Energy Reports 7 (2021) 2534–2545

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Research paper

# Predicting energy consumption for residential buildings using ANN through parametric modeling

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ARTICLE INFO

*Article history:*
Received 5 May 2020
Received in revised form 18 April 2021
Accepted 27 April 2021
Available online 4 May 2021

*Keywords:*
Energy simulation
Parametric analysis
Artificial Neural Network
Residential buildings
Conceptual design phase

ABSTRACT

Controlling buildings energy consumption is a great practical significance. During early design stage, accurate and rapid prediction of energy consumption could provide a quantitative basis for energy-saving designs. Currently, the key problem that are still facing designers is the interoperability between building modeling and energy simulation tools. In addition, design challenges gained recognition due to the complexity of the prevalence of large numbers of independent interrelated variables. Artificial Neural Networks (ANNs) are the most broadly applied artificial intelligence method in buildings' performance field due to its competence to handle nonlinear variables' relationships accurately and promptly. This paper presents a methodology based on the ANNs to improve the prediction of energy usage for residential buildings in early design stages. The model is created using a dataset resulted from the calculation of energy consumption by simulating multiple design options with randomly input variables. The proposed methodology can mitigate technical barriers while integrating and automating available commercial tools into a workflow from a parametric model to the simulation of building energy. The developed ANN model is evaluated and validated and used to predict the energy consumption with acceptable accuracy. Finally, a user-friendly interface is designed to facilitate energy consumption prediction without any experience in modeling and simulation tools acting as a decision support tool, which is simple, reliable and easy to use.



## 1. Introduction

Today, climate change is one of the main global environmental challenges worldwide. The root cause of climate changes is Greenhouse Gases (GHG) emissions, which are emitted from human activities burning fossil fuels (coal, oil and gas). The construction industry includes such activities where buildings are one of the main energy consumers. They produce a large portion of GHG emissions, air pollutants and solid wastes (Akan et al., 2017). Buildings' construction and operation consume about 30% of the world total delivered energy and almost 50% of world GHG emissions. Therefore, there is an urgent need to reduce these wastes into the environment and to reduce buildings' related energy consumption. Furthermore, buildings are comparatively having long lifecycles with complicated and energetic behaviors (Sharif and Hammad, 2019). As such, more research is needed to incorporate environmental performance as a criterion in building design. Recognizing energy consumption behavior in buildings is valuable to end-users, facility managers, and utility companies because it can improve both environment and energy efficiency. Research on building energy efficiency and energy saving has drew the attention of many researchers (Zhang et al., 2021) (Pham et al., 2020) (Mohandes et al., 2019) (Guo et al., 2018) (Killian and Kozek, 2016) (Foucquier et al., 2013). To increase building energy performance, an integrated approach is recommended to evaluate a wide range of design alternatives. One approach to improve buildings design is to simulate their performance during the conceptual design phase. Where, decisions that are made during this phase have significant impact on buildings' performance. About 30%–40% of building energy consumption can be reduced simply by getting the proper shape and the appropriate orientation of buildings without extra cost (Sahu et al., 2012). Thermal design procedures are complicated and multi-criteria problems, where the interaction among design parameters can be difficult to assess without the use of simulation tools. New innovations in technologies such as parametric modeling, simulation and ANNs improve models' accuracy and computational capabilities. Limited research has been performed involving the integration of simulation and ANN models (Sharif and Hammad, 2019). A simulation-based ANN models often needs hundreds, or thousands of simulations runs. To achieve reliable results, the

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https://doi.org/10.1016/j.egyr.2021.04.053
2352-4847/

energy consumption of each design option should be calculated by creating the whole building model and using simulation tools considering the specific characteristics of the building. Architects and designers perform a series of parametric analysis to evaluate the impact of individual energy efficiency parameters. They spend 40% to 50% of their time in creating designs and using available tools for simulation to justify the selected design alternative, not to explore multiple alternatives (Welle et al., 2013). One feasible method to resolve this problem is to implement parametric modeling and building energy simulation through artificial intelligence. This paper presents a novel approach for generating multiple design alternatives which facilitate both simulation and prediction process of residential buildings for energy performance in early design stages. The gab to be bridged through this research is to encourage the design of less energy consumption buildings. Such gab resulted from: the interoperability between building modeling and simulation energy tools; the lack of studies considering Egyptian climate and available information is incomplete and outdated. In this contribution, ANN is employed to predict buildings' energy consumption during the conceptual design phase. Then, the developed ANN model is automated through developing a user-friendly interface acting as a decision support tool which allows designer to figure out the energy demand with no need for modeling and simulation experience.

## 2. Literature review

Recently, integrating optimization algorithms and prediction methods for building energy consumption to improve the efficiency of energy performance during the conceptual design phase has become a research hotspot. Therefore, an accurate and fast estimation technique for building energy consumption is essential for the conceptual design phase (Liu et al., 2013). As such, ANNs are utilized to forecast buildings energy consumption (Li et al., 2019). The next two sub-section represent research literature review. The first sub-section presents ANN energy consumption models and the second one refers to energy models, which are developed using Rhinoceros/Grasshopper platform.

### 2.1. ANN energy consumption prediction models

ANN is a machine-learning algorithm with a structural design based on the human brain. The main computational aspects of ANN are their ability to learn from given instances, then determine patterns and consistencies in data through self-organization (Haykin, 1998). Several modeling procedures have been endeavored to approximate energy consumption including engineering, statistical and artificial intelligence methods. ANNs have many advantages over other methods as per their ability to solve non-linear complex problems and resistance to faults and noise (Zhao and Magoulès, 2012).

