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Prediction of an Efficient Energy-Consumption Model for Existing Residential Buildings in Lebanon Using an Artificial Neural Network as a Digital Twin in the Era of Climate Change

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Abstract: Environmental factors, such as climate change, have serious consequences for existing buildings, including increased resource consumption and footprint, adverse health effects, and reduced comfort for the occupants. To promote sustainability and address climate change, architecture must embrace digitalization. Buildings can be built digitally, analyzed in real time, optimized for energy consumption, and utilized to reduce carbon emissions and achieve zero energy consumption using digital twin technology. Currently, Lebanon's residents are turning to solar power to generate renewable energy as a result of a lack of energy supplied by the government. In this study, a digital twin model was designed using an artificial neural network (ANN) to investigate the energy consumption of residential buildings. The main idea was to assist architects and engineers in forecasting energy consumption for different design materials by selecting the most effective alternate design for materials with building envelope characteristics, such as exterior walls, roof insulation, and windows, to minimize the consumption of energy in a residential building, hence resulting in a green building. The data simulations used in the digital twin model were carried out using Quick Energy Simulation Tool (eQuest) software; 1540 simulation results were used for different thicknesses of insulation material, values of conductivity, and window types. The digital twins were designed using an artificial neural network model. The results of the investigation and the accompanying eQuest output results were found to be precise and very similar.

Keywords: energy performance prediction; digital twin technologies; zero-energy buildings; eQuest; intelligent buildings; climate change

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1. Introduction

Energy efficiency has received increasing attention from the Architecture, Engineering, Construction, and Operations (AECO) industry over the last few decades. A digital twin has the potential to advance various phases of operations and maintenance (O&M) [1]. Global warming was one of the most critical aspects of the United Nations Climate Change Conference in Glasgow, UK, in 2021. During the conference, commitments were sought to implement the Paris Agreement and the UN framework convention on climate change sustainably. Limiting global warming to 1.5 degrees Celsius is one way to achieve this [2–4]. The Intergovernmental Panel on Climate Change (IPCC) estimated in its 2018 report that global greenhouse gas emissions will need to be net zero by 2050 to maintain a "high confidence" level that temperatures will remain below sustainable levels [5].

The transition toward net zero emission targets requires significant changes at the societal and industrial levels; therefore, governments and corporations are increasing their

reliance on technological innovations. It may be possible to use digital technologies to deliver sustainable solutions to many seemingly intractable societal challenges associated with climate change in the future [6].

In addition to climate change, the world is facing several crises, such as the COVID-19 pandemic, economic crisis, and the Ukraine–Russia war, which have significant impacts on petroleum and electricity prices. All these factors affect developing countries by increasing electricity bills and the amount of electricity provided by governments. It is evident in Lebanon that all previous effects are still being felt in the current situation, as the government continually fails to provide residents with adequate electricity supplies throughout the day.

There is growing interest in digital twins among practitioners and scholars alike. Virtual objects and simulations of operational processes are provided via technology across many industries today. As of 2019, the digital twin has become an essential function for organizations, according to a Gartner survey in the Mohsen article published in 2023 in the *Decision Analytics Journal*. Digital twin technology will be used by 75% of Internet of Things (IoT) organizations by 2020, according to the report [7]. According to another Mohsen article that was published (2023) in the *Decision Analytics Journal*, Gartner stated that more than 40% of large companies worldwide will use digital twins to increase revenues by 2027 [8]. Global Market Insight estimates that between 2023 and 2032, the compound annual growth rate of the digital twin market will be around 25%. From 2021 to 2026, the digital twin market is expected to grow by nearly USD 32 billion, according to another recent report by Global Technology Research [9].

Furthermore, approximately 60% of executives in a wide range of industries expect to implement digital twins in their operations by 2028, according to a 2022 survey [10]. The digital twin is a cutting-edge technology that has transformed business by replicating nearly every aspect of a product, process, or service. It can digitally recreate everything in the physical world and offer engineers input from a virtual environment. As a result, firms can identify and address physical problems sooner, create and build better products, and realize value and advantages faster than ever before. Furthermore, digital twin technology enables companies to improve their business operations and performance [11].

Presently, most Lebanese people have moved to support themselves with sufficient energy using renewable resources, particularly solar panels and storage batteries, which emphasize the importance of zero-energy buildings in presenting optimal solutions for the construction sector to provide sufficient, efficient, and comfortable buildings considering economic crises.

In this paper, an energy performance prediction model is presented for existing residential buildings in coastal cities of Lebanon. The simulation was performed using eQuest software version 6.34. Validation and verification were carried out during this simulation.

This paper presents the modeling and simulation of a smart residential building energy model using artificial intelligence to assist architects and engineers in selecting the optimum alternative design of a building envelope that minimizes the cost of energy consumption of residential buildings in Tripoli. Most residential buildings in Tripoli, Lebanon, are the same in terms of the building envelope, area, and number of floors on the same street. Thus, for each residential building that is similar to the studied building, the proposed methodology could be applicable. Therefore, this model represents an alternative tool for predicting the energy consumption of residential buildings according to the alternative design options for building envelope optimization, with time and money savings, because modeling and simulation in eQuest are complex and time-consuming.

eQuest software is an energy simulation and analysis tool. It enables users to perform detailed analyses of building design technologies, including the most sophisticated building energy simulation techniques, without requiring extensive experience.

