Environmental impacts cost assessment model of residential building using an artificial neural network

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Abstract

Purpose- Buildings are major contributors to greenhouse gases (GHG) along the various stages of the building life cycle. A range of tools have been utilised for estimating building energy use and environmental impacts; these are time-consuming and require massive data that are not necessarily available during early design stages. Therefore, this study aimed to develop an Environmental Impacts Cost Assessment Model (EICAM), that quantifies both energy and environmental costs for residential buildings.

Design/methodology/approach- An Artificial Neural Network (ANN) was employed to develop the EICAM. The model consists of six input parameters including wall type, roof type, glazing type, window to wall ratio (WWR), shading device and building orientation. In addition, the model calculates four measures: annual energy cost, operational carbon over 20 years, envelope embodied carbon and total carbon per square metre. The ANN architecture is 6:13:4:4, where the conjugate gradient algorithm was applied to train the model and minimise the mean squared error (MSE). Furthermore, regression analysis for the ANN prediction for each output was performed.

Findings- The MSE was minimised to 0.016 while training the model. Also, the correlation between each ANN output and the actual output was very strong, with an R^2 value for each output of almost 0.998. Moreover, validation was conducted for each output, with the error percentages calculated at 0.26%, 0.25%, 0.03% and 0.27% for the annual energy cost, operational carbon, envelope materials embodied carbon and total carbon per square metre respectively. Accordingly, the EICAM contributes to enhancing design decision-making concerning energy consumption and carbon emissions in early design stages.

Research limitations/implications – This study provides theoretical implications to the domain of building environmental impact assessment, through illustrating a systematic approach for developing an energy-based prediction model that generates four environmental-oriented outputs namely: energy cost, operational energy carbon, envelope embodied carbon, and total carbon. The model developed has practical implications for the architectural/engineering (A/E) industries, through providing a useful tool to easily predict environmental impact costs during the early design phase. This would enable designers in Saudi Arabia to make effective design decisions that would increase sustainability in the building life cycle.

Originality- This study endeavours to bridge the gap between energy costs and environmental impacts in a predictive model for Saudi residential units by providing a holistic predictive model entitled EICAM. The novelty of this model is that it is an alternative tool that quantifies both energy cost as well as building's environmental impact in one model by using a machine learning approach. Besides, EICAM predicts its outcomes more quickly than conventional tools such as DesignBuilder, and is reliable for predicting accurate environmental impact costs during early design stages.

Keywords- Artificial Neural Networks, building envelope, embodied carbon, energy cost, operational carbon

1. Introduction

Buildings have a significant impact on the natural environment and they account for a significant proportion of global warming due to greenhouse gas (GHG) emissions (Alrashed and Asif, 2014; Ingrao et al., 2018). It has been reported that the built environment consumes 40% of worldwide energy and is responsible for one-third of the GHGs which cause carbon emissions (Ching and Shapiro, 2014; Lu et al., 2020). In Saudi Arabia, buildings consume about 80% of total electrical energy at the national level during the operational phase. The residential sector accounts for half of the total electrical energy consumed in the building sector (Al-Ghamdi and Alshaibani, 2018). The Electricity and Cogeneration Regulatory Authority (ECRA) has reported that 70% of electrical energy is consumed for cooling the residential buildings (SEEC, 2018). Additionally, around 71% of Saudi houses lack thermal insulation, which leads to low energy efficiency performance (AlFaraidy and Azzam, 2019). The architectural design process is a fundamental phase where early design decisions play a vital role in a building's environmental impact and energy performance. Therefore, researchers have highlighted the significance of forecasting building energy consumption and environmental impacts during the early architectural design phase (Asadi, Amiri, et al., 2014; Basbagill et al., 2013; Russell-Smith et al., 2015; Schwartz et al., 2016). There are various building energy simulation tools that are utilised for estimating the amount of building energy use. These tools provide reliable solutions for forecasting the impact of different design alternatives (Tsanas and Xifara, 2012). However, previous studies have revealed that buildings' environmental impacts are not widely quantified during the early design stage. This is because conducting life cycle assessment (LCA) and running energy simulation, can be challenging, time-consuming and requiring user-expertise to run such tools. Besides, there is a lack of required data during early design stages and design changes often occur during the conceptual design stage (Attia et al., 2013; Han et al., 2018; Østergård et al., 2016; Russell-Smith et al., 2015). An artificial neural network (ANN) can be applied for predicting building energy use, which its advantages over energy simulation tools include simplicity and the fast speed of calculations (Tsanas and

Xifara, 2012; Turhan et al., 2014). This study aimed to develop a simplified model titled Environmental Impact Cost Assessment Model (EICAM). It is utilised for estimating the operational energy cost, operational carbon, building envelope embodied carbon and total carbon per square metre. The EICAM supports early design decisions by selecting the desired building envelope combination. This was achieved by creating the model's data set spreadsheet and developing an ANN-based model for establishing the EICAM.

2. Previous Studies

The concept of predictive models has evolved rapidly in the fields of architectural and construction management. Previous studies have shed light on developing models for assessing building energy, environmental impacts and labour productivity (Graupe, 2007; Ma et al., 2019; Nasirzadeh et al., 2020). Various studies have highlighted the significance of developing ANN models as a decision support system to assess different aspects related to architectural design decisions. For instance, an ANN has been utilised for forecasting building energy based on the amount of daylight, which was developed by performing daylighting and energy simulations. The study found that the ANN model provided accurate results due to its high correlation values and low mean squared error (MSE) (Walger et al., 2013). Another study applied ANN to predict operational energy, global warming, acidification, ozone depletion, eutrophication, and smog formation (Azari et al., 2016). In addition, ANN can be integrated with building information modelling (BIM). Ma et al. (2019) developed a BIM and ANN-based system for evaluating individual thermal comfort. This system is a plugin within the Revit package incorporating the C# programming language. The plugin uses the ANN model for estimating the personal thermal comfort evaluation (Ma et al., 2019). Moreover, an ANN was developed as an "Energy Cost Prediction Model" that incorporates three-dimensional (3D) BIM, which predicts annual energy costs for Saudi residential buildings. This model was based on 185 data sets of existing houses in six cities in the eastern region of Saudi Arabi. Furthermore, the study affirmed that the model does not require a professional user to run it. It was also recommended that other effective factors such as roof type and building orientation be adopted (Alshibani and Alshamrani, 2017). This study is limited to estimating energy costs, disregarding environmental impacts such as embodied and operational carbon.

In comparison, a comprehensive predictive model has been developed that forecasts both energy and environmental building performance, which aims to support decisions during the design phase. It consists of 29 inputs and generates seven outputs, including heating demand, and six environmental impacts categories. This model can be utilised by non-expert users in LCA or building energy modelling (Amico et al., 2019). Another study developed a model that links Simulation-Based Multi-Objective Optimization (SBMO) with ANN. It aims to provide a comprehensive prediction of total energy consumption, Life Cycle Costing (LCC) and LCA for various renovation scenarios and aiding in selecting optimum scenarios. The application of this model is less time-consuming than using building energy simulation (Amirhosain and Hammad, 2019).

Environmental impact cost, also known as eco-cost, cover three impact types, emissions, energy and transportation. It also refers to the impact value of pollution generated through consumption actions on the environment. Adding to that, it is utilised for assessing environmental aspects to mitigate the ecological impacts of such activities (Baeza-Brotons et al., 2014; Wang et al., 2020). To date, there are insufficient studies that have considered the quantification of environmental impact costs in predictive models. These previous studies on the applications of ANN in the building industry have contributed to reducing the time consumed in performing building energy simulation modelling as well as forecasting building environmental impacts. ANN models have the potential to be integrated during the early design phase, which assists building designers in decision-making and management. None of the studies described above provided a holistic predictive model that quantifies both energy and environmental cost for residential buildings in Saudi Arabia. Therefore, this study attempts to bridge the gap between energy cost and environmental impacts in a novel predictive mode entitled EICAM. This model is a robust tool that quantifies carbon emissions and energy costs quickly which has the potential to be utilised easily during early design stage.