Li and Yao (2021) developed a framework to predict energy consumption of residential and nonresidential buildings through generating energy database which used to train different machine learning models. Zou et al. (2021) utilized a simulation-based technique to forecast residential buildings' life cycle energy. The simulation for heating and cooling energy calculations is performed on parametric simulation tool (Grasshopper). Ciulla et al. (2019) used ANNs to determine the thermal balance of nonresidential buildings using a database of different buildings' shapes and characteristics for training and validation. D'Amico et al. (2019) developed an ANN model to determine the energy performance of nonresidential buildings. The ANN trained using database created by the simulation of several building models in different climatic conditions. Ngo (2019) proposed an ANN model to forecast buildings cooling loads with common parameters (floors numbers, building plan aspect ratio, window to wall ratio, rate ratio of outdoor area, floor area, U-factor of glass window, U-factor of exterior envelope walls, density of occupants, equipment loads, lighting loads, heating and cooling set point temperatures, location, floor height and overhang depth) in the conceptual design phase. The developed model predicted cooling load values in buildings with correlation coefficient (R) of 0.98 to 0.99, MAPE of 6.17–12.93%. (Sharifa and Hammad, 2019) proposed an ANN model to predict total consumed energy, life cycle cost and life cycle assessment for different renovation scenarios using data from a simulation. Wei et al. (2019) developed an ANN model to predict electricity consumption by an air conditioning system using the blind system identification considering the number of occupants as an input. Lee et al. (2019) employed an ANN to forecast user-based energy consumption with respect to user activities and characteristics. This research exploited the actual 24-h schedules of 5240 single-person households. Li et al. (2019) used ANN for forecasting building energy consumption for complex architecture forms during early design phase. To eliminate the building complexity, they divide the building into multiple simple blocks. Álvarez et al. (2018) used the data from 453 residential buildings located in Spain to forecast the building U-opaque value. Different ANN architectures were trained and tested for the real measured values with correlation coefficient of 0.967. Beccali et al. (2017) proposed the use of ANN for predicating the energy performance of buildings. Also, it is acting as a decision support tool for optimizing the retrofit actions of buildings located in Italy. Ahmad et al. (2017) compared the performance of ANN and random forest for the prediction of electricity consumption of HVAC in hotels. The results showed that the ANN is slightly better than the random forest. Martellotta et al. (2017) used the ANN to forecast heating energy consumptions. The dataset used for the ANN training is simulated using EnergyPlus. Williams and Gomez (2016) introduced a study to predict the energy consumption on monthly basis for a single-family home using building attributes and monthly climatic data using data collected from 426,305 homes. Turhan et al. (2014) predicted heating energy using 148 residential buildings for training and testing of an ANN model, with successful prediction rate of 0.977. Sun and Han (2013) developed an ANN model with input parameters: orientation, floor height, no. of floors, bays number, depths number, windows per each bay and window dimensions. Simulation results for 2000 rectangle office buildings in cold area used to create the dataset for ANN model training and testing with mean square error of 0.6%. Wong et al. (2010) used ANN for predicting total energy consumption using nine input variables associated to the surrounding weather circumstances, four for the building envelope and one for day type (working or weekend). Ekici and Aksoy (2009) used ANN to predict buildings heating energy. The finite difference approach is used to generate the training and testing datasets.

This study concerns automating the process of modeling and simulation using one platform to generate energy consumption database and overcome the interoperability problem between simulation and modeling tools. The most previous studies performed simulation "manual sampling" to obtain many samples data by manually adjusting the input parameters. The parametric analysis facilitates the "automatic sampling" to adjust the input values for each parameter through the batch processing tool to get a large amount of sample data automatically, timely and accurately.

### 2.2. Literature review within Rhino/Grasshopper

To improve design space exploration, parametric modeling make it possible to identify the relationships between input variables and resulting outputs. Parametric studies are used to determine the impact of various energy efficiency measures (EEMs) early in the design process (Lewis, 2014). It provides the designer a complete dynamic control throughout the geometry and components of model to get the most appropriate results on complicated models with the change of several alternatives at the same time (Touloupaki and Theodosiou, 2016). Visual and graphical coding tools such as Grasshopper for Rhinoceros® is used in modeling/design process to implement the concept of parametric modeling utilizing the capabilities and powerful of visual programming in automating complex tasks. Additionally, to employ the parametric modeling considering energy performance-based design using simulation tools, EnergyPlus is used in building energy analysis. However, coupling both parametric and performance-based methods can cause a monotonous iterative cycle of model–simulate–evaluate–remodel. The interoperability between energy analysis software and modeling tools may restrict the depth of exploration within the design space (Santos et al., 2017).

Felkner et al. (2019) presented a framework for real-time analysis of buildings' operating energy performance. SOFiSTiK structural analysis software is used in structural analysis, also EnergyPlus through the DIVA plug-in for Rhino/Grasshopper is used for thermal analysis to determine the most efficient structural design with respect to operational energy (cooling/heating) demand using multi objective optimization. Chi et al. (2018) developed an approach to determine daylight impact on annual consumed heating energy, cooling and lighting. DIVA/Grasshopper is used for daylight simulations. Also, Archism plugin for Grasshopper is used for energy modeling. Elbeltagi et al. (2017) developed a workflow to visualize parametric energy analysis of residential buildings. The proposed model was automated to simulate and analyze energy efficiency accurately, timely, and effectively. Eltaweel and Yuehong (2017) used Rhino platform and Grasshopper plugins to introduce a control method of daylight effectiveness of office buildings. A case study was conducted for an office building in New Cairo, Egypt. Samuelson et al. (2016) presented a framework for parametric energy simulation of residential buildings during conceptual design phase. The studied parameters are building orientation, building shape, wall insulation, windows to wall ratio and glass types. Touloupaki and Theodosiou (2016) proposed a workflow coupling both genetic algorithms (GAs) and energy simulation through Rhinoceros/Grasshopper and using Ladybug and Honeybee plugins to minimize buildings' lifecycle energy requirements. González and Fiorito (2015) integrated the DIVA plugin and GAs embedded in the evolutionary solver Galapagos for Rhinoceros/Grasshopper to calculate energy consumption, daylight metric and CO2 emissions. Attia et al. (2012b) presented an energy-oriented model for both energy simulation and building modeling to facilitate decision making for sustainable design of buildings. Jakubiec and Reinhart (2011) developed a workflow integrating DAYSIM with DIVA and EnergyPlus for the simulation analysis of energy and daylighting, incorporating the performance of daylight analysis and thermal comfort.

## 3. Materials and methods

The present study proposed a workflow integrating parametric modeling and simulation tools to generate energy consumption database. The database is related to the characteristics of 12,000 simulations were investigated in automated way using one platform Rhinoceros/Grasshopper. In addition, EnergyPlus software and ANN were used to create a prediction model including energy efficiency measures. The study is conducted as illustrated in Fig. 1.

### 3.1. Conceptual design stage

Conceptual design stage is an innovative process which encompasses the generation of alternative solutions for ill-defined problem and incomplete requirements (Cavieres et al., 2011). It is the first step to achieve and meet the functional purpose of a building and decisions made in this stage have significant impact on buildings' energy demand. Design concepts depend on experience, implicit knowledge, information background and thinking skills. Energy consumption prediction in early design stage is a vital element that can allow designers to select the appropriate alternative design that enhances building energy performance. However, energy prediction at the conceptual design stage is difficult task due to the absence of sufficient information (Alshibani and Alshamrani, 2017). In this stage, designers have to decide on important factors such as building envelope, building shape, structural system, orientation, dimensions, insulation system and other parameters. These decisions which are taken with often inadequate data on the climatic condition, site location, topography, affect the performance of the final output (Çavuşoğlu, 2015).

### 3.2. Parametric simulation

Recently, paranematic design has been widely used in architecture design (Villamil, 2014). Parametric simulation is an approach that utilizes the design parameters or variables for the geometric properties. Parametric modeling's name is taken from the design parameters, which are modified through the process of simulation. Parametric simulation tools have been developed distinctively for the early design stage (Samuelson et al., 2016). In conceptual design phases, using parametric simulation, a designer can evaluate numerous prospective designs to produce guidance that design teams can use as an informed starting point for the design process. In this research, the parameters used include several design decisions, such as building dimensions, building orientation, windows to wall ratio (WWR), building envelope, glazing type, lighting occupancy, plug loads and temperature settings. The architectural baseline parameters set to meet the Egyptian Specifications for Thermal Insulation Work Items (ETSTIW, 2007) and ASHRAE 90.1 2010 standards. At any time in the design process, the defined parameters could be linked together throughout a set of relations that allow reiterating the logic definitions upon changing of the upstream parameters. Existing modeling software, such as Rhino/Grasshopper allows the modeler to integrate digital models through mathematical and algorithms functions (Elbeltagi et al., 2017).

