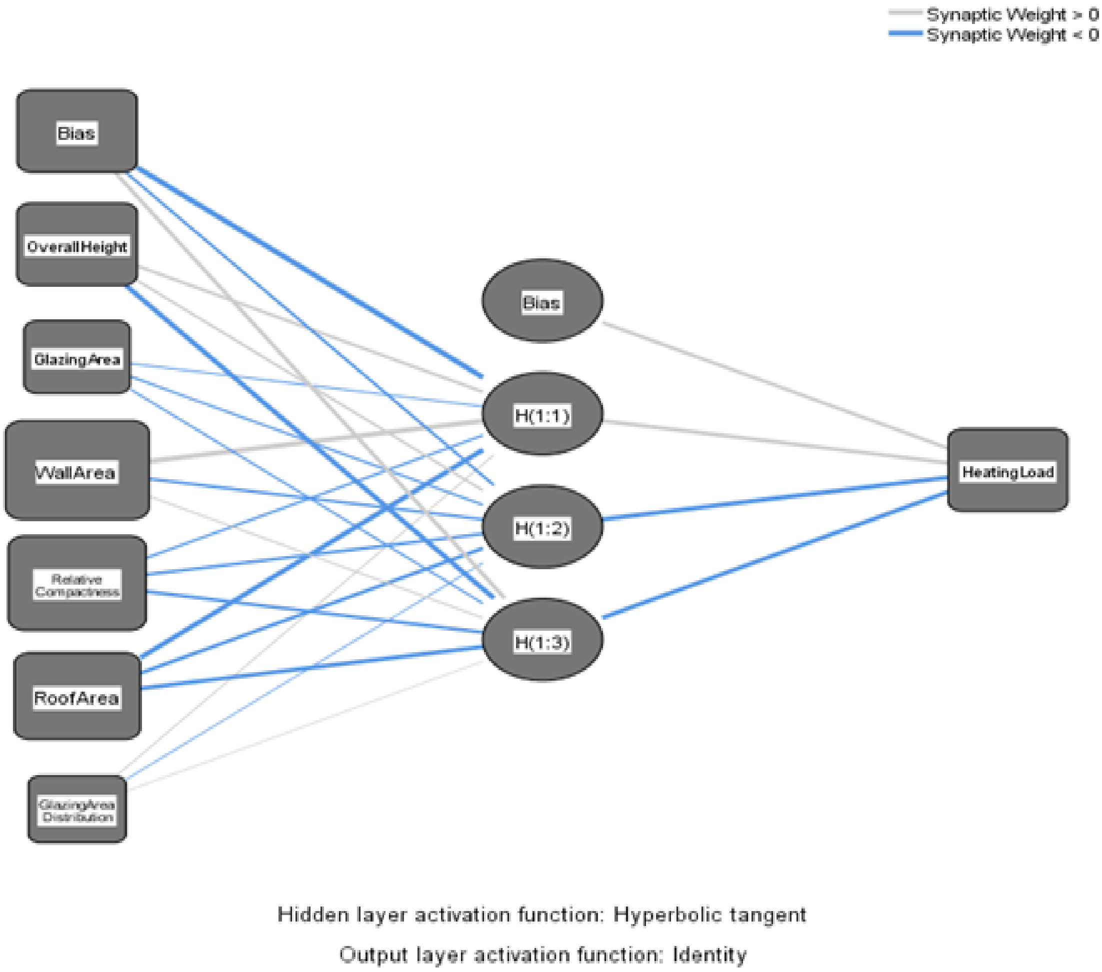

Fig. 1. MLR-ANN Architecture for Heating Load of Residential Buildings

3. Results

The MSE and R^2 metrics were analyzed to determine the best model. The MSE and R^2 are the basic metrics for estimating statistical performance, which are used to assess the precision of the proposed models' predictive capacity [36]. Table 3 and Table 4 tabulate the best MLR-ANN model summary with R^2 value equals to 0.916 and residual MSE equals to 8.600. These data were statistically analyzed, and the following conclusions were reached: the determination coefficient R^2, an indicative of the goodness of the model fitting, is close to 92%. The model attempted to address less than 8% of total variances, indicating that it provides a good approximation. By calculating the data explained by the model, the R^2 describes the variance amount. Indeed, R^2=0.916 is very near to 1, indicating lower error variance [37].

Table 3
The model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
	.957[f]	.916	.916	2.93251	.001	8.505	1	761	.004	.654

Predictors: (Constant), OverallHeight, GlazingArea, WallArea, RelativeCompactness, RoofArea, GlazingAreaDistribution
Dependent Variable: HeatingLoad

Table 4
The ANOVA[a]

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	71545.554	6	11924.259	1386.608	.000[a]
Residual	6544.289	761	8.600		
Total	78089.842	767			

a. Predictors: (Constant), OverallHeight, GlazingArea, WallArea, RelativeCompactness, RoofArea, GlazingAreaDistribution

The significance of the network's model-predicted value in relation to the different values of the independent variable is then reflected by the independent variable importance. Table 5 shows the coefficients values for MLR analysis. Based on Table 5, the significant variables are Overall Height (p-val=0.00), Glazing Area (p-val=0.00), Wall Area (p-val=0.038), Relative Compactness (p-val=0.00), Roof Area (p-val=0.00), and Glazing Area Distribution (p-val=0.04). The percentages of importance divided by the highest importance values yields the normalized importance. Table 6 shows the parameter estimates of the MLR-ANN used in this research, Table 7 tabulates the independent variable importance, and Figure 2 depicts the normalized importance analysis produced.