3. Methodology

In accordance with previous studies, ANN datasets are developed using existing data or based on performing simulations. In this methodology section, as illustrated in **Figure 1,** the process of developing EICAM is divided into two main parts; data sets development and modelling approach (These processes are explained in the following subsections).

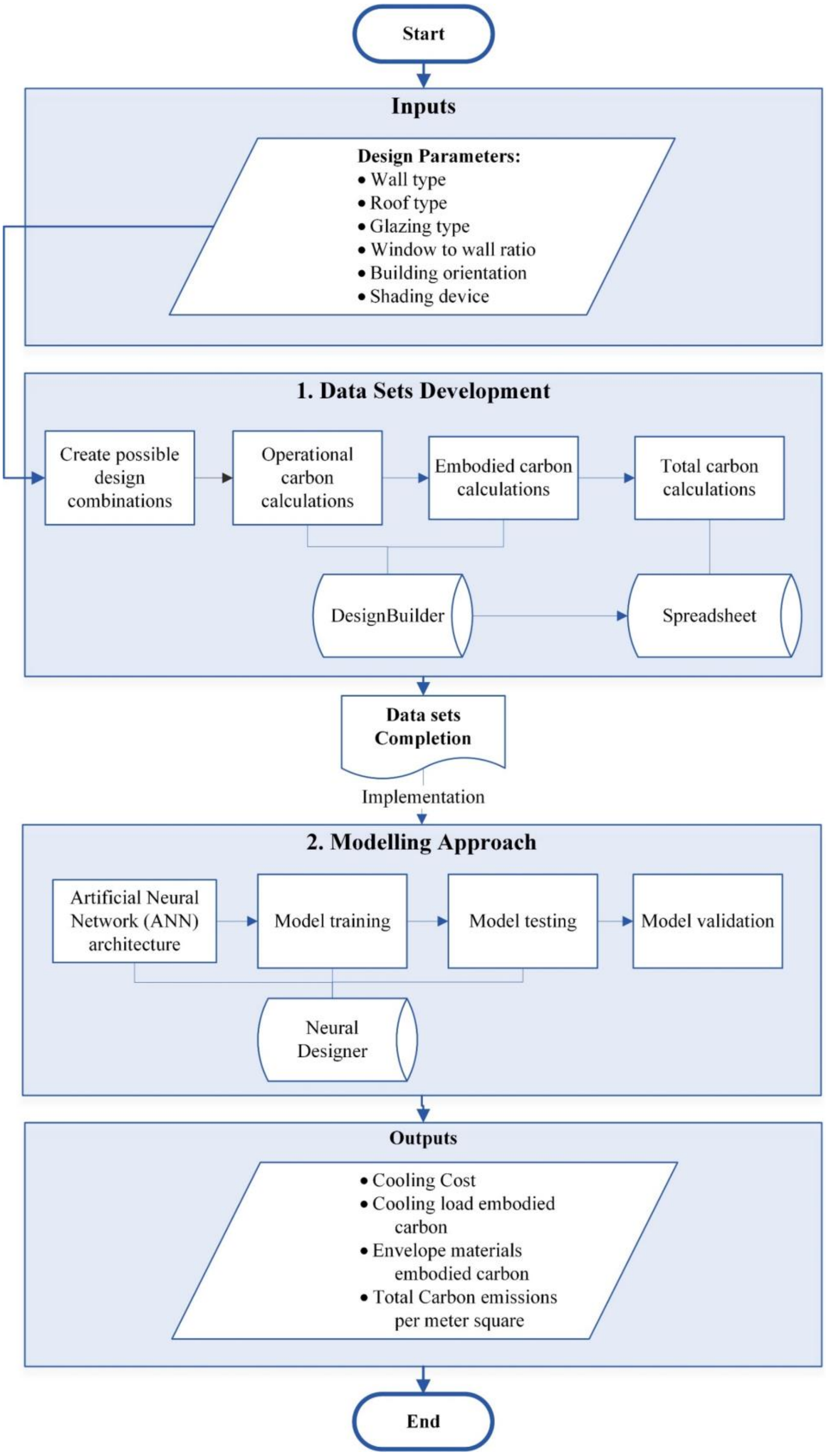

Figure 1. EICAM development process

3.1 Data sets development

The EICAM's data sets, which are formed in an Excel spreadsheet, are based on energy simulations. This spreadsheet includes a wide range of design combinations of input parameters and their output variables, and is presented in **Appendix I**. The outline of the data set's spreadsheet consists of 10 main columns, where the first six columns are referred to as the model's six input parameters, and the last four columns represent the four model outputs. The spreadsheet's rows identify each building envelope design combination. The EICAM input parameters include wall type, roof type, glazing type, window to wall ratio, shading devices, and building orientation. These parameters were chosen due to their vital role in building cooling loads as well as their environmental impacts. Also, they are the basic design parameters that are significant in early design phase decisions. The four model outputs are energy cost, operational carbon, envelope embodied carbon, and total carbon per square metre. The value of each output variable is influenced by the determined combination of the input parameters.

In this study, Riyadh city, (24.70° N Latitude, 46.73° E Longitude and 620 m above sea level), is chosen as the base case model's location for several reasons: (1) Riyadh is the capital city of Saudi Arabia as well as the largest city in the country, (2) Riyadh is developing rapidly, and (3) Riyadh's population has increased dramatically from 5.2 to 7.23 million between 2010 and 2020, which will increase the demand for housing (Alqahtany, 2020). Riyadh is categorised under climate zone 1 according to the Saudi Energy Conservation Code for a low-rise residential building (SBC 602). Also, Riyadh is an extremely hot region with maximum Dry Bulb of 47.2°C, and Cooling Degree Day 10 around 6107 (SBCNC, 2018). The SBC 602 is based on the International Energy Conservation Code (IECC) and the American Society of Heating Refrigerating and Air-Conditioning Engineers (ASHRAE) (Alfaraidy and Sulieman, 2019). Accordingly, the

EICAM input parameters comply with SBC 602 requirements. **Table I** identifies the six input parameters with their categorised choices, where each is encoded by a numerical value. This table is used for creating the possible design combinations of the base case model that are generated in **Appendix I**.

Table I. Model inputs variables with their specification and code

Input	Description		Specification	Code
1. Wall type	Thermal block wall with expanded polystyrene insulation	**U-factor:** W/ m^2. k	0.20	1
	Efficient block wall with marble		0.24	2
	Thermal block wall with polyurethane insulation		0.31	3
	External Insulation and Finish System		0.33	4
2. Roof type	Green roof		0.19	1
	Siporex light concrete Tiles		0.18	2
	Reinforced Concrete Insulated slab		0.20	3
3. Glazing type	6 mm doubled low-e glazing with 12 mm air gap		1.65	1
	6 mm doubled bronze tint glazing with 12 mm air		2.16	2
	6 mm doubled low-e clear glazing with 12 mm argon gas		1.52	3
	6 mm doubled low-e tint glazing with 12 mm argon gas		1.16	4
4. Window to wall ratio	10%		-	10
	20%		-	20
	25%		-	25
5. Shading device	Overhang\ Vertical- shading device		-50 cm projection -Overhang applied for South, while vertical side fins applied for East and West windows	1
	Louver shading device		-15 cm projection from window -5 blades -35 cm vertical spacing -300 angles -25 cm blade depth -Applied in all windows except the north	2
6. Building orientation (Main elevation faces direction)	East		-	0
	South		-	90
	West		-	180
	North		-	270

A typical Saudi house is selected as the base case model for this study, which was developed by the Ministry of Housing. There are 500,000 units of this prototype that are established or to be built among the main cities in Saudi Arabia (Lasker, 2016; Ministry of Housing, 2019). **Table II** demonstrates the typical Saudi house characteristics, which follow the minimum SBC 602 requirements.