### 3.3. Building energy modeling

Building Energy Modeling (BEM) allows modelers and designers to evaluate the energy performance of buildings and assist them estimate building energy consumption through the design stage. To predict the buildings' energy consumption at several climate zones, building simulation tools are used to construct and simulate the configurations of buildings which are formed in accordance with local, regional, or national energy codes. There are several factors needed to describe the building features being evaluated during energy modeling simulation which impact energy consumption (Ciulla and D'Amico, 2019) (Kapetanakis et al., 2017). The consumed energy depends on weather conditions, building type (whether residential or commercial) and spaces interaction (Dodoo et al., 2017). The methodology utilized in the current study is based on creating ANN model capable of predicting energy consumption of residential buildings. This methodology is part of the overall study methodology followed by the authors as previously published in Elbeltagi et al. (2017). Energy modeling steps taken in this study are as follows:

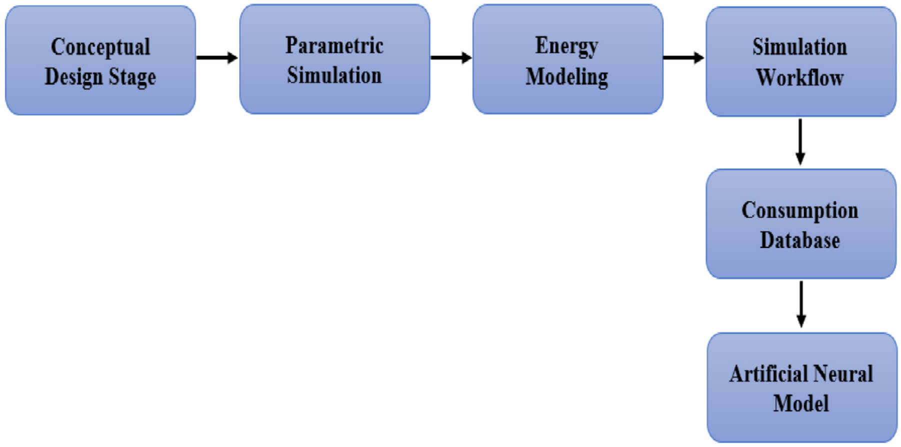


**Fig. 1.** Flow chart depicting research process.

*3.3.1. Choosing modeling software*

To simulate and estimate building energy loads, EnergyPlus is used. It is a free, open-source engine established by the U.S. Department of Energy (DOE) which presents advanced energy performance facilities, containing multi-zones, sub-hourly, heat and mass transfer calculations. EnergyPlus necessitates two basic inputs to launch the simulations: weather data, in EnergyPlus Weather (.epw), and the building model, in (.idf) format. Since one of the aims is to overcome the interoperability between building modeling and energy simulation tools, this research employed Rhino acting as one platform to get simulations accurately, timely, and simply. Then, a visual basic code is developed in Grasshopper to iterate through all the simulations. This study used DIVA, a plug-in for grasshopper to transform the information of building model into EnergyPlus using text input files (.idf). The energy simulation input and output results are automatically compiled into Excel Comma Separated Values format. The integration, as such, helps creating a reliable database using the power of parametric modeling and energy simulation.

*3.3.2. Identifying weather file*

Weather data sources could be found throughout airfields, airports, publications, and meteorological services. The EPW file contains the weather data, including location (region), longitude, latitude, elevation, holidays, humidity, temperature, wind speed, rainfall, and solar radiation. The U.S. DOE offers typical year weather information for more than 2100 universal locations in more than 100 countries, some of these are hot humid and hot dry. Consequently, it is important to define the building site and the simulation analysis input data such as weather data that will be applied during energy simulation. For this research, the EnergyPlus weather data file (EPW) (Cairo International Airport 6233660) used to complete the simulation process (EnergyPlus, 2017).

*3.3.3. Identifying input values and design parameters*

For this study, the design parameters assessed include several early design stage decisions, such as building dimensions, building orientation, envelope constructions, WWR and glazing type. It is assumed that the envelope of a building consists of three elements: walls (3 types), roof (2 types) and slab on grade (2 types), with each type of building envelope elements has its U-value. In addition, the input parameters that has a constant value are lighting and equipment loads needed for artificial lights and appliances. Further parameters are varied within a range of values (min and max) in accordance with Egyptian energy standards. More details on modeling parameters can be found in Elbeltagi et al. (2017). Varied and constant design parameters are listed in Tables 1 and 2, respectively. Each building envelope element is decomposed into its layers (components). The heat flow through these layers is characterized by their material resistance, thermal capacity, absorption, transmission, etc. In Egypt, for example, the Housing and Building Research Center (HBRC1998) published a guideline manual for the installation of thermal insulation. The manual includes the thermal and physical properties of most of the building materials used in Egypt, including density, thermal conductivity, and specific heat capacity (Attia and Wanas, 2012) . The Egyptian Residential Energy Code (EREC) standards stated the maximum allowable U-values or minimum insulation R-values for buildings' envelope elements. It additionally stated the maximum permissible U-factor and Solar Heat Gain Coefficient (SHGC) for glazing as a function of the WWR. However, the U-values given for envelope constructions included only roofs and external walls, with no mention of the U-value of floors or ground decks, and only the thermal properties of a limited group of materials are available. Visible transmittance (VT) is the visible light percentage that passes through a window or other glazing units; also, it represents the point of opening that lets natural light pass through. Solid walls would have a 0% of VT, where any empty opening would have 100%; various plastic materials and un-tinted glass have of 90% or more (Dutton, 2017).

**Table 1**
Design parameters with varied values.

| Input name | Option | Parameter values | |
|---|---|---|---|
| | | Minimum value | Maximum value |
| Building dimensions | Length | 10.0 m | 30.0 m |
| | Depth | 10.0 m | 30.0 m |
| | Height | 10.0 m | 15.0 m |
| Building orientation | | 0° | 360° |
| Windows to wall ratio | North | 0% | 80% |
| | South | 0% | 80% |
| | East | 0% | 80% |
| | West | 0% | 80% |
| Glazing type | U-value | 0 | 1.2 |
| | SHGC | 0 | 1.0 |
| | VT | 0 | 1.0 |
| Temperature set point | Cooling | 18° C | 28 °C |
| | Heating | 18 °C | 26 °C |

*3.3.4. Specifying thermal simulation settings*

Modeler must specify thermal simulation settings, model inputs, the other parameters, and should be aware of EnergyPlus