Based on the analysis of many publications, different key topics have been identified according to the target and objective of each paper. Most publications focus on four subjects: design optimizations (Subject 1); user comfort (Subject 2); the maintenance and operation

of buildings (Subject 3); and energy-consumption simulations (Subject 4). Although the use of a digital twin to improve energy efficiency often occurs during usage and maintenance, some academics have explored approaches to improve building design using a digital twin. Two pertinent approaches are taken into account when using and maintaining a building: one is user-centric and focuses on occupant comfort; the other is performance- and maintenance-focused. To simulate and predict future events, several academics have concentrated their investigations on analyzing real energy data obtained by digital twins (Subject 4). In the relevant publications, there is a gap in identifying the current state of existing buildings, which represents a huge sector of housing [12].

A retrofit approach has been employed in most studies on design optimization; these involve modifying the entire building or a specific component (such as an HVAC system or solar chimney). The digital twin was used to simulate and inform more energy-efficient retrofit scenarios. Few investigations have been conducted on basic designs. It is vital to pay attention to the initial layout of specific building components intended to be integrated into existing buildings. As part of this strategy, the model is designed to resemble an existing entity and is known as a "digital twin". Conceptualizing the design from the beginning as a digital twin for energy efficiency objectives may have a significant impact on both the design process and the final design [13].

In most cases, digital twins or digital counterparts of built assets are based on building information modeling (BIM). When publications detail the specific software used for modeling the digital twin, Autodesk Revit is most frequently mentioned. Additionally, it is frequently combined with other programs from the same vendor, typically for particular construction models, such as Green Construction Studio, Insight, and Dynamo. Building performance simulations that employ building energy modeling (BEM) tools at the building level and UBEM tools at the urban level (city) paired with GIS information are typical solutions for these scenarios, analyzing more than one building at the same time [14]. Furthermore, using the BIM tools stated by El Sayary, 2021, BIM can be used to determine the number of solar panels required to provide the building with the annual amount of energy consumption in the building. In this regard, the designer will offer the real number of solar cells required to produce clean and economical electricity. This calculation in the initial design phase will give a designer the full image of the operation phase and is applied specifically under sustainable green construction practices, with greater attention paid to the carbon footprint of the building [15].

BEM is a powerful technique for analyzing the energy efficiency of buildings and for the best evaluation of architectural design choices made when planning to select building envelope materials and other systems (HVAC, lighting, power, etc.). When energy-saving solutions for buildings are proposed, the envelope of the building needs to be given the greatest consideration because it has the greatest impact on the performance and energy savings of the building. Heat loss and energy use are reduced through building envelope design optimization. The walls, roofs, and windows account for most of a building's energy loss. In cold climates, adequate insulation of the external wall and roof can minimize heat loss, while in hot climates, it can reduce excess heat infiltration. During the architectural design phase, it is important to consider parameters such as the shading coefficient and the U-value, in addition to the thickness and conductivity of the insulation material on the exterior walls and roof [16].

According to Figure 1, there are three different categories of energy modeling techniques:

1. White models (engineering models).
2. Black models (statistical methods).
3. Gray models (hybrid models).

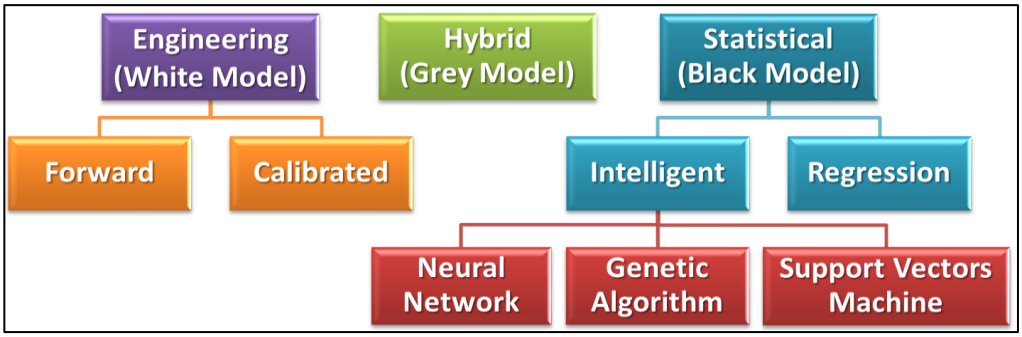


Figure 1. Energy modeling techniques.

Calibration and forward (classical) methods are two engineering models (white models). The investigation of a building's dynamic energy performance using approaches for simulations with computer modeling is part of the forward (classical) approach.

Artificial neural networks (ANNs) have many applications, such as prediction and inverse models for complicated models of multiple inputs and multiple outputs. The main dilemma in the ANN prediction model is how to manipulate big data while obtaining a successful and accurate model, with many applications on direct models and inverse models for vehicles; the simulations were performed using ANNs [17–19].

Future power consumption was predicted using MATLAB software 2018 and time series of the ANN, using real-time training data. The aim was to reorder the energy consumption, and the input was the time in hours. We fed these lines into an ANN to train it to look for a pattern in a long-term dataset using data from a power plant at VIT University. As a result, predictions were made with fewer errors and good accuracy. This prediction can help us to calculate the power required in a technology tower. It can be switched to renewable energy whenever the load demand is low [14].