Table II. Characteristics and specifications of typical Saudi house -base case model

Weather File	**SAU_RIYADH.404380_IWEC**	
Orientation	Front elevation facing the East	
Geometry	**Number of stories**	2
	Total gross built are	375 m^2
	Total gross floor area	230 m^2
	Ground floor area	194 m^2
	First floor area	90 m^2
	Plan proportion	6:7
	Height	6.7 m
	Gross wall area	318 m^2
	Glazing area	15 m2
	WWR	5%
External Wall Construction	**Layers:**15 mm cement plaster, 100 mm concrete block, 90 polystyrene, 100 mm concrete block, 15 mm cement plaster	
	U-value	0.34 w / m^2. K
Roof Construction	**Layers:** 20 mm Ceramic tile, 20 mm mortar, 10 mm sand, 100 mm polyurethane, 4 mm bitumen felt, 200 mm concrete slab, 15 mm cement plaster	
	U-value	0.21 w / m^2. K
Glazing Type	Double clear glazing (6 mm glass, 12 mm air gap, 6 mm glass)	
	U-value	2.6 w / m^2. K
	Air Leakage	1.5 L/ s / m^{2,} 0.75 ach
	External shading devices	Overhanded 30 cm
Occupants	**Numbers**	6 (2 adults+ 4 children)
Lighting	**Lighting Display Density**	7.3 kW/ m^2
	Target Illuminance	150 lux
HVAC System	**Package terminal air conditioner (DX system)** CoP: 2.5	
	Heating	21.1 ^{0}C
	Heating setback	18.1 ^{0}C
	Cooling	23.9 ^{0}C
	Cooling setback	27.9 ^{0}C
	Humidification setpoint	30 %
	Dehumidification setpoint	50 %

Under this base case model, the design combinations of the model input parameters are generated, as they are implemented **in Appendix I**.

The DesignBuilder simulation tool has a graphical user interface (GUI) and uses the latest version of EnergyPlus as a dynamic simulation engine for energy calculations (Abdul and Budaiwi, 2015; AlHashmi et al., 2017). It is utilised in this study as it is an easy-to-use interface that enables quantifying building energy performance using advanced tools for 3D modelling (DesignBuilder, 2019a; IBPSA-USA, 2019). It also quantifies the embodied carbon of building materials (AlHashmi et al., 2017). The carbon data are obtained from the Inventory of Carbon Energy (ICE) database developed by the University of Bath (DesignBuilder, 2019b; Kumanayake and Luo, 2017). The EICAM outputs play a vital role in predicting the environmental impact costs, which are calculated as follows:

(1) Energy cost

Considering the energy cost in the early design process is essential in order to select the optimum design alternatives that mitigate the amount of operational energy costs (Alshibani and Alshamrani, 2017). The energy costs are obtained by multiplying the value of energy use by the related costs (Mora et al., 2018). The energy cost of each kWh is 0.18 SAR (around 0.048 USD) for Saudi residential units, provided the energy does not exceed 6000 kWh per month (Saudi Electricity Company, 2018). Accordingly, the energy cost is considered in EICAM and is calculated as equation (1).

$$\mathrm{EC} = \mathrm{OE} \times \mathrm{AC} \tag{1}$$

Where,
EC= Energy cost (SAR)
OE= Operational energy -annual cooling load- generated by DesignBuilder (kWh)
AC= actual energy cost per kWh (SAR)

(2) Operational energy carbon

The operational energy carbon is emitted during the building operational stage, and it is the highest amount of the total carbon footprint along the building lifetime (Iddon and Firth, 2013; Monahan and Powell, 2011). The carbon factor for electrical energy in Saudi Arabia is 0.757 $kgCO_2/kWh$ (Krarti et al., 2017). Based on the “Demography Survey 2016” issued by the General Authority for Statistics, most of Saudi houses in Riyadh City have a life span of 20 years (General Authority for Statistics, 2016). Consequently, the operational energy carbon is quantified in equation (2).

$$\mathrm{OE_{CO2}} = \mathrm{OE} \times \mathrm{CF} \times \mathrm{A} \qquad (2)$$

Where,
OE_{CO2}= Operational Energy carbon emissions ($kgCO_2$)
OE= Operational energy generated by DesignBuilder (kWh)
CF= Carbon factor ($kgCO_2$/kWh)
A= Approximate age

(3) Envelope Embodied Carbon

The embodied carbon includes the sum of carbon emissions resulting from energy that is consumed during life cycle of all the materials life cycle starting from harvesting to disposal (Ching and Shapiro, 2014). In this study, the embodied carbon was quantified based on the ICE database, which provides equivalent carbon ($kgCO_2$) for material manufacturing processes (DesignBuilder, 2019b). In this study, the materials are limited to the external walls, roof type, glazing type, and shading device materials.

(4) Total Carbon Emissions

The total carbon emissions are the sum of the operational carbon and embodied carbon, divided by the building area. The total carbon emissions per square metre ($\mathrm{CO_2/m^2}$) were calculated in equation (3).

$$\text{Total } \mathrm{CO_2/m^2} = (\mathrm{OE_{CO2}} + \mathrm{E_{CO2}}) \div \text{Building Area} \qquad (3)$$

Where,
OE_{CO2}= Operational carbon ($kgCO_2$)
E_{CO2}= Embodied (envelope materials) carbon emissions ($kgCO_2$)

3.2 Modelling Approach

There are various ANNs approaches that are used widely for developing predictive models, such as multi-layer feed-forward, general regression, recurrent, group method of data handling, auto regressive with an exogenous inputs, and radial basis function neural networks (Reza et al., 2019). The feed-forward neural network is considered the simplest and most prominent type of network (Asadi, Silva, et al., 2014; Hee et al., 2017; Tso and Yau, 2007). It consists of three main layers: input, hidden and output layers (He and Xu, 2009). Each layer comprises several neurons that are connected by mathematical processing, where neurons receive an input signal (x). Each input neuron is associated with a corresponding weight value (*w*). The sum obtained by multiplying the input value and its weight is added to the (b) value, which is called bias; this factor is associated with information storage (Kim, 2017). The network's neurons are connected in a single direction. It is commonly organised in a layered form where there are no connections between neurons located in the same layer, but each neuron is connected to another neuron in its neighbouring forwarding layer (Du and Swamy, 2019).

Figure 2 represents the computational flow chart of EICAM, where a feed-forward neural network is applied to develop the model in this study.