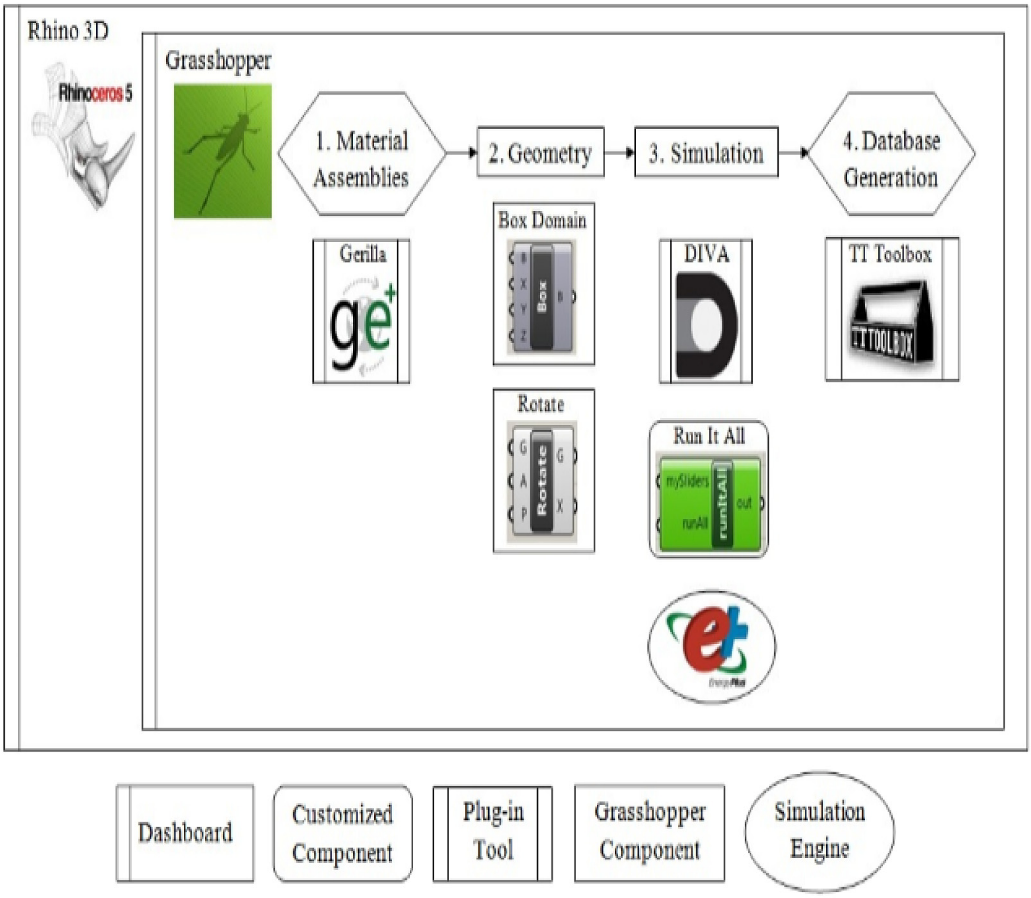


**Fig. 2.** Simulation workflow.

**Table 2**
Design parameters with constant values.

| Input name | Option | Parameter values |
|---|---|---|
| Building envelope | Walls | Wall type 1<br>Wall type 2<br>Wall type 3 |
| | Roof | Roof type 1<br>Roof type 2 |
| | Slab-on-Grade (SOG) | SOG type 1<br>SOG type 2 |
| Lighting Loads | | 7.3 W/m$^2$ |
| Equipment Loads | | 7.0 W/m$^2$ |

default settings for calculating annual cooling, heating, lighting, and equipment's (plug-in equipment) energy. Table 3 summarizes the used thermal simulations settings/assumptions.

### 3.4. Simulation workflow

In this paper, the workflow developed by Elbeltagi et al. (2017) which associated different tools linked together in one platform (Rhino) is used to generate a generic energy consumption database to be used for the training of the ANN model. The workflow integrates the building modeling and energy simulation through generating information data for the model by entering building's shape, dimensions, orientation, construction materials and windows properties. Then, linking the building information inputs in Grasshopper (as a middleware) with thermal energy simulation tool. DIVA for Grasshopper is used for thermal energy analysis, which converting the building shape, orientation, and material assemblies into a simulation engine (EnergyPlus). Fig. 2 illustrates the implemented workflow, which is comprised of bridging a set of functionalities to meet each need to fulfill the research objective. The design of the workflow includes the existing objects of Rhino/Grasshopper and the formation of customized elements to achieve some specific requirements that were not able to be met with the existing software's functionalities (Wefki, 2017).

### 3.5. Energy consumption database

To develop the ANN model, it is essential to implement an appropriate database for training and validation of residential buildings and signifies the investigated problem in any general form and condition. For this reason, the authors used the energy database created in a previous published work (Elbeltagi et al., 2017). The energy modeling and simulation for this study is based on developing a set of cases of residential buildings with different dimensions, orientations, and characterized by thermal parameters in accordance with the Egyptian energy standards for residential buildings (Wefki, 2017). The input data for modeling parameters and its units are as follow:

1. People density [people/m$^2$]
2. Lighting Load (Lights) [W/m$^2$]
3. Equipment Load (EquiP) [W/m$^2$]
4. Heating Set Point (HtgSetP) [°C]
5. Cooling Set Point (ClgSetP) [°C]
6. Infiltration [ L/s/m $^2$]
7. Fresh Air (FreshAir) [m$^3$/h/person]

**Table 3**
Thermal simulations settings.

| Setting | Attribute |
|---|---|
| Simulation type | Residential Buildings |
| Run Period | Annual |
| Time Steps per Hour | 6 |
| Outputs | Annual energy consumption for heating<br>Annual energy consumption for cooling<br>Annual energy consumption for lights<br>Annual energy consumption for appliances |
| People density (people/m$^2$) | 0.033 people/m$^2$ (Attia et al., 2012a) |
| Lighting Load (W/m$^2$) | 7.3 W/m$^2$ (Ihm and Krarti, 2012) |
| Equipment Load (W/m$^2$) | 7.0 W/m$^2$ (Attia et al., 2012b) |
| Heating type | N/A |
| Cooling Type | Air Conditioner, COP 3.0 (Standard efficiency) (Ihm and Krarti, 2012) |
| Infiltration Rate (L/s/m$^2$) | 0.7 (Ihm and Krarti, 2012) |
| Fresh Air (m$^3$/h/person) | 20 (Attia et al., 2012b) |

8. Building Length [m]
9. Building Width [m]
10. Building Height [m]
11. Orientations [° ]
12. Wall U-value [W/m$^2$ K]
13. Roof U-value [W/m$^2$ K]
14. Slab-on-Grade (SOG) U-value [W/m$^2$ K]
15. Glass type U-value [W/(m$^2$ K)]
16. Solar Heat Gain Coefficient (SHGC)
17. Visible Transmittance (VT)

After the creation of building zone, the model is ready for thermal performance simulation. DIVA/Grasshopper has two components one is used for the analysis of daylight performance. The other (Viper) is used for energy consumption calculations. This component performs thermal analysis for Grasshopper using the simulation engine (EnergyPlus). Fig. 3 shows the "Viper" component and its input parameters. In this study, the building design data at the conceptual phase are presented in Tables 1 and 2. Having a combination of these options form one design. *In this paper, the workflow developed by*, roof, and slab on grade (3 × 2 × 2, respectively). Then, for each design option 1000 scenario is randomly created by changing the building dimensions, orientation, WWR, glazing type and temperature set point randomly from the ranges specified for these variables presented in Table 1. Thus, a total number of 12,000 simulations are performed in this study (12 design options × 1000 scenarios). The simulations outputs are the energy consumption estimated for all the developed 12,000 design options.