The prediction of residential energy use in the United States was prepared from 1984 to 2010. The connection mass method was used in the energy forecast to assess the factors that influence the type of energy consumption. An ANN with an accuracy of 0.97903 was used successfully for the prediction [20].

An ANN was developed to study the energy efficiency of buildings. The case study concerned an existing building in Perugia. TRNSYS developed a 3D model to compare its results with the ANN results. The results indicated that the indoor air temperature trend was closer to the measured data than that simulated by TRNSYS, with mean MSE values and smaller errors (less than 7% difference) [16].

Energy calibration was performed to assess the precision of the Energy Plus virtual building model. A pair of calibrated environmental sensors and a weather station were installed in a five-story office building. The model was calibrated to achieve lower mean deviation values of 5% and a 10% cumulative change in the base-root mean square error (RMSE) value using the ASHRAE 14 indicator guidelines. Every year, the updated Energy Plus model can predict spacetime [21,22].

Based on simulated building energy performance data, an artificial neural network (ANN) model was created to predict buildings' cooling and heating loads. Total height, relative compaction, area, wall area, roof area, orientation, and distribution of the building's glazing area are examples of input variables. The loads for heating and cooling are the output variables. The simulation data used to train the model were published data for different combinations of residential buildings. ANNs have the advantage of adequately estimating output values for given input values, but they have limitations in obtaining the effects of individual input variables. As a result, the overall height, relative compression, wall area, and glazing area have a significant effect on reducing heating and cooling loads. In addition, the surface affects the heating load, and the roof surface affects the cooling load [23].

Statistical machine learning was used to study the effects of eight input variables (the glazing area, the roof area, the surface area, the wall area, relative compactness, orientation, the distribution of the glazing area, and the overall height); two output variables (cooling and heating loads) of residential buildings have been developed. They compare the classical linear regression method with the powerful advanced nonlinear nonparametric method, Random Forest, for the estimation of heating and cooling loads. Extended simulations of 768 diverse residential buildings show that we can predict heating and cooling loads with low mean absolute error deviations from the actual reality established using Ecotect (0.51 and 1.42, respectively) [24].

A simulation based on the ANN was used to characterize the behavior of buildings and then combined with an optimization tool (multi-objective genetic algorithm). In this study, this technique was used to reduce energy use and increase thermal comfort in a residential home. The heating and cooling set points, the Rh setpoints, start and stop delays, airflow from the supply, and concrete thickness were the decision variables. The ANN training data were obtained using TRNSYS; then, using two different optimization techniques, the variables of the HVAC system, the passive solar design, and the thermostat were taken into account. Compared with the traditional optimization method, the total simulation time was greatly reduced by incorporating the ANN into the optimization. The results of the adjustment demonstrate a significant reduction in thermal comfort and energy consumption [25].

A comparison was performed between the physics-based model (Energy Plus version 2005) and the data-driven model. The object of the research was the administrative building of the University of So Paulo, which covers an area of about 3000 square meters and has a building population of approximately 1000 employees. Simulation parameters were user-defined through meteorological parameter profiles. Both the physical model and the base ANN model were suitable in 80% of cases. The results show that the temperature of the dry bulb alone is a very good predictor; the addition of other parameters (i.e., humidity and solar irradiance) improved the models, but not significantly [26].

An overview of ANNs and their applications, especially modeling and forecasting, has been presented in the field of building energy systems. This field includes solar and wind radiation forecasting models, solar power systems applicable in buildings, energy-consumption forecasting, energy conservation, system modeling, HVAC, and naturally ventilated buildings [27].

The overall goal of the decision-making model is to derive a simplified set of building parameters from the user. The suggested methodology is based on the ANN approach, which has several limitations. Future research should take into account the various climatic zones in Lebanon, the different geometries and shapes of residential buildings, life cycle cost analysis, the automatic selection of multi-objective optimization solutions, and online optimization applications.

2. Materials and Methods

2.1. Materials and Case Study

The case study was a building situated in the coastal zone of Lebanon; the objective was to predict the energy consumption in a typical residential unit. Figure 2 shows a medium-sized residential building in Tripoli, Lebanon, with a three-dimensional view and internal partitions of this building. The longer axis is aligned northwest/southeast. This building consists of 10 floors, each with two apartments and a total floor space of 2540 m^2, with a floor height of 2.80 m. The shop space is on the ground floor. Each floor has two units, and the first through tenth floors are similar. The unit itself consists of three bedrooms, a kitchen, two bathrooms, a reception, and living rooms. The design of the building represents an ideal subject of investigation for this study because, in terms of internal partitions and room layout, it is comparable to other residential building constructions in Lebanon. eQuest software was used to create an energy model to examine some energy-saving strategies.



3D View perspective Internal Partition of the Building eQuest Model (BEM)

Figure 2. View of a medium-sized residential building (Red Arrow identify the selected buildings in 3D View. Moreover, the red color in Internal Partition of the Building explain the Living spaces, the green color for Salon spaces, Yellow color for Kitchen spaces, Blue color for entrance, gray color for Bedrooms).

The project was modeled and simulated using eQuest software to determine the energy consumption for the proposed model and the baseline model. eQuest used the DOE-2 building energy simulation engine as an analysis tool for building energy consumption on an hourly basis. To simulate the building, the key parameters had to be defined, such as the project site, weather data, building design, construction, internal loads, and HVAC systems.