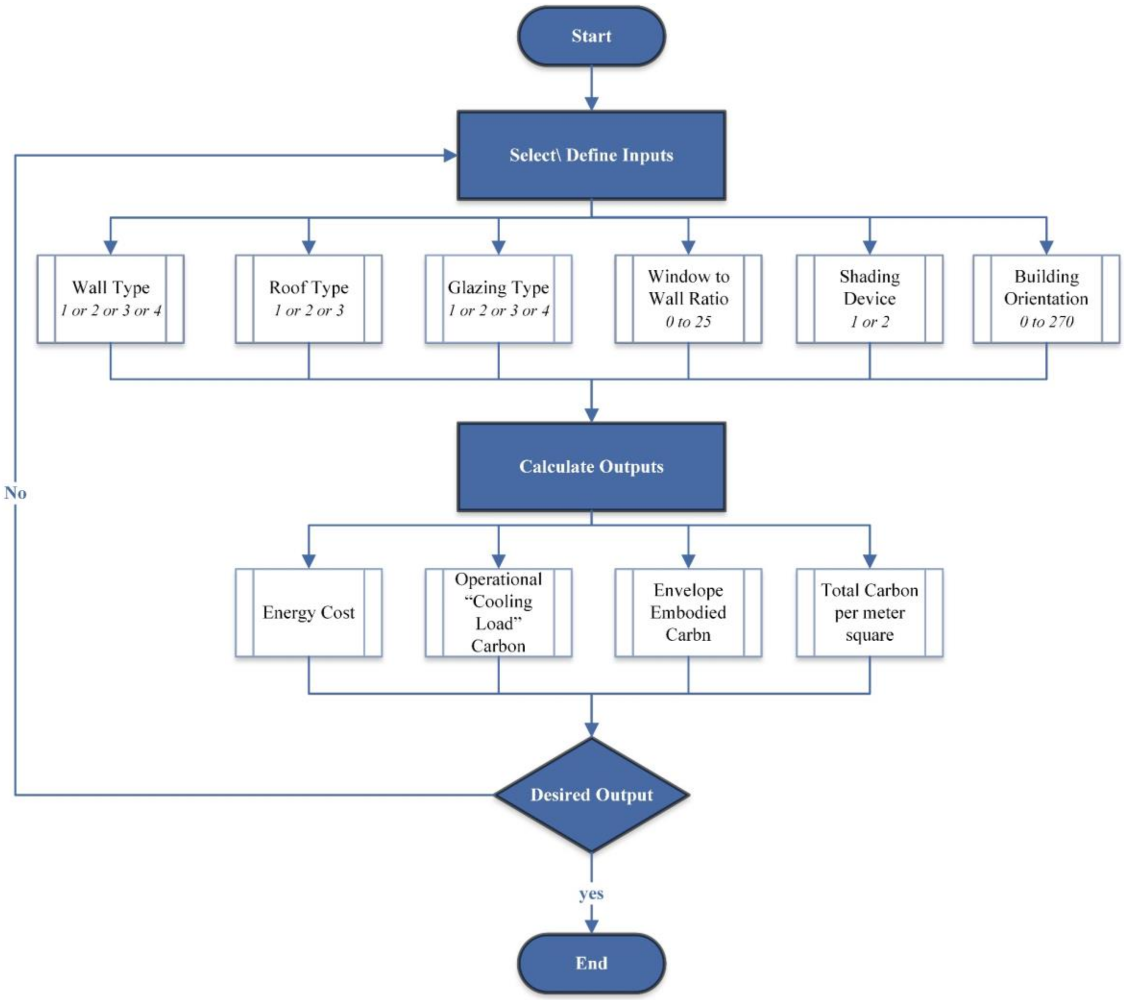

Figure 2. EICAM computational flow chart

3.2.1 ANN Architecture

"Neural Designer" software was utilised in this study for developing EICAM. It implements neural network algorithms that allow predictive models to be built. Its user interface guides the model builder through a sequence of well-defined stages to simplify data entry. It comprises five sequential phases: data set, neural network, training strategy, model selection, and testing analysis (Neural Designer, 2019a).

EICAM's input layer consists of six neurons, while the output layer (target) comprises four neurons. The neurons in the hidden layer are calculated by equation (4) (Biswas et al., 2016; Moon, 2009).

$$n_h = (2 \times n_i) + 1 \quad (4)$$

Where,
n_h = number of hidden neurons
n_i = number of input neurons

Accordingly, the hidden layer comprises 13 neurons, where **Figure 3** illustrates the architecture of EICAM, which is 6:13:4:4.

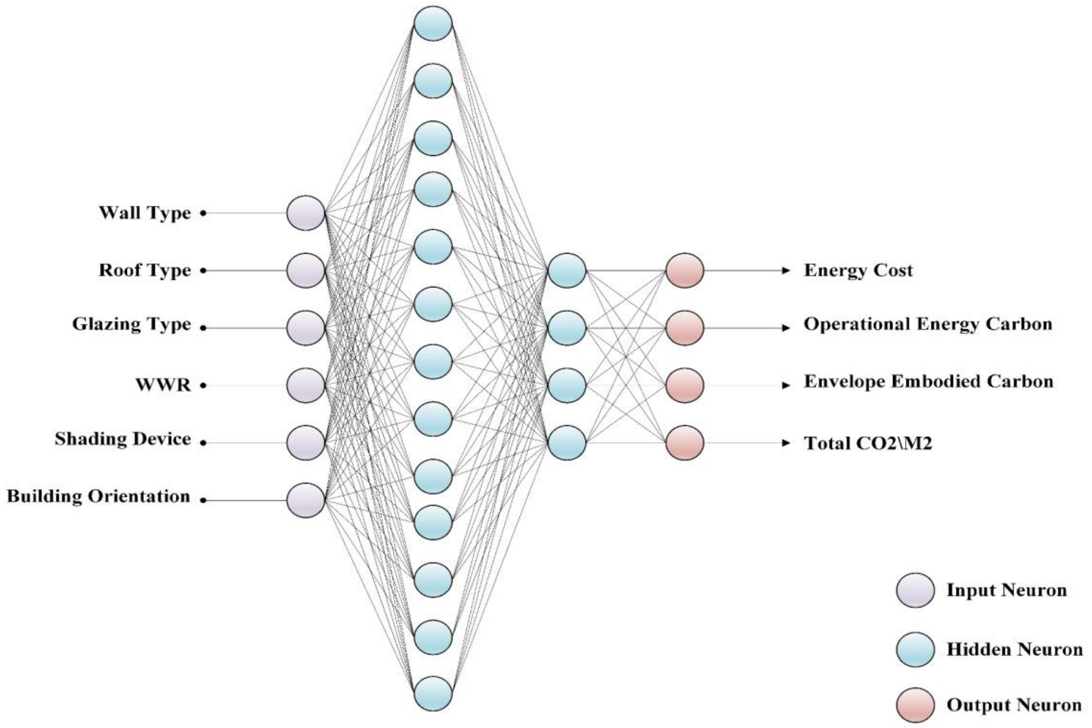

Figure 3. Artificial Neural Network architecture for developing EICAM

The minimum number of required data sets to establish the ANN model is 64, as calculated by equation (5) (Biswas et al., 2016; Moon, 2009).

$$n_d = \left(n_h - \left(\frac{n_i + n_o}{2}\right)\right)^2 \quad (5)$$

Where,
n_d = minimum data sets number
n_h = number of hidden neurons

n_i = the input neuron numbers
n_0 = number of output neurons.

In this study, 201 data sets, gathered in an Excel spreadsheet, were implemented in Neural Designer software in the first step “Data set”. The data sets were divided into three main categories, of which 70% used for training, 15% were used for testing and 15% were used only for validation. **Table III** includes the statistical analysis of the model data sets including maximum, minimum, mean and standard deviation for both input and output variables.