TT-toolbox is a Grasshopper plugin that transfers data from Grasshopper to Microsoft Excel, while for each time step DIVA/EnergyPlus saves results during simulation process. Therefore, TT-toolbox is applied to collect the simulations results (inputs and outputs data) and recorded these data automatically in Excel. The simulations are performed with different values for the parameters that frequently varying, and the data are recorded for the entire simulations. Table 4 presents a sample of the database generated which includes input parameters and the predicted Energy Use Intensity (pEUI), which is considered for this study as the summation of required energy in one year measured in watts for cooling, heating, lighting, and equipment's loads.

### 3.6. Artificial neural network model

One of this study aims is to propose an ANN model that can be used for predicting the energy usage of residential buildings in Egypt. The steps of developing the ANN model are presented below.

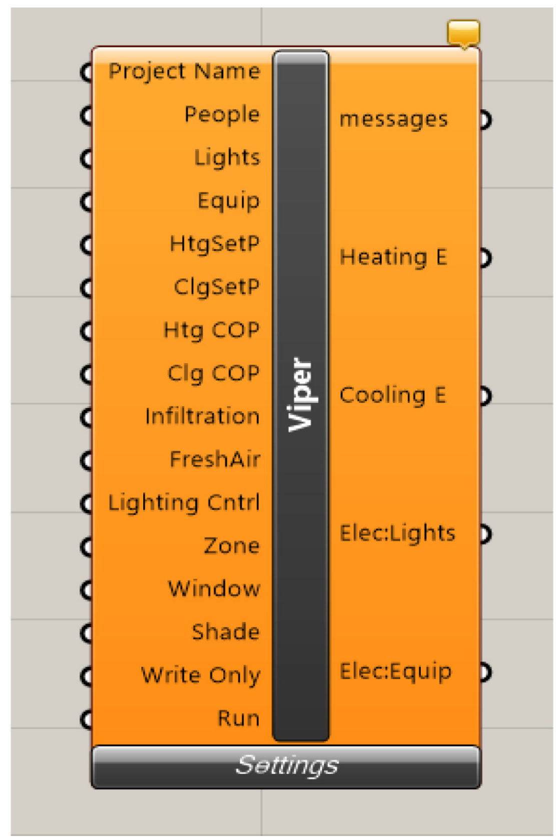


**Fig. 3.** "Viper" component and its input parameters.

#### 3.6.1. ANN initial model development

The first step is to determine the initial ANN structure including: the activation function, number of hidden layers, number of neurons in each layer and learning method. NeuroSolutions version 5.0 and its Excel toolbox are applied to generate the initial ANN model. The input nodes represent the building envelope (walls, roof, and slab on grade), building orientation, building dimensions (length, width, and height), WWR, glass properties (U-value, SGHC and VT), cooling set point, and heating set point. Whereas the output node represents the pEUI which is the total of cooling, heating, lighting, and equipment (plug-ins) electricity consumption (Table 5).

An initial backpropagation ANN model is constructed with one input layer representing 16 parameters as described before, one hidden layer with 10 neurons and the output layer for one

**Table 4**
Energy consumption database sample.

| Wall type | Roof type | SOG | Dimensions | | | Orientation | Windows to wall ratio | | | | Glass properties | | | Temp. set points | | pEUI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Width | Depth | Height | | South | East | North | West | U-Value | SHGC | VT | Heating | Cooling | |
| 2 | 1 | 1 | 28.41 | 16.2 | 10.6 | 216 | 5% | 68% | 0% | 33% | 0.98 | 0.72 | 0.1 | 11 | 18 | 95122 |
| 2 | 0 | 0 | 27.29 | 28.83 | 11.73 | 52 | 38% | 37% | 52% | 58% | 0.29 | 0.09 | 0.28 | 11 | 24 | 65435 |
| 2 | 0 | 1 | 13.79 | 22.39 | 13.42 | 39 | 58% | 46% | 12% | 5% | 1.18 | 0.08 | 0.55 | 11 | 19 | 52742 |
| 2 | 0 | 0 | 29.41 | 22.23 | 9.23 | 132 | 40% | 74% | 44% | 27% | 0.76 | 0.74 | 0.49 | 12 | 26 | 60643 |
| 2 | 0 | 0 | 21.61 | 24.33 | 6.85 | 138 | 59% | 48% | 73% | 77% | 0.53 | 0.76 | 0.75 | 12 | 24 | 60467 |
| 1 | 0 | 1 | 12.78 | 22.16 | 6.25 | 71 | 72% | 66% | 38% | 34% | 0.93 | 0.07 | 0.89 | 12 | 23 | 24703 |
| 2 | 0 | 1 | 23.83 | 11.85 | 14.76 | 323 | 51% | 7% | 64% | 13% | 0.26 | 0.89 | 0.49 | 8 | 27 | 48268 |
| 0 | 1 | 0 | 22.35 | 18.97 | 5.23 | 360 | 43% | 15% | 21% | 5% | 1.13 | 0.2 | 0.35 | 11 | 18 | 58613 |
| 1 | 1 | 1 | 15.27 | 22.72 | 10.42 | 32 | 37% | 20% | 11% | 62% | 1.12 | 0.76 | 0.05 | 10 | 22 | 117217 |
| 0 | 0 | 1 | 22.44 | 28.47 | 5.45 | 99 | 43% | 71% | 36% | 15% | 0.98 | 0.32 | 0.53 | 11 | 22 | 63734 |
| 1 | 1 | 0 | 20.53 | 28.73 | 6.08 | 212 | 76% | 62% | 21% | 8% | 0.49 | 0.4 | 0.7 | 9 | 25 | 44796 |
| 2 | 1 | 0 | 17.06 | 17.2 | 4.62 | 162 | 20% | 36% | 66% | 62% | 0.48 | 0.92 | 0.25 | 9 | 20 | 47642 |
| 0 | 1 | 1 | 28.34 | 15.29 | 12.76 | 164 | 59% | 53% | 77% | 45% | 0.27 | 0.36 | 0.04 | 10 | 27 | 37210 |
| 1 | 1 | 1 | 18.74 | 19.59 | 6.19 | 198 | 54% | 0% | 12% | 42% | 0.42 | 0.82 | 0.08 | 11 | 27 | 26147 |
| 0 | 0 | 0 | 13.81 | 26.96 | 13.09 | 159 | 0% | 71% | 46% | 62% | 0.31 | 0.75 | 0.53 | 9 | 25 | 63773 |
| 0 | 0 | 0 | 22.52 | 12.94 | 4.56 | 221 | 7% | 52% | 68% | 39% | 0.83 | 0.69 | 0.86 | 8 | 21 | 38660 |