Table 5
Coefficients

Variables	Unstandardized Coefficients		Standardized	t	Sig.
	B	Std. Error	Coefficients Beta		
(Constant)	83.933	19.019		4.413	.000
OverallHeight	4.170	.338	.724	12.345	.000
GlazingArea	19.933	.813	.263	24.503	.000
WallArea	-.026	.013	-.114	-2.074	.038
RelativeCompactness	-64.774	10.283	-.679	-6.299	.000
RoofArea	-.175	.034	-.781	-5.115	.000
GlazingAreaDistribution	.204	.070	.031	2.916	.004

Table 6
The Parameter Estimates

Predictor		Predicted			
		Hidden Layer 1			Output Layer
		H(1:1)	H(1:2)	H(1:3)	HeatingLoad
Input Layer	(Bias)	-3.239	-.277	1.100	
	OverallHeight	.655	.223	-1.958	
	GlazingArea	-.075	-.146	-.114	
	WallArea	3.040	-.388	.081	
	RelativeCompactness	-.158	-.646	-.667	
	RoofArea	-2.090	-.696	-1.348	
	GlazingAreaDistribution	.050	-.026	.022	
Hidden Layer 1	(Bias)				1.088
	H(1:1)				1.282
	H(1:2)				-1.686
	H(1:3)				-1.555

Table 7
The Independent Variable Importance

	Importance	Normalized Importance
OverallHeight	.156	50.7%
GlazingArea	.064	20.8%
WallArea	.309	100.0%
RelativeCompactness	.269	87.1%
RoofArea	.193	62.4%
GlazingAreaDistribution	.009	2.9%

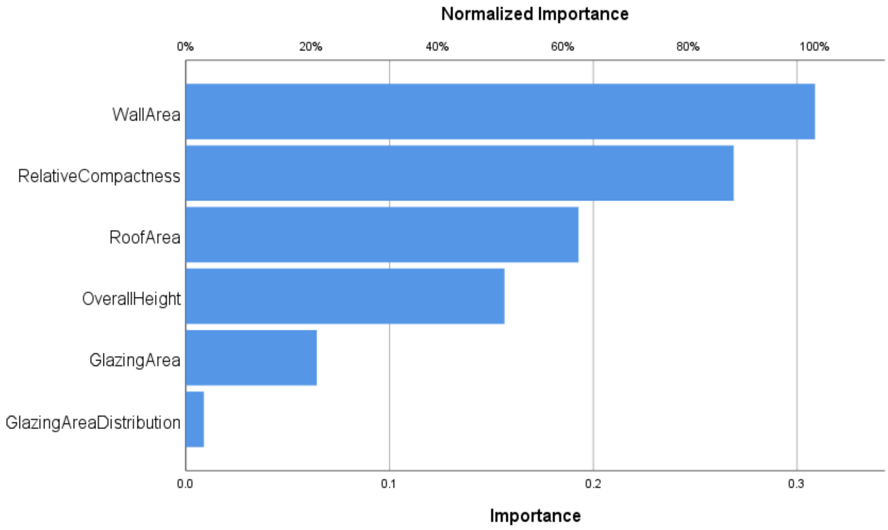

Fig. 2. Normalized Importance

Based on the Table 6 and Figure 2, the Wall Area was monitored to return an excellent percentage of normalized importance which is 100%. The Relative Compactness, Roof Area, and Overall Height were also found to have the high effects on the HL of residential buildings which produced 87.1%, 62.4%, and 50% of normalized importance respectively. On the other hand, the Glazing Area and Glazing Area Distribution reflected the slightest effects on HL which are 20.8% and 2.9% normalized importance only.

In summary, the MLR-ANN model was used to estimate the contributing factors of HL on residential buildings. The MSE, determination coefficients R^2, as well as the percentage of normalized importance analysis, were used to assess the statistical prediction capabilities of the MLR-ANN model. As a result, the MLR-ANN model's results revealed that the measured R^2 between the output and the desired data was good, with R^2 of 0.916, a residual MSE of 8.600, and a 100% normalized importance for Wall Area. Thus, it clearly signifies that the Wall Area is the most contributing factor towards HL, followed by the Relative Compactness, Roof Area, Overall Height, Glazing Area, and Glazing Area Distribution.

4. Conclusions

This paper investigates the effects of six input variables which are Overall Height, Glazing Area, Wall Area, Relative Compactness, Roof Area, and Glazing Area Distribution on one output variable, namely Heating Load (HL) of residential buildings. The Multiple Linear Regression and Artificial Neural Network (MLR-ANN) approaches were employed on the 768 dataset of residential buildings. The two-layer hyperbolic tangent-identity transfer functions with 6-3-1 configurations were identified as the best neural network model. Based on the findings of MLR-ANN analysis, it was found that the Wall Area is the most significant contributor to HL, followed by Relative Compactness, Roof Area, Overall Height, Glazing Area, and Glazing Area Distribution. It is advised that HVAC (heating, ventilation, and air conditioning) systems need to installed in residential buildings to minimize energy use. Natural ventilation of vernacular design, and radiant heating and cooling systems is encouraged in buildings as it is a particularly effective and efficient way of ensuring thermal comfort within a structure.

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