The simple possible energy model is shown in Figure 2; the goal was to compare a conventional building to one that has implemented several energy-saving techniques to improve the building envelope, which will be covered in detail in the following paragraphs. In the energy study of the baseline model scenario, the climatic data of Tripoli city were used for the simulation. General construction details are shown in Table 1. Notably, eQuest cannot directly model thermal bridges, which was not taken into account in this study.

This paper presents the modeling and simulation of a smart residential building energy model using artificial intelligence to assist architects and engineers in selecting the optimum alternative thermal performance design of a building envelope that minimizes the energy-consumption cost of residential buildings in Tripoli. For this reason, only the energy consumption of the building is presented. Additionally, the building services system used is briefly described in Table 1. Each strategy used for building envelope optimization was analyzed; however, all other input parameters and schedules (geometry, weather, lighting, equipment, occupancy, internal load, HVAC, etc.) remained the same between the proposed model and baseline model because the aim was to represent building energy efficiency measures of the building envelope alone.

According to the ASHRAE 90.1 specifications for residential buildings, each apartment is represented by a single thermal zone [28]. On the other hand, each floor's stairwell and lift cores are likewise treated as separate heat zones. The building envelope was chosen to reflect the construction standards in Lebanon. Its exterior and interior walls were plastered, and its flat, uninsulated roof was made of concrete slabs. According to the thermal standard for buildings in Lebanon (2010), there was no insulation layer on any component of the building envelope, ensuring that the basic model case did not meet Lebanon's mandated minimum energy performance criteria. The design, materials, and insulated fenestration of the baseline building model are detailed in Table 2.

Table 1. Baseline energy model and general building information.

Building Type		**Residential Building**
Areas	Gross Floor Area	2540 [m^2]
	External Walls Area	1997 [m^2]
	Windows Area	422 [m^2]
	Roof Area	448 [m^2]
Dimension and Heights	Average floor height	2.80 [m]
	Window height	1.25 [m]
	Window-to-wall ratio	33%
Construction Envelope	External Walls	1 cm Cement Plaster + 20 cm Parpaing + 1 cm Cement Plaster (U-value = 3.02 W/m^2.K)
	Roof	2 cm Concrete Tiles + 2 cm Cement Mortar + 6 cm Sand + 4 mm Bitumen + 20 cm Reinforced Concrete + 1 cm Cement Plaster (U-value = 2.45 W/m^2.K)
	Windows	Single-pane simple glass (U = 6.16 W/m^2.K, SC = 0.95)
Operating Hours	Monday to Sunday	24 h
Internal Loads	Total number of persons	130
	Lighting Load	6.7 W/m^2
	Equipment Load	7.5 W/m^2
Hvac Parameters	ACH	0.3
	Cooling System	Heat Pump Package Unit
	Heating System	Heat Pump Package Unit
	Thermal Set Points	21 °C (Heating), 24 °C (Cooling)

Table 2. Building baseline model envelope information.

Envelope Components	**Materials**	**Thickness (mm)**	**Conductivity (W/m.K)**	**Density (Kg/m^3)**	**Specific Heat (J/Kg.K)**	**Resistance (m^2.K/W)**	**U-Value (W/m^2.K)**
Exterior Wall							
	Outside Surface Resistance	-	-	-	-	0.044	3.02
	Cement Plaster	10	0.73	1400	1000	0.014	
	Parapaing Concrete Block	200	1.43	1950	1000	0.140	
	Cement Plaster	10	0.73	1400	1000	0.014	
	Inside Surface Resistance	-	-	-	-	0.12	
Roof							
	Outside Surface Resistance	-	-	-	-	0.044	2.45
	Concrete Tiles	20	1.1	2100	1000	0.018	
	Cement Mortar	20	1.4	2200	1000	0.014	
	Sand and Gravel	60	2	1850	1050	0.030	
	Bitumen	4	0.23	1050	1000	0.017	
	Reinforced Concrete Slab	200	1.8	2400	1000	0.111	
	Cement Plaster	10	0.73	1400	1000	0.014	
	Inside Surface Resistance	-	-	-	-	0.16	
Window	Aluminum Frame + Single Glazing	6	-	2500	750	U =	6.16
						SC =	0.95

The external walls were made of hollow concrete blocks with 0.01 m thick plaster. The roof was made of reinforced concrete, 0.01 m of plaster, and 0.004 m of bitumen. Under the roof, there was an additional 0.06 m of gravel and sand, 0.02 m of cement mortar, and 0.02 m of concrete tiles. The calculated U-values for the exterior walls were 3.02 $W/m^2.K$, 2.45 $W/m^2.K$, and 6.16 $W/m^2.K$. All windows with aluminum frames had single glazing with a shading coefficient (SC) of 0.95, and the building's façades lacked any shading elements. The window distribution was consistent, and the glazing ratio was 33%.

There were different scenarios for 14 types of external wall (EW0, EW1, EW2, EW3, EW4, EW5, EW6, EW7, EW8, EW9, EW10, EW11, EW12, and EW13) with 11 types of roof (R0, R1, R2, R3, R4, R5, R6, R7, R8, R9, and R10) and 10 types of glazing (W0, W1, W2, W3, W4, W5, W6, W7, W8, and W9). Thus, the total number of combinations was $14 \times 11 \times 10 = 1540$.