**Table 5**
The ANN model input and output parameters.

| Components | Parameters |
|---|---|
| Input Layer | Wall Type<br>Slab on Grade Type<br>Roof Type<br>Building Length<br>Building Width<br>Building Height<br>Building Orientation<br>WWR (South)<br>WWR (North)<br>WWR (West)<br>WWR (East)<br>Glass U-value<br>Glass SGHC<br>Glass VT<br>Heating Set Point<br>Cooling Set Point |
| Output Layer | Predicted Energy Use Intensity (pEUI) |

**Table 6**
Initial ANN model components and values.

| Parameter | | Component and values |
|---|---|---|
| ANN structure | 16-10-1 | Input layer: 16 neurons<br>1st hidden layer: 10 neurons<br>Output layer: 1 neuron |
| Transfer function | Hidden neuron<br>Output neuron | TanhAxon<br>TanhAxon |
| Training method | Goal<br>Epoch<br>Algorithm | 0.01 (mean square error)<br>1000 times<br>Levenberg Marquardt |

node (pEUI). The transfer function used in all layers is TanhAxon function along with Levenberg Marquardt learning algorithm. Prior to training, all inputs and output data are scaled within the range of [−1, 1]. The initial ANN model components and values are summarized in Table 6.

The training is considered to have achieved convergence if both the Mean Absolute Percentage Error (MAPE) and the determination coefficient ($R^2$) stabilized over certain number of iterations. The MAPE and $R^2$ related to the initial ANN model are calculated for the predicted and the desired outputs as 6.4% and 0.971, respectively. The determination of the appropriate ANN topology and transfer function are explained in Step 2 below.

*3.6.2. Selecting appropriate ANN parameters*

To get stable and accurate prediction performance from the proposed network, the architecture of the initial ANN and training methods are optimized using a parametrical optimization process (Moon et al., 2015). The transfer function, number of neurons and number of hidden layers are sequentially optimized through trial-and-error process. In this process, a given parameter values are changed and the other parameters are kept fixed with their initial values. After the appropriate value of this parameter is identified, the following parameters are then identified one by one.

– **Transfer function**

The appropriate transfer function is determined by changing the transfer function in both hidden and output layers in the initial ANN model (16-10-1) structure. Then, the MAPE and $R^2$ are calculated for the testing phase to measure the ANN performance. The transfer function (SigmoidAxon) which produces the minimum MAPE (5.58%) and $R^2$ (0.98) is chosen. The results of these experiments are presented in Table 7.

– **Neural network structure**

There is no direct and exact method to determine the suitable number of hidden layers and neurons assigned to each hidden layer. For this study, a number of network structures are developed with one hidden layer, with 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 25 and 33 neurons: and two hidden layers with a random number of neurons for each hidden layer. From Table 8, the ANN model structure (16-10-16-1) with the least MAPE (5.36%) and highest $R^2$ (0.99) is selected. Then, the proposed ANN model structure consists of one input layer having sixteen neurons, two hidden layers with ten and sixteen neurons, respectively, and an output layer with single neuron as shown in Fig. 4. Training was set to stop after 1,000 iterations. The MAPE and $R^2$ statistical measures used to measure the performance of the ANN. Fig. 5 is a scatter plot that shows the relationship between the simulated energy and ANN predicted energy for the selected network.

*3.6.3. ANN model performance evaluation*

Testing the proposed ANN model accuracy is an important step to assure the prediction capabilities of the developed ANN model. In this study, 1800 data sets are extracted randomly from the overall energy simulations database and used for validation (i.e., not used in the training phase). The validation results plotted in Fig. 6 show the relationship between the predicted values and the targeted energy consumption (Watts), with MAPE of 5.36% and $R^2$ of 0.98. The achievement of these positive results (MAPE <20% and $R^2$>95%) confirmed that the ANN application to predict energy performance in residential buildings is an attractive and valid alternative solution to predict energy demand (Ciulla et al., 2019; Peurifoy and Oberlender, 2002).