Table III. Statistical analysis of model data

		Maximum	**Minimum**	**Mean**	**Slandered deviation**
Inputs	Wall Type	1	4	-	-
	Roof Type	1	3	-	-
	Glazing Type	1	4	-	-
	WWR	10	25	19.63	6.67
	Shading Device	1	2	-	-
	Building Orientation	0	270	110.15	102.80
Outputs	Annual Energy cost	2617	4096	3289.86	369.02
	Operational Energy Carbon	220181	344556	276713.40	31038.53
	Envelope Embodied Carbon	20056	32538	26484.19	3486.18
	Total Carbon per square metre	1024	1530	1263.32	129.26

3.2.2 The ANN Activation Functions

The neural network creates a function which, when given inputs, produces outputs. In general, the approximation of the function depends on the input domain as well as the repetition of applying training data (Taylor, 2006). The hidden layer is where the sums of the weighted inputs are stored, and the output layer results from the transformation of the total weighted inputs by using an activation function (Kim, 2017). The weighted sum is calculated according to mathematical equation (6) (Zhang, 2010).

$$\mathrm{V} = \sum \mathrm{W1i.Xi} + \mathrm{b} \tag{6}$$

Where,

v= weighted sum
$W1i$ = connection weight of input neuron i that targets neuron 1
$i = 1, 2, ..., n$,
b = bias that is a real number

Each input signal from the input layer is multiplied by the weight before it reaches the node in the hidden layer, and the sum of the weighted signals are stored at the node (Kim, 2017). The network output is defined by the activation function (*f*) according to the weighted sum (*v*), which is usually a non-linear function (He and Xu, 2009). The following equation, (7), represents the activation function's general formula.

$$y_i = f(v) \tag{7}$$

Where,
y_i= output of neuron
f= activation (response) function
v= weighted sum

The most commonly applied activation functions are sigmoidal functions such as the hyperbolic tangent function and logistic function (Du and Swamy, 2019; Kim, 2017). The activation function for the hidden neurons in developing EICAM is followed by the logistic function, as formulated in equation (8), where its outputs always have positive values (Enquist and Ghirlanda, 2013).

$$a = \frac{1}{1+ e^{-v}} \tag{8}$$

3.2.3 ANN Training (Learning) Methods

"Learning Algorithm" refers to the procedure utilised for conducting the training process. The main function of the learning algorithm is to obtain the desired output objective by modifying the network weights in an orderly fashion (Kialashaki, 2014). These algorithms are gradually mitigate the approximation error (He and Xu, 2009). In this study, the mean squared error (MSE) in equation (9) was utilised to calculate the model error (Azari et al., 2016).

$$E = \frac{1}{N} \times \left(\sum_{i=1}^{N} y_i - y_t\right)^2 \qquad (9)$$

Where,

E = error value
N = training data number
y_i = ANN output
y_t = target values

There is a wide range of learning algorithms for feed-forward ANN, where the Backpropagation (BP) algorithm and its diverse methods are applied effectively (He and Xu, 2009). The most common training algorithms in building energy analysis are Steepest/ Gradient Descent (GD), Conjugate Gradient (CG), Newton's Method (NM) and Levenberg-Marquardt (LM) (Mohandes et al., 2019). The CG algorithm is a common substitute for BP (Du and Swamy, 2019), which was used for training the EICAM.

4. Results

4.1 Model Training

The loss index plays a vital role in training the neural network, as it provides a measure of the neural network accuracy that is required for the training process. The error is the most essential term in the loss expression, as it calculates how the neural network fits the training instances to the data sets (Neural Designer, 2019b). In this regard, MSE was used for calculating the error values by quantifying the average squared error between the model output and the output target in the actual data sets. The initial value of the training error was 80.52 and the initial selection error was 81.70. Since the accuracy of error minimisation, as well as the speed of model training, are significant in acquiring a reliable model, an optimisation algorithm (CG) was employed for minimising the error through an iteration (epochs) process. The training and selection errors were minimised through 735 iterations to 0.0162 and 0.00659 respectively.

4.2 ANN Testing

Linear regression analysis is a statistical tool that is applied for evaluating the performance of ANN model output (Amico et al., 2019; Ascione et al., 2017). The coefficient of determination value, known as R^2, indicates the correlation between the actual output value and the model output value. When R^2 is close to 1, it indicates optimal correlation, where the actual and model outputs are close (Alqahtani and Whyte, 2013; Alshibani and Alshamrani, 2017). In this study, four regression analyses, illustrated in **Figure 4**, were carried out to test the correlation between each EICAM output variable and its actual target value. In the energy cost linear regression, the y-intercept is 54.6 and the slope is 0.981; chart (A) shows that the correlation between the actual and predicted energy cost is high, where R^2 is 0.993. In the operational carbon linear regression, the y-intercept is 5920.14 and the slope is 0.981; chart (B) shows that the correlation between the actual and predicted carbon is high, where R^2 is 0.993. For the envelope embodied carbon linear regression, the y-intercept is 575 and the slope is 0.976; chart (C) illustrates a strong correlation between actual and predicted envelope embodied carbon, with a R^2 value of 0.998. In the total carbon per square metre linear regression, the y-intercept is 21.3 and the slope is 0.981. Chart (D) indicates a high correlation, where the R^2 value is 0.993.

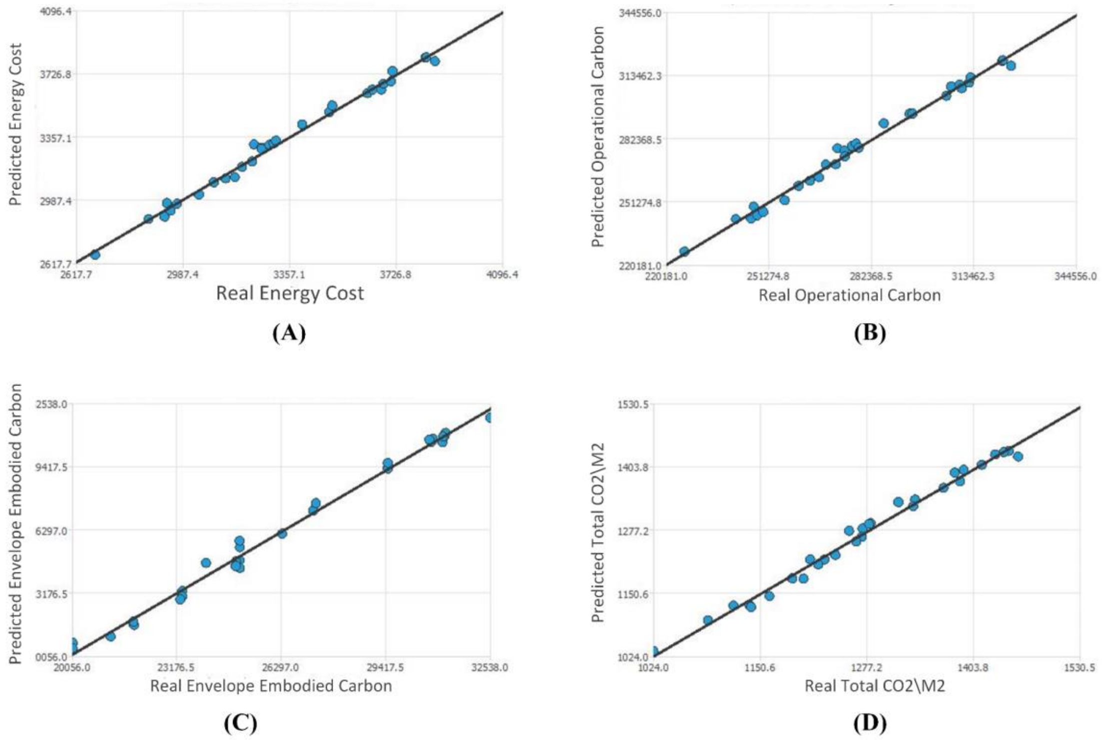

Figure 4. Correlation between real outputs and predicted outputs of EICAM

4.3 Model Validation

"Neural Designer" software provides a tab "Model deployment", which refers to utilising the developed model for predicting any new input; consequently, it will generate a report of outputs. Based on this, a set of combinations of input variables in the data set was implemented in "Model deployment" tab to calculate the four model outputs. Each of the output variables obtained from EICAM was compared to the actual values in the data sets. Furthermore, the error percentage of each model output was calculated to ensure the accuracy of EICAM. includes four graphs validating EICAM performance. Each graph represents a comparison between the output values obtained from ANN and actual values in the data sets. Firstly, graph (A) illustrates the comparison of energy cost values, where error percentage is 0.26%. Secondly, graph (B) shows the difference between operational carbon values, where error percentage is 0.25%. Thirdly, graph (C) clarifies the comparison of envelope embodied carb values, where error percentage is 0.03%. Fourthly, graph (D) demonstrates the comparison of total carbon per square metre values, where error percentage is 0.27%.