The single zone heat pump package system in each apartment's HVAC system has a cooling system coefficient of performance of 2.92. Each zone's lighting and electrical equipment have power densities of 6.7 W/m^2 and 7.5 W/m^2, respectively, in accordance with the ASHRAE 90.1 standard [28]. Six people can fit in each apartment. The set points of heating and cooling are 21 °C and 24 °C, respectively. According to the ASHRAE 90.1 standard, the lighting, equipment, occupant, and HVAC set points are scheduled. The baseline model was simulated from 1 January 2019 to the end of December 2019 for 365 days (one year). The results of the simulation of the baseline model scenario indicate that this building uses 445,696 kWh of energy annually.

2.2. Methodology

Estimation of building energy performance was facilitated using comprehensive building thermal performance simulation models, such as the whole building energy simulation program and the eQuest tool. However, running these simulation programs requires time-consuming and complicated procedures. This study covers a methodology for creating a building energy database using eQuest energy modeling software to train the ANN and calculate the building energy consumption of the building in an ideal time with good accuracy. It also provides a framework for creating a building envelope optimization tool that can identify the best building envelopes. The main components of the building envelope should be because it serves as a significant barrier between the conditioned space and the outside environment.

A building's roof receives the most solar radiation, which significantly increases internal heat gain. To achieve proper U-value (thermal conductance value), the over-deck insulation should protect the roof from excessive heat gain. As with internal walls, exterior walls must be externally insulated to reduce conduction gains. Mineral wool slabs, glass wool, expanded/extruded rock wool polystyrene, polyurethane foam, etc., are some types of roof and wall insulation that are frequently utilized. The proper selection of window assemblies is also critical for further reductions in heat load, particularly in view of conduction gains and solar heat loads. When a high-performance window assembly is included, heat transfer into and out of the building can be decreased, reducing the demand for heating and cooling while increasing the amount of natural light entering the room: a solar control coating and multi-layered glazing yield high-performance glass.

The proposed model was developed using "eQuest" software to analyze different energy-saving techniques to optimize the building envelope. Tables 3 and 4 present information on the construction, materials, and insulated frames of the proposed building model. To gradually improve the parameters of the external boundaries of the building compared with the basic model, the proposed model was run parametrically. The proposed model is intended to represent the building envelope energy efficiency measurements of building envelopes commonly used in Lebanon; therefore, all other input parameters and schedules (such as the building shape, climate, lighting, equipment, people, internal load, and the HVAC) were left unchanged between the proposed model and the baseline model. The following design parameters were considered during the optimization pro-

cesses: different types of windows with varying U-values, shadow factor (SC), thermal insulation materials for external walls with varied conductivities and thicknesses, and thermal insulation materials for roofs with different conductivities with thicknesses. The set of possible solutions using these design features is called an energy-efficient solution. It was agreed that creating material alternatives for each decision variable would represent the available materials in the Lebanese construction market.

Table 3. Roof and external wall insulation material characteristics [29].

Envelope Component	ID	Material Name	Thickness [mm]	Conductivity [W/m.K]	U-Value [W/m^2.K]	Specific Heat [J/kgK]	Density [kg/m^3]	Cost [USD/m^2]
ROOF (R)	R1	XPS-extruded polystyrene foam board	20	0.035	1.02	1500	30	2.12
	R2		40	0.035	0.65	1500	30	4.16
	R3		60	0.035	0.47	1500	30	6.03
	R4		80	0.035	0.37	1500	30	8.33
	R5		100	0.035	0.31	1500	30	11.69
	R6	Glass wool	100	0.04	0.34	840	14	1.90
	R7		120	0.04	0.29	840	14	2.26
	R8		140	0.04	0.26	840	14	2.70
	R9		180	0.04	0.20	840	14	3.47
	R10		200	0.04	0.19	840	14	3.84
WALL (W)	EW-1	Rock wool	40	0.037	0.71	840	150	3.73
	EW-2		60	0.037	0.51	840	150	5.59
	EW-3		80	0.037	0.4	840	150	7.47
	EW-4		120	0.037	0.28	840	150	11.20
	EW-5	EPS-expanded polystyrene foam board	30	0.039	0.91	1500	16	1.21
	EW-6		50	0.039	0.62	1500	16	2.01
	EW-7		70	0.039	0.47	1500	16	2.79
	EW-8		100	0.039	0.35	1500	16	4.00
	EW-9		140	0.039	0.25	1500	16	5.59
	EW-10	XPS-extruded polystyrene foam board	40	0.035	0.68	1500	30	2.85
	EW-11		60	0.035	0.49	1500	30	4.11
	EW-12		80	0.035	0.38	1500	30	5.75
	EW-13		120	0.035	0.27	1500	30	10.50

Consequently, based on materials often utilized in the Lebanese construction sector, several material possibilities were selected, together with their thermophysical characteristics and unit price values, including labor and VAT, as well as sufficient space for the optimization procedure. Five glass wool materials and five extruded polystyrene (XPS) sheet materials were developed in a variety of thicknesses for thermal insulation of the roof, as shown in Table 3. As a result, nine different types of windows and 13 different external wall insulation materials with thermophysical characteristics ranging from single to triple-pane were chosen from Table 4. In total, 1540 variations were created when the various design options were combined with the baseline. The duration of each simulation run was 15 min. Using Intel core i7 quad-core 2.8 GHz, 16-gigabyte memory RAM, a 256 solid-state drive, and a 2-terabyte HDD laptop, this scenario ran continuously for around 16 days. Based on the following scenarios, the proposed model

of this project was simulated and run parametrically with incremental improvements in the parameters of the building envelope.