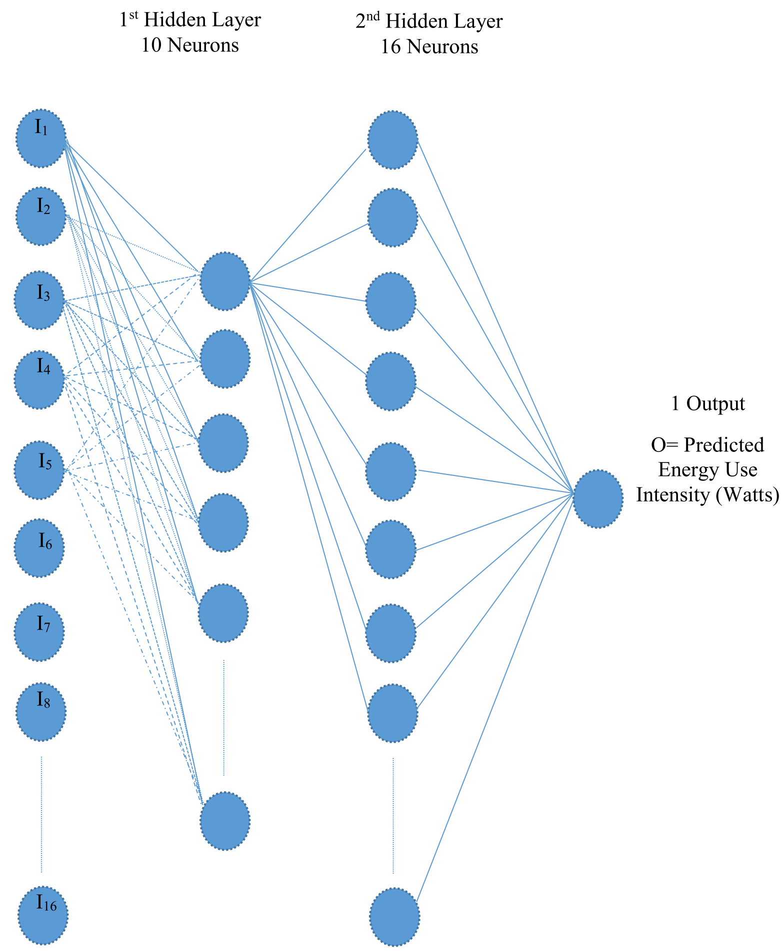


**Fig. 4.** Topology of the Selected ANN Model.

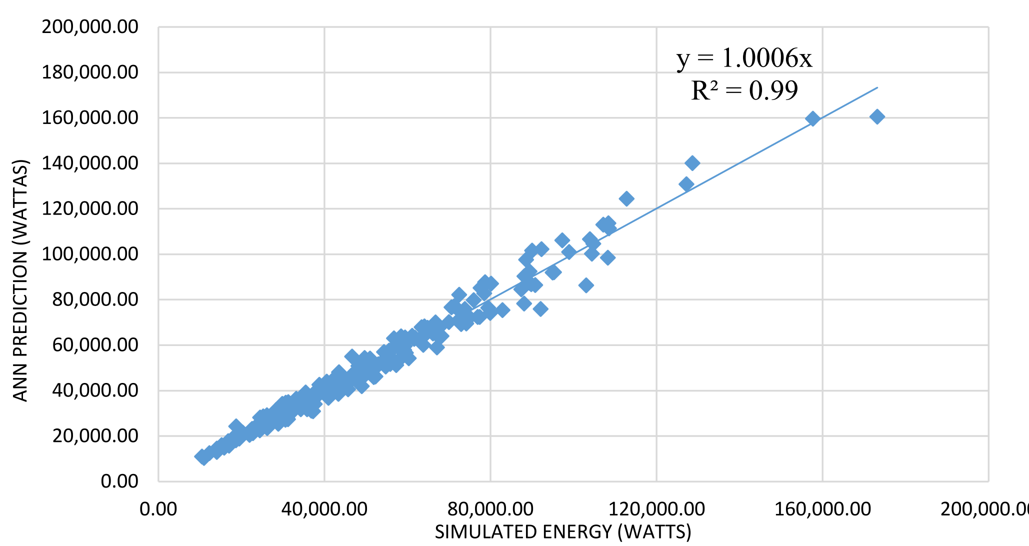


**Fig. 5.** The distribution of the simulated energy versus ANN prediction energy.

## 4. ANN model automation and implementation

After developing the ANN model, a user-friendly interface is developed to facilitate its use in predicting energy consumption without having experience in modeling and simulation tools. This interface, developed using Visual Basic (VB) programming language, provides the user with many alternative options according to the input parameters, which describe the model. The Custom solution wizard is a tool that will take the proposed neural network created with NeuroSolutions and automatically generate and compile a Dynamic Link Library (DLL). This facilitates incorporating neural network models easily into other NeuroDimension products and other application such as Visual Basic. The generated neural network DLL provides a simple protocol for

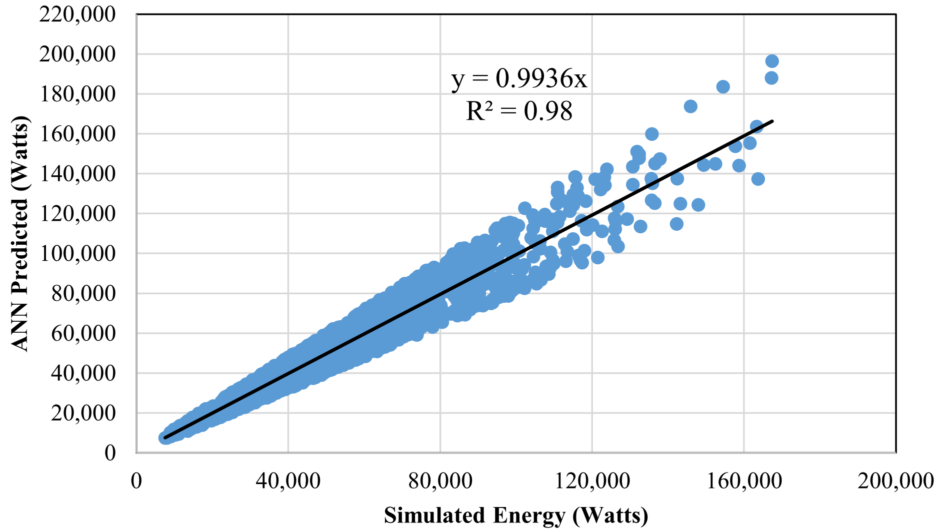


**Fig. 6.** The distribution of the simulated energy versus ANN prediction for validation process.

**Table 7**
Experiments for ANN proposed transfer function.

| No. | Transfer function | | Test data | |
|---|---|---|---|---|
| | Hidden layer | Output layer | MAPE (%) | $R^2$ |
| 1 | TanhAxon | TanhAxon | 6.40% | 0.97 |
| **2** | **SigmiodAxon** | **SigmiodAxon** | **5.58%** | **0.98** |
| 3 | TanhAxon | LinearTanhAxon | 8.00% | 0.96 |
| 4 | SigmiodAxon | LinearSigmiodAxon | 23.31% | 0.73 |
| 5 | TanhAxon | LinearSigmiodAxon | 23.45% | 0.84 |
| 6 | SigmiodAxon | LinearTanhAxon | 5.85% | 0.98 |
| 7 | TanhAxon | SigmiodAxon | 7.31% | 0.97 |
| 8 | SigmiodAxon | TanhAxon | 6.42% | 0.97 |
| 9 | TanhAxon | Linear | 7.02% | 0.97 |
| 10 | SigmiodAxon | Linear | 6.07% | 0.97 |
| 11 | Linear | TanhAxon | 10.02% | 0.94 |
| 12 | Linear | SigmoidAxon | 10.01% | 0.94 |

**Table 8**
Experiments to determine the Optimum ANN Architecture.

| Test order No. | ANN structure | MAPE | $R^2$ |
|---|---|---|---|
| 1 | 16-4-1 | 7.01% | 0.97 |
| 2 | 16-5-1 | 6.47% | 0.97 |
| 3 | 16-6-1 | 6.17% | 0.97 |
| 4 | 16-7-1 | 6.28% | 0.97 |
| 5 | 16-8-1 | 6.30% | 0.97 |
| 6 | 16-9-1 | 6.07% | 0.94 |
| 7 | 16-10-1 | 5.58% | 0.97 |
| 8 | 16-11-1 | 6.08% | 0.97 |
| 9 | 16-12-1 | 5.98% | 0.97 |
| 10 | 16-13-1 | 6.32% | 0.97 |
| 11 | 16-14-1 | 5.38% | 0.97 |
| 12 | 16-15-1 | 7.74% | 0.94 |
| 13 | 16-16-1 | 5.47% | 0.99 |
| 14 | 16-17-1 | 5.59% | 0.97 |
| 15 | 16-18-1 | 5.76% | 0.98 |
| 16 | 16-20-1 | 6.22% | 0.97 |
| 17 | 16-25-1 | 6.33% | 0.97 |
| 18 | 16-33-1 | 6.25% | 0.97 |
| 19 | 16-10-10-1 | 5.97% | 0.97 |
| 20 | 16-10-12-1 | 5.71% | 0.97 |
| 21 | 16-10-14-1 | 7.52% | 0.96 |
| 22 | 16-10-16-1 | 7.28% | 0.88 |
| 23 | 16-8-8-1 | 6.59% | 0.94 |
| 24 | 16-6-6-1 | 7.14% | 0.96 |
| 25 | 16-6-4-1 | 8.64% | 0.95 |
| 26 | 16-10-8-1 | 6.87% | 0.96 |
| **27** | 16-10-16-1 | **5.36%** | **0.99** |
| 28 | 16-10-18-1 | 7.53% | 0.96 |
| 29 | 16-16-16-1 | 6.06% | 0.98 |
| 30 | 16-8-16-1 | 7.42% | 0.96 |

assigning the network input and producing the corresponding network output. After the network DLL has been created, the Custom Solution Wizard created a project shell in the format of Visual Basic 6. The shell is provided as a guide to help developing a custom application using the generated neural network DLL. Fig. 7 shows the developed interface using VB in Microsoft Excel using source code that will load in DLL and allow training the network and getting the networks output.