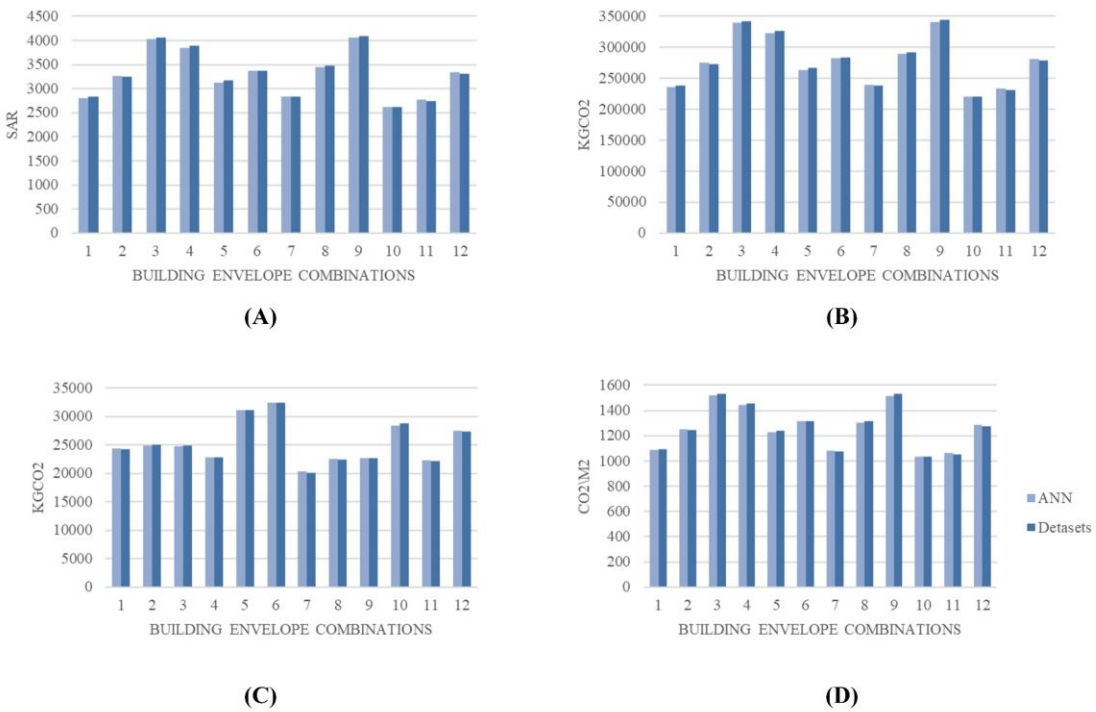

Figure 5. EICAM validation

5. Discussion

According to the training process, the MSE initiated value was 80.52, then after 735 iterations using CG it was minimised to 0.016, which is near zero. This indicates that EICAM properly predicted the data behaviour. Regarding the testing phase, linear regression provided the correlation of each EICAM's output, where the R^2 values were equal to approximately one (ranging from 0.993 to 0.998). These results ensure the reliability of EICAM. Moreover, the performance of EICAM was further checked through conducting a comparison between the obtained output values by ANN and the actual dataset, which revealed that the error percentage of each predicted output was less than 1 percent. Furthermore, a new input combination that was not used in the data sets was examined. These input data were implemented in both tools, EICAM and DesignBuilder. **Figure 6** demonstrates the EICAM deployment window, where each input value is determined; accordingly, the outputs are calculated.

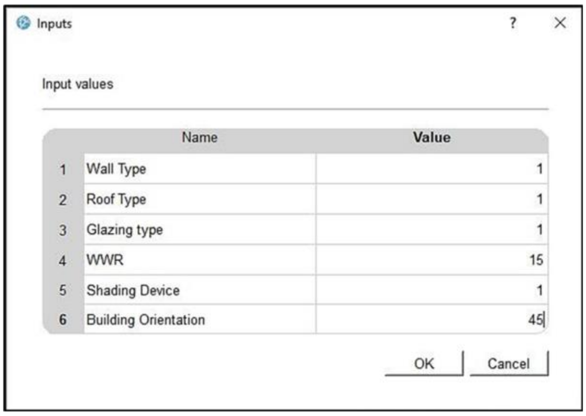

Figure 6. EICAM deployment window for validation

Figure 7 shows the results of each of the four outputs generated by both tools in bar chart format. The results are almost the same. Hence, the performance of EICAM for the new combination is accepted as providing validation, and accurate results for any new inputs not included in the model's original data sets.

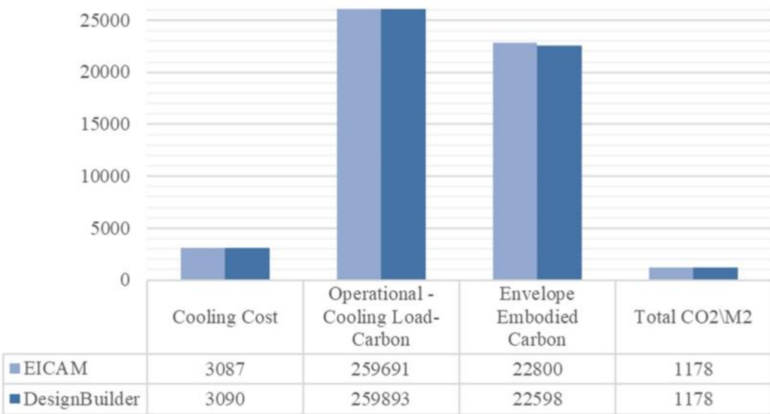

Figure 7. EICAM performance for further validation

Without doubt DesignBuilder is a reliable tool that performs energy simulations, carbon emissions calculations, and evaluates energy costs (Alhuwayil et al., 2019; Cho et al., 2019). The advantage of EICAM over DesignBuilder is that it estimates the environmental impact costs quickly and accurately without developing a 3D model of the building during early design decisions. Besides, EICAM's user doesn't require experience to run the model. Hence, the developed model can be used by the A/E industry as well as building owners and real-estate developers to forecast environmental impact costs.

6. Conclusion

This study provides theoretical contributions to the field of building environmental impact assessment, by representing a systematic approach for developing an energy-based prediction model (EICAM) that estimates four environmental-oriented outputs namely: energy cost, operational energy carbon, envelope embodied carbon, and total carbon emissions. EICAM contributes practical implications to the A/E industry by providing a decision support tool for easily predicting the environmental impact costs during the early design stage. This would enable the designers to evaluate different design alternatives with effective design decisions that would fulfill sustainability requirements. EICAM was developed in this paper through two main procedures; data sets and ANN modelling. The data sets were developed through conducting energy simulation and carbon calculations, including 201 combinations organised in a spreadsheet. Every combination was defined by six input variables, and its four model outputs. The data sets were implemented into ANN to develop the model. Accordingly, EICAM evolved through three main steps; training, testing, and validation. The results revealed that deploying EICAM is easy and fast, compared to the time required by other building energy modelling methods for calculating all four output variables with valid results.

Hence, it is recommended that architectural firms adopt the use of EICAM during the early design phase of residential units to select the desired building envelope, regarding environmental impact costs.

However, aesthetic factors are not considered as EICAM is limited to being utilised during the schematic design phase. Accordingly, for future research work, it is recommended that a wider range of detailed model inputs, such as building area, location, and interior finishes, continue to be considered. Choices of input variables, such as wall types, can include wall assemblies from the field. In addition, model output categories could be expanded to include additional output variables such as the total operational carbon resulting from lighting loads and heating loads. When considering the embodied carbon in materials, construction and demolition phases should be accounted for.