Table 4. Alternative window characteristics. [29].

	ID	Material Name	U-Value [W/m^2.K]	SC	Visible Transmittance	COST [USD/m^2]
WINDOW (Win)	Win1	Low-e single glazing, 4 mm	4.2	0.75	0.79	12.09
	Win2	Tinted low-e single glazing, 4 mm	4.2	0.62	0.71	12.77
	Win3	Clear double glazing, argon-filled, 4-12-4 mm	2.7	0.86	0.8	17.11
	Win4	Low-e double glazing, air-filled, 4-12-4 mm	1.6	0.64	0.79	17.33
	Win5	Low-e double glazing, air-filled, 4-16-4 mm	1.3	0.64	0.79	17.56
	Win6	Low-e double glazing, argon-filled, 4-16-4 mm	1.1	0.64	0.79	18.25
	Win7	Tinted low-e double glazing, air-filled, 4-12-4 mm	1.6	0.51	0.71	18.25
	Win8	Tinted low-e double glazing, air-filled, 4-16-4 mm	1.3	0.51	0.71	18.47
	Win9	Clear triple glazing, air-filled, 4-12-4-12-4 mm	1.1	0.84	0.78	19.62

- First scenario: to find the best external wall insulation material in the proposed model that yielded the minimum energy consumption and the shortest payback period. For this reason, various types of insulation material and characteristics of the external wall that were used in the simulation of the proposed model are presented in Table 3. The window parameters (U-value and shading coefficient) in the proposed model were kept the same as in the baseline model.
- Second scenario: to find the best insulation material for the roof in the proposed model that yielded the minimum energy consumption and the shortest payback period. For this reason, various types of insulation material and roof characteristics that were used in the simulation of the proposed model are presented in Table 3. The window parameters (U-value and shading coefficient) in the proposed model were kept the same as in the baseline model.
- Third scenario: to find the best window type in the proposed model that yielded the minimum energy consumption and shortest payback period. For this reason, various window types and characteristics that were used in the simulation of the proposed model are presented in Table 4. The exterior walls and the roof composition in the proposed model were kept the same as in the baseline model.
- Fourth scenario: to find the best combination of the building envelope (windows, roof, and external wall) that provides the minimum energy consumption and the shortest payback time.

Based on the above scenarios, 1540 simulations were used for different thicknesses of insulation materials, values of conductivity, and window types.

The results concerning the scenarios identified in the preceding paragraph are reviewed and discussed in this section. The following metrics are organized and reported: energy consumption, material cost (USD), percentage energy savings, net saving cost, and payback time.

Equations (1)–(3) describe the net savings cost, the payback time, and the cost of energy savings.

$$Net\ Saving\ Cost\ (USD) = Cost\ of\ Materials(USD) - Cost\ of\ Energy\ saving\ (USD) \quad (1)$$

$$Payback\ Period\ (Year) = Cost\ of\ Materials(USD)/Cost\ of\ Energy\ saving\ (USD) \quad (2)$$

$$Cost\ of\ Energy\ Saving\ (USD) = Energy\ Saving\left(\frac{\text{KWh}}{\text{year}}\right) \times Energy\ Rate\ Cost\ \left(\frac{USD}{\text{KWh}}\right) \quad (3)$$

where the cost of insulated exterior roof/wall insulation is the material cost, energy savings is the difference in energy consumption between the baseline and the proposed model, and the cost of energy = USD 0.17/kWh (including the cost of generator supply and Electricity Lebanon (EDL) [30,31]. It is important to clarify that energy cost data were supported with standards from the Republic of Lebanon Ministry of Public Works and Transport General Directorate of Urban Planning (2005), Energy Analysis, and Economic Feasibility study (Development of viable solutions for the Thermal Standard for Buildings in Lebanon).

The building was modeled without many details to be as simple as possible because, in this study, the objective was to perform a comparison between a baseline building model (real case in Lebanon) and a proposed building model depending on several energy conservation measures of building envelope thermal performance improvements. The objective of this paper was to be clear and understandable for researchers, engineers, and architects.

3. Results and Discussions

3.1. External Wall Simulation Results

Table 5 and Figures 3 and 4 describe the simulation results for the insulation characteristics of the external wall material (thickness and conductivity) and fixed window with the characteristic values according to the baseline model. The EW-9 option (14 cm wall thickness and insulation of EPS polystyrene material) used the least amount of energy, consuming around 404 MWh per year and saving approximately 9.3%, according to the results of a comparative analysis of numerous design possibilities for external walls (U-Value 0.25 W/m^2.K). It is recommended to examine various exterior wall design ideas that have been researched through multi-criteria decision-making to promote transparency and clarity. Three additional variables were taken into account in addition to energy usage and savings: net savings cost, material costs, and payback period. This method chose the best option from a range of alternatives for the design of the exterior wall. Table 5 shows that although the EW-9 external wall used the least amount of energy, it was not the best option due to its lengthy 1.6-year payback period. Table 5 also shows that EW-5 (EPS polystyrene insulation and 3 cm wall) is the optimum external wall type to select based on multi-criteria decision-making. With a U-value of 0.91 W/m^2.K, energy consumption is 417 MWh/year, energy savings are 6.3%, and the payback period is 0.5 years, making it a client-attractive option as long as the roof and window are left unaltered.

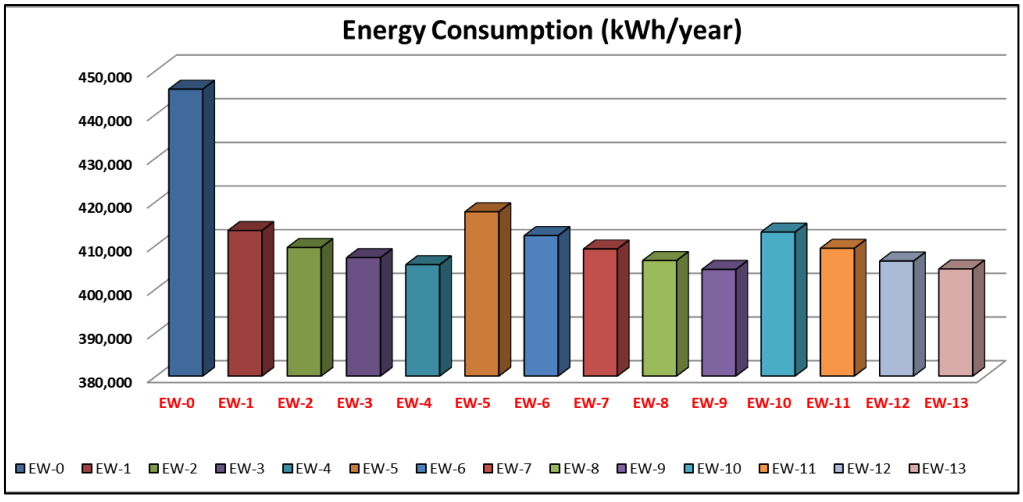


Figure 3. Simulation results for external wall energy consumption.

Table 5. Alternative types of external wall design.

Input		Output						
ID	**Wall Name Type**	**Wall U-Value**	**Energy Consumption**	**Energy Saving**	**Energy-Saving Cost**	**Material Cost**	**Net Saving**	**Payback Period**
		W/m^2.K	**kWh/Year**	**%**	**USD/Year**	**USD**	**USD**	**Year**
EW-0	Wall–No Insulation	3.01	445,696			Baseline		
EW-1	Wall–4 cm Rockwool	0.71	413,331	7.3%	−USD 5502	USD 7452	USD 1950	1.4
EW-2	Wall–6 cm Rockwool	0.51	409,452	8.1%	−USD 6161	USD 11,168	USD 5007	1.8
EW-3	Wall–8 cm Rockwool	0.40	407,113	8.7%	−USD 6559	USD 14,924	USD 8365	2.3
EW-4	Wall–12 cm Rockwool	0.28	405,504	9.0%	−USD 6833	USD 22,376	USD 15,544	3.3
EW-5	Wall–3 cm EPS Polystyrene	0.91	417,625	6.3%	−USD 4772	USD 2417	−USD 2355	0.5
EW-6	Wall–5 cm EPS Polystyrene	0.62	412,160	7.5%	−USD 5701	USD 4016	−USD 1685	0.7
EW-7	Wall–7 cm EPS Polystyrene	0.47	409,098	8.2%	−USD 6222	USD 5574	−USD 648	0.9
EW-8	Wall–10 cm EPS Polystyrene	0.35	406,450	8.8%	−USD 6672	USD 7992	USD 1320	1.2
EW-9	Wall–14 cm EPS Polystyrene	0.25	404,411	9.3%	−USD 7018	USD 11,168	USD 4150	1.6
EW-10	Wall–4 cm XPS Polystyrene	0.68	412,977	7.3%	−USD 5562	USD 5694	USD 132	1.0
EW-11	Wall–6 cm XPS Polystyrene	0.49	409,255	8.2%	−USD 6195	USD 8211	USD 2016	1.3
EW-12	Wall–8 cm XPS Polystyrene	0.38	406,332	8.8%	−USD 6692	USD 11,488	USD 4796	1.7
EW-13	Wall–12 cm XPS Polystyrene	0.27	404,521	9.2%	−USD 7000	USD 20,978	USD 13,978	3.0