The proposed model was then applied to a case study representing a residential building in New Cairo City, Egypt (Fig. 8). Table 9 summarizes the set of information that are represent the basic characteristics of the building envelope. There are many possible combinations of building design options/scenarios. Where the large number of combinations requires important computing time, moreover the interoperability between modeling and simulation tools. The design team has difficulties in trade-off between design parameters to generate group of design options, then simulate each design option to calculate the energy usage. The developed interface is used to predict energy consumption for ten different combinations of building design options with respect to building baseline dimensions and exchanging other input parameters such as wall types, orientation, WWR, glass properties and temperature set points. Then, the ten design options are simulated in Grasshopper and the outcomes computed by EnergyPlus were compared with the predicted values form the developed model. The mean absolute percentage error was about 5.14% which is acceptable range as mentioned before.

## 5. Conclusions

Improvement in residential building design and thermal analysis performance have significant role in improving energy consumption. Numerous decisions that highly affect building performance are made at the early design stage when many competitive alternatives are generated and compared and requires considerable input data describing climate conditions, building shape, and material thermal properties. This process involves the implementation of expensive and complex dynamic simulation tools, nearly continuously unreachable to nonexpert and untrained users. Therefore, there is a necessity for a consistent model for energy performance analysis to forecast energy consumption in residential buildings to assist decision makers and

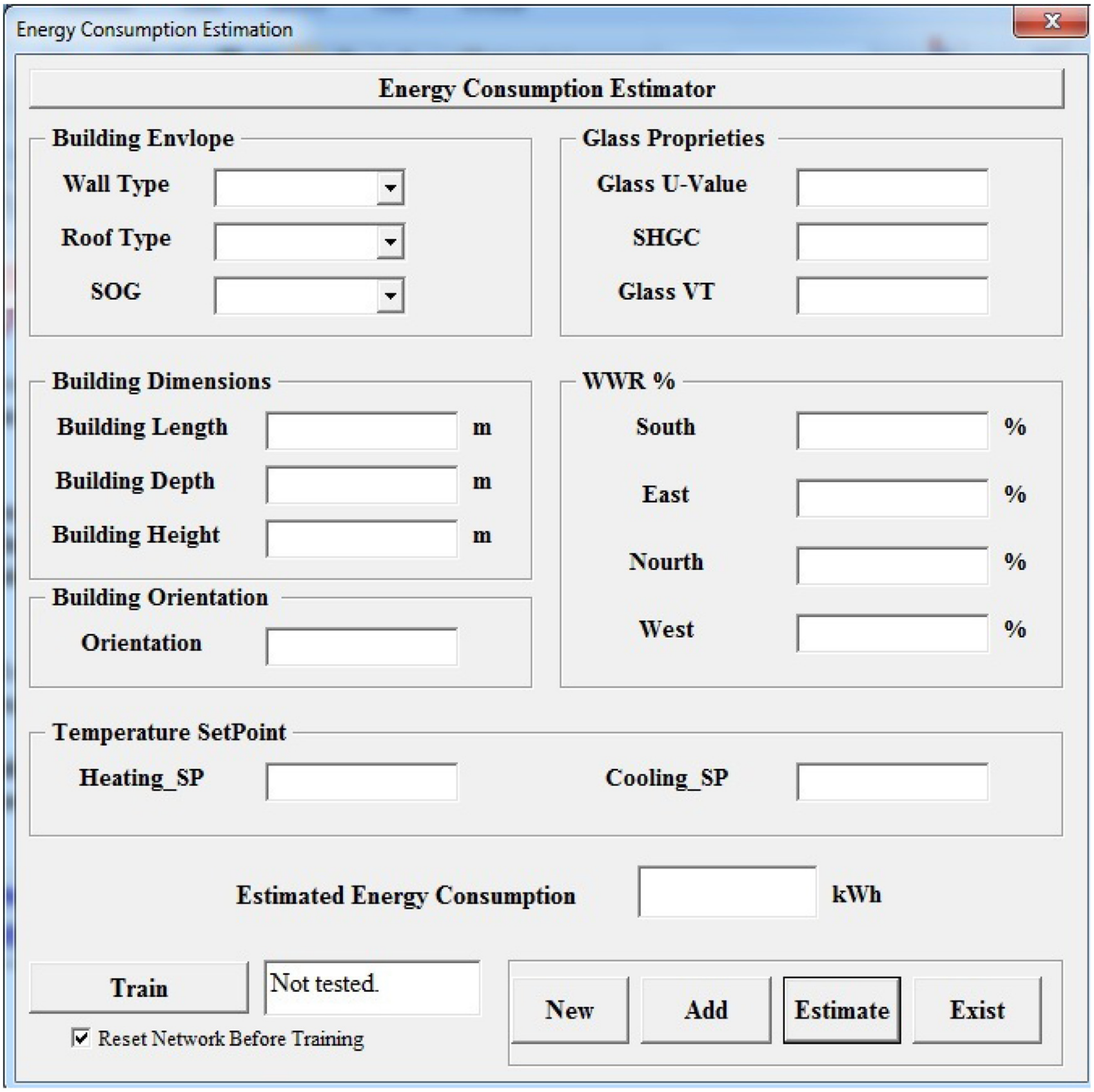


**Fig. 7.** User interface for the energy consumption prediction model.

**Fig. 8.** Isometric of residential building case study.

**Table 9**
Characteristics of case study building.

| Location | New Cairo |
|---|---|
| Floor area | 252 $m^2$ |
| Building Length | 14 m |
| Building Depth | 18 m |
| Floor-to-floor height | 3 m |
| Number of floors | 3 |
| Exterior wall area | 380 $m^2$ |

designers in finding an effective design. In this study, a parametric analysis is employed to model, simulate, and evaluate energy usage and occupants' thermal performance. The developed simulation workflow in one platform (Rhino/Grasshopper) giving a simplified and automated method to analyze, model and simulate building energy performance timely, accurately, and efficiently. Also, it overcomes the interoperability problems by integrating parametric modeling and energy simulation engine in one platform.

Then, ANNs is used to predict the thermal performance of residential buildings in accordance with the Egyptian energy standards. With this aim, a database of 12,000 scenarios were created with different dimensions and characteristics of buildings. Each parameter had a several values that generated randomly within defined minimum and maximum ranges, then these parameters are performed throughout a various simulation process to generate energy consumption database. Based on this reliable database, an ANN model is developed, trained and tested. The proper ANN structure was determined to be composed of one input layer of 16 neurons (representing the input parameters), two hidden layers with 10 and 16 neurons and transfer function was TanhAxon for both layers. This model generates the best results with the lowest MAPE of 5.36% and the highest $R^2$ of 0.98. This achievement of positive results ($R^2$) is very close to one, substantiated that the ANN models is valid and attractive alternative solution for energy consumption prediction in residential buildings. The proposed ANN model was then able to accurately predict the studied metrics with a mean percentage average error under the generally accepted levels. Finally, a user-friendly interface is developed to facilitate the implementation of the developed model and to act as a decision support tool, which is very easy, trustworthy, and handy for immediate use without any experience in modeling and simulation tools.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgment

All authors approved the version of the manuscript to be published.

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