Appendix I. Model data sets

Combination NO	Wall Type	Roof Type	Glazing type	WWR	Shading Device	Building Orientation	Energy cost	Operational Carbon	Envelope Embodied Carbon	CO_2/m^2
1	1	1	1	25	1	-	3,628	305,162	23,348	1,369
2	1	2	1	25	1	-	3,663	308,129	21,206	1,372
3	1	3	1	25	-	-	3,676	309,219	25,064	1,393
4	1	1	2	25	1	-	3,833	322,376	23,294	1,440
5	1	1	3	25	1	-	3,684	309,855	23,348	1,388
6	1	1	4	25	1	-	3,381	284,359	23,348	1,282
7	1	1	1	20	1	-	3,361	282,709	22,972	1,274
8	1	1	1	10	1	-	2,832	238,167	22,219	1,085
9	1	1	1	25	1	90	3,598	302,618	23,355	1,358
10	1	2	1	25	1	90	3,632	305,480	21,213	1,361
11	1	3	1	25	1	90	3,646	306,630	25,070	1,382
12	1	1	2	25	1	90	3,810	320,499	23,301	1,432
13	1	1	3	25	1	90	3,656	307,509	23,355	1,379
14	1	1	4	25	1	90	3,368	283,285	23,355	1,278
15	1	1	1	10	1	90	2,826	237,713	22,222	1,083
16	1	2	2	25	1	-	3,861	324,753	21,152	1,441
17	1	2	3	25	1	-	3,713	312,323	21,206	1,390
18	1	2	4	25	1	-	3,399	285,934	21,206	1,280
19	1	2	2	10	1	-	2,942	247,494	20,056	1,115
20	1	2	3	10	1	-	2,870	241,377	20,077	1,089
21	1	2	4	10	1	-	2,769	232,868	20,077	1,054
22	1	1	1	25	1	180	3,629	305,207	23,350	1,369
23	1	2	1	25	1	180	3,664	308,175	21,208	1,372
24	1	3	1	25	2	180	3,248	273,156	25,066	1,243
25	1	1	2	25	2	180	3,427	288,266	23,296	1,298
26	1	1	3	25	2	180	3,273	275,291	23,350	1,244
27	1	2	4	10	2	180	2,683	225,692	20,078	1,024
28	1	1	1	20	2	180	3,045	256,139	22,973	1,163
29	1	3	3	10	2	180	2,769	232,899	23,936	1,070
30	1	1	1	25	2	90	3,206	269,689	23,355	1,221
31	1	2	1	25	2	90	3,229	271,627	21,213	1,220
32	1	3	4	25	2	90	3,096	260,378	25,070	1,189
33	1	1	3	10	2	90	2,743	230,734	22,222	1,054

Combination NO	Wall Type	Roof Type	Glazing type	WWR	Shading Device	Building Orientation	Energy cost	Operational Carbon	Envelope Embodied Carbon	CO_2/m^2
34	1	1	4	10	2	90	2,682	225,571	22,222	1,032
35	1	1	1	20	2	90	3,044	256,033	22,977	1,163
36	1	1	2	10	2	90	2,819	237,092	22,201	1,080
37	1	1	1	25	1	270	3,612	303,814	23,355	1,363
38	1	1	3	25	1	270	3,671	308,750	23,355	1,384
39	1	3	4	20	1	270	3,205	269,568	24,683	1,226
40	1	1	2	10	1	270	2,933	246,661	22,201	1,120
41	1	2	3	10	1	270	2,870	241,422	20,080	1,090
42	1	2	4	10	2	270	2,685	225,813	20,080	1,025
43	2	1	1	25	1	-	3,518	295,881	30,776	1,361
44	2	2	1	25	1	-	3,551	298,682	28,635	1,364
45	2	3	1	25	1	-	3,564	299,772	32,492	1,384
46	2	1	2	25	1	-	3,716	312,535	30,724	1,430
47	2	1	3	25	1	-	3,577	300,847	30,777	1,382
48	2	1	4	25	1	-	3,287	276,456	30,777	1,280
49	2	1	1	20	1	-	3,262	274,382	30,820	1,272
50	2	1	1	10	1	-	2,756	231,793	30,908	1,095
51	2	1	1	25	1	90	3,489	293,459	30,783	1,351
52	2	2	1	25	1	90	3,521	296,154	28,641	1,353
53	2	3	1	25	1	90	3,534	297,274	32,499	1,374
54	2	1	3	25	1	90	3,550	298,606	30,783	1,372
55	2	1	4	25	1	90	3,274	275,412	30,783	1,276
56	2	1	2	20	1	90	3,413	287,054	30,783	1,324
57	2	1	1	10	1	90	2,752	231,460	30,910	1,093
58	2	2	2	25	1	-	3,750	315,396	28,582	1,433
59	2	2	3	25	1	-	3,604	303,163	28,635	1,382
60	2	2	4	25	1	-	3,304	277,940	28,635	1,277
61	2	2	2	10	1	-	2,862	240,726	28,744	1,123
62	2	2	3	10	1	-	2,794	235,003	28,765	1,099
63	2	2	4	10	1	-	2,698	226,933	28,765	1,065
64	2	1	1	10	2	180	2,646	222,528	30,908	1,056
65	2	2	1	25	1	180	3,552	298,742	28,637	1,364
66	2	3	4	20	1	180	3,116	262,073	32,538	1,228
67	2	1	2	10	1	180	2,852	239,863	30,887	1,128
68	2	1	3	25	1	180	3,577	300,892	30,779	1,382
69	2	1	4	25	2	180	2,983	250,885	30,779	1,174
70	2	3	3	20	2	180	3,045	256,139	32,538	1,203
71	2	2	1	10	2	180	2,653	223,179	28,766	1,050
72	2	1	1	25	2	90	3,115	261,967	30,784	1,220
73	2	2	4	10	2	90	2,620	220,393	28,768	1,038
74	2	3	1	25	2	90	3,151	265,056	32,499	1,240
75	2	1	3	20	2	90	3,014	253,489	30,826	1,185
76	2	1	4	25	2	90	2,984	250,961	30,783	1,174
77	2	1	2	20	2	90	3,137	263,830	30,783	1,228
78	2	1	1	10	2	90	2,647	222,619	30,910	1,056
79	2	1	2	25	2	270	3,333	280,363	30,731	1,296
80	2	2	3	25	2	270	3,204	269,462	28,641	1,242
81	2	2	4	25	2	270	2,998	252,142	28,641	1,170
82	2	1	2	10	2	270	2,745	230,855	30,889	1,091
83	2	2	3	10	2	270	2,681	225,525	28,768	1,060
84	2	2	4	10	2	270	2,618	220,181	28,768	1,037
85	3	1	1	25	1	-	3,632	305,450	29,483	1,396
86	3	2	1	25	1	-	3,649	306,888	27,340	1,393
87	3	3	1	25	1	-	3,666	308,341	31,198	1,415
88	3	1	2	25	1	-	3,828	321,998	29,429	1,464
89	3	1	3	25	1	-	3,697	310,991	29,483	1,419
90	3	1	4	25	1	-	3,416	287,297	29,483	1,320
91	3	1	1	20	1	-	3,384	284,602	29,454	1,309
92	3	1	1	10	1	-	2,893	243,300	29,397	1,136
93	3	1	1	25	1	90	3,602	302,951	29,489	1,385
94	3	2	1	25	1	90	3,619	304,359	27,347	1,382
95	3	3	1	25	1	90	3,636	305,828	31,205	1,404
96	3	1	3	25	1	90	3,670	308,674	29,489	1,409
97	3	1	4	25	1	90	3,403	286,207	29,489	1,315
98	3	1	2	20	1	90	3,533	297,123	29,416	1,361
99	3	1	1	10	1	90	2,888	242,891	29,399	1,135
100	3	2	2	25	1	-	3,847	323,587	27,287	1,462
101	3	2	3	25	1	-	3,711	312,096	27,340	1,414
102	3	2	4	25	1	-	3,423	287,887	27,340	1,313
103	3	2	2	10	1	-	2,990	251,506	27,233	1,161
104	3	2	3	10	1	-	2,925	246,040	27,255	1,139
105	3	2	4	10	1	-	2,833	238,258	27,255	1,106
106	3	1	1	25	2	180	3,236	272,142	29,485	1,257
107	3	2	4	25	2	180	3,114	261,892	27,342	1,205