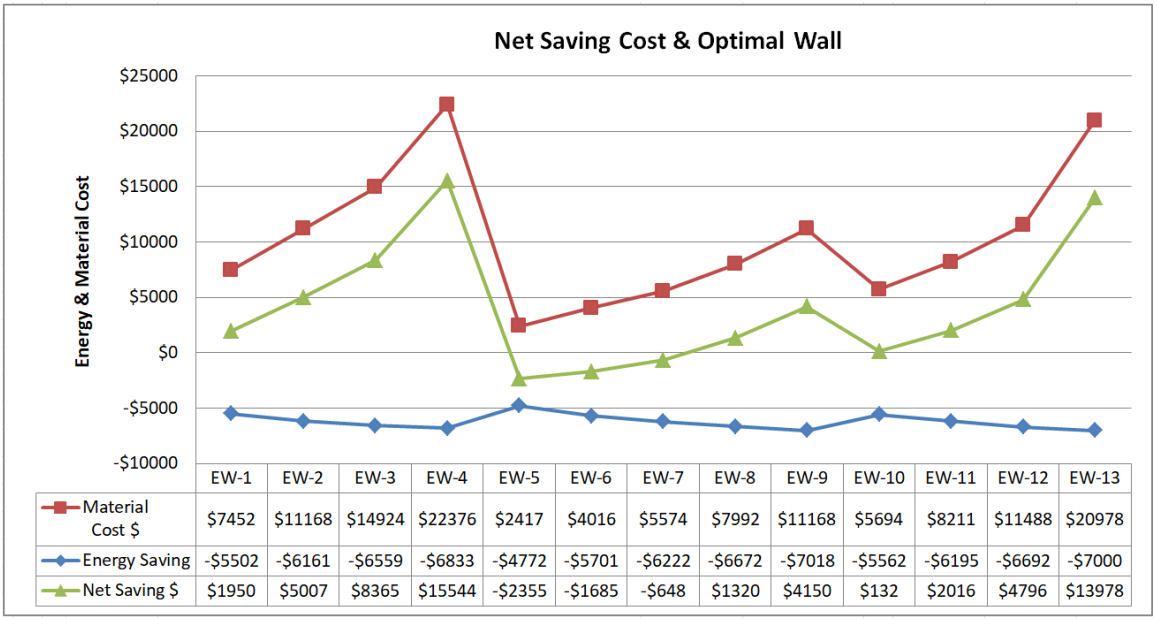


Figure 4. Results of simulations for the optimal wall, net savings cost, and external wall.

3.2. Results of the Roof

The results of the roof simulations are described in Table 6 and Figures 5 and 6. According to the comparative analysis results of several alternative roof design alternatives, RF-10 (glass wool material insulation roof 20 cm) uses the least amount of energy, averaging 438 MWh/year and saving approximately 1.72%, for a U-value of 0.19 W/m^2.K. It is preferable to compare the numerous roof design possibilities under investigation using multi-criteria decision-making for more clarity and openness. Three additional indicators, net saving cost, material cost, and payback time, were considered in addition to energy consumption and energy savings. In addition to other design possibilities, this procedure ensures a perfect roof. Table 6 summarizes all the evaluation criteria presented. It is clear that the RF-10 external wall consumed the least amount of energy and is thus not the best choice in terms of payback duration.

Table 6. Alternative roof design options.

Input		Output						
ID	**Roof Type Name**	**Roof U-Value**	**Energy Consumption**	**Energy Saving**	**Energy-Saving Cost**	**Material Cost**	**Net Saving**	**Payback Period**
		W/m^2.K	**kWh/Year**	**%**	**USD/Year**	**USD**	**USD**	**Year**
RF-0	Uninsulated Roof (Baseline)	2.45	445,696			Baseline		
RF-1	Roof–2 cm XPS Polystyrene	1.02	440,927	1.07%	−USD 811	USD 951	USD 140	1.17
RF-2	Roof–4 cm XPS Polystyrene	0.65	439,674	1.35%	−USD 1024	USD 1865	USD 841	1.82
RF-3	Roof–6 cm XPS Polystyrene	0.47	439,060	1.49%	−USD 1128	USD 2704	USD 1575	2.40
RF-4	Roof–8 cm XPS Polystyrene	0.37	438,701	1.57%	−USD 1189	USD 3735	USD 2546	3.14
RF-5	Roof–10 cm XPS Polystyrene	0.31	438,463	1.62%	−USD 1230	USD 5241	USD 4012	4.26
RF-6	Roof–10 cm Glasswool	0.34	438,606	1.59%	−USD 1205	USD 852	−USD 353	0.71
RF-7	Roof–12 cm Glasswool	0.29	438,419	1.63%	−USD 1237	USD 1013	−USD 224	0.82
RF-8	Roof–14 cm Glasswool	0.26	438,283	1.66%	−USD 1260	USD 1211	−USD 50	0.96
RF-9	Roof–18 cm Glasswool	0.20	438,081	1.71%	−USD 1295	USD 1556	USD 261	1.20
RF-10	Roof–20 cm Glasswool	0.19	438,011	1.72%	−USD 1306	USD 1722	USD 415	1.32

On the other hand, the data in Table 6 and multi-based decision processes show that RF-6 is the ideal type of roof (10 cm thick roof glass wool material). This roof type has a U-value of 0.34 W/m^2.K and consumes 438 MWh/year, therefore saving about 1.59%. The payback period is 0.71 years; thus, it is a desirable choice for customers if the main wall and the window remain unchanged.

3.3. Simulation Results for Window

The results of the window simulations are presented in Table 7 and Figures 7 and 8. A comparison of the analysis results of various window design possibilities is shown in these tables. Regarding energy use and savings, W-8 (air-filled 4-16-4 mm with tinted low-e double glazing) comes last, using about 407 MWh annually while saving 9.3%. This window has a payback time of 1.211 years, a U-value of 1.3 W/m^2.K, and an SC of 0.51, and it is the best option overall.