Combination NO	Wall Type	Roof Type	Glazing type	WWR	Shading Device	Building Orientation	Energy cost	Operational Carbon	Envelope Embodied Carbon	CO_2/m^2
108	3	3	3	20	2	180	3,166	266,328	31,171	1,240
109	3	1	2	10	2	180	2,880	242,240	29,376	1,132
110	3	1	3	25	1	180	3,698	311,036	29,485	1,419
111	3	1	4	25	1	180	3,416	287,327	29,485	1,320
112	3	3	1	20	1	180	3,415	287,236	31,171	1,327
113	3	2	1	10	1	180	2,896	243,603	27,255	1,129
114	3	1	3	25	2	90	3,303	277,834	29,489	1,281
115	3	2	3	10	2	90	2,813	236,593	27,257	1,099
116	3	3	1	25	2	90	3,261	274,276	31,205	1,273
117	3	1	3	25	2	90	3,303	277,834	29,489	1,281
118	3	1	4	20	2	90	2,990	251,506	29,459	1,171
119	3	1	2	20	2	90	3,259	274,155	29,416	1,265
120	3	1	1	10	2	90	2,782	234,019	29,399	1,098
121	3	1	2	20	2	270	3,262	274,337	29,416	1,266
122	3	2	3	25	2	270	3,315	278,818	27,348	1,276
123	3	1	4	25	1	270	3,415	287,251	29,389	1,319
124	3	2	2	10	1	270	2,993	251,763	27,236	1,162
125	3	2	3	10	1	270	2,925	246,040	27,257	1,139
126	3	3	4	10	1	270	2,860	240,559	31,115	1,132
127	4	1	1	25	1	-	3,862	324,859	24,950	1,458
128	4	2	1	25	1	-	3,889	327,130	22,808	1,458
129	4	3	1	25	1	-	3,904	328,341	26,666	1,479
130	4	1	2	25	1	-	4,067	342,103	24,895	1,529
131	4	1	3	25	1	-	3,924	330,082	24,950	1,479
132	4	1	4	25	1	-	3,626	304,995	24,950	1,375
133	4	1	1	20	1	-	3,602	302,997	24,652	1,365
134	4	1	1	10	1	-	3,085	259,515	24,056	1,182
135	4	1	1	25	1	90	3,830	322,149	24,957	1,446
136	4	2	1	25	1	90	3,857	324,375	22,815	1,447
137	4	3	1	25	1	90	3,872	325,646	26,672	1,468
138	4	1	3	25	1	90	3,895	327,584	24,957	1,469
139	4	1	4	25	1	90	3,612	303,799	24,957	1,370
140	4	1	2	20	1	90	3,758	316,063	24,613	1,419
141	4	1	1	10	1	90	3,080	259,030	24,059	1,180
142	4	2	2	25	1	-	4,096	344,556	22,753	1,530
143	4	2	3	25	1	-	3,784	318,243	22,808	1,421
144	4	2	4	25	1	-	3,640	306,146	22,808	1,371
145	4	2	2	10	1	-	3,194	268,659	21,892	1,211
146	4	2	3	10	1	-	3,122	262,618	21,914	1,186
147	4	2	4	10	1	-	3,023	254,246	21,914	1,151
148	4	1	4	25	2	180	3,303	277,804	24,952	1,261
149	4	2	3	25	2	180	3,522	296,275	22,810	1,330
150	4	3	1	10	2	180	2,991	251,581	25,773	1,156
151	4	1	2	20	2	180	3,465	291,430	24,609	1,317
152	4	1	3	25	1	180	3,924	330,067	24,952	1,479
153	4	2	4	25	1	180	3,640	306,131	22,810	1,371
154	4	3	1	20	1	180	3,640	306,131	26,369	1,385
155	4	1	3	10	1	180	3,116	262,089	24,057	1,192
156	4	1	2	25	2	90	3,658	307,660	24,901	1,386
157	4	2	2	20	2	90	3,478	292,535	22,471	1,313
158	4	3	2	20	2	90	3,496	294,064	26,329	1,335
159	4	1	3	25	2	90	3,507	294,942	24,957	1,333
160	4	1	4	25	2	90	3,304	277,864	24,957	1,262
161	4	1	1	20	2	90	3,282	276,032	24,657	1,253
162	4	1	1	10	2	90	2,968	249,643	24,059	1,140
163	4	2	2	25	1	270	4,083	343,451	22,859	1,526
164	4	1	3	25	1	270	3,907	328,599	24,957	1,473
165	4	3	4	20	1	270	3,447	289,931	26,373	1,318
166	4	2	2	10	1	270	3,194	268,674	21,895	1,211
167	4	2	3	10	2	270	3,001	252,429	21,917	1,143
168	4	2	4	10	2	270	2,936	246,964	21,917	1,120
169	4	3	2	25	2	270	3,696	310,885	26,617	1,406
170	4	3	3	25	2	270	3,543	297,970	26,672	1,353
171	4	3	4	25	2	270	3,332	280,287	26,672	1,279
172	4	3	2	10	2	270	3,097	260,484	25,752	1,193
173	4	3	3	10	2	270	3,022	254,170	25,775	1,166
174	4	3	4	10	2	270	2,957	248,690	25,775	1,144
175	3	3	2	20	2	270	3,289	276,623	31,132	1,282
176	3	3	3	20	2	270	3,169	266,555	31,175	1,241
177	3	3	4	25	1	270	3,441	289,462	31,205	1,336
178	3	3	2	20	1	270	3,574	300,635	31,132	1,382
179	3	3	3	10	1	270	2,947	247,842	31,115	1,162
180	3	2	4	10	1	270	2,838	238,743	27,257	1,108
181	1	1	2	25	2	270	3,430	288,523	23,301	1,299

Combination NO	Wall Type	Roof Type	Glazing type	WWR	Shading Device	Building Orientation	Energy cost	Operational Carbon	Envelope Embodied Carbon	CO_2/m^2
182	1	3	3	25	2	270	3,312	278,561	25,070	1,265
183	1	3	4	25	2	270	3,098	260,590	25,070	1,190
184	1	2	2	10	2	270	2,827	237,804	20,058	1,074
185	1	3	3	10	2	270	2,771	233,080	23,938	1,071
186	1	3	4	10	2	270	2,705	227,494	23,938	1,048
187	1	3	2	25	2	-	3,468	291,657	25,010	1,319
188	1	3	3	25	2	-	3,310	278,440	25,064	1,265
189	1	3	4	25	2	-	3,095	260,317	25,064	1,189
190	1	3	2	10	2	-	2,843	239,106	23,914	1,096
191	1	3	3	10	2	-	2,769	232,868	23,935	1,070
192	1	3	4	10	2	-	2,701	227,191	23,935	1,046
193	2	3	2	25	2	-	3,368	283,300	32,440	1,316
194	2	3	3	25	2	-	3,219	270,733	32,492	1,263
195	2	3	4	25	2	-	3,012	253,338	32,492	1,191
196	3	2	3	20	2	-	3,149	264,829	27,312	1,217
197	3	2	3	25	2	-	3,315	278,818	27,340	1,276
198	3	2	4	10	2	-	2,750	231,279	27,255	1,077
199	4	2	2	25	2	-	3,679	309,446	22,753	1,384
200	4	2	3	20	2	-	3,352	281,907	22,510	1,268
201	4	2	4	10	2	-	2,934	246,767	21,914	1,120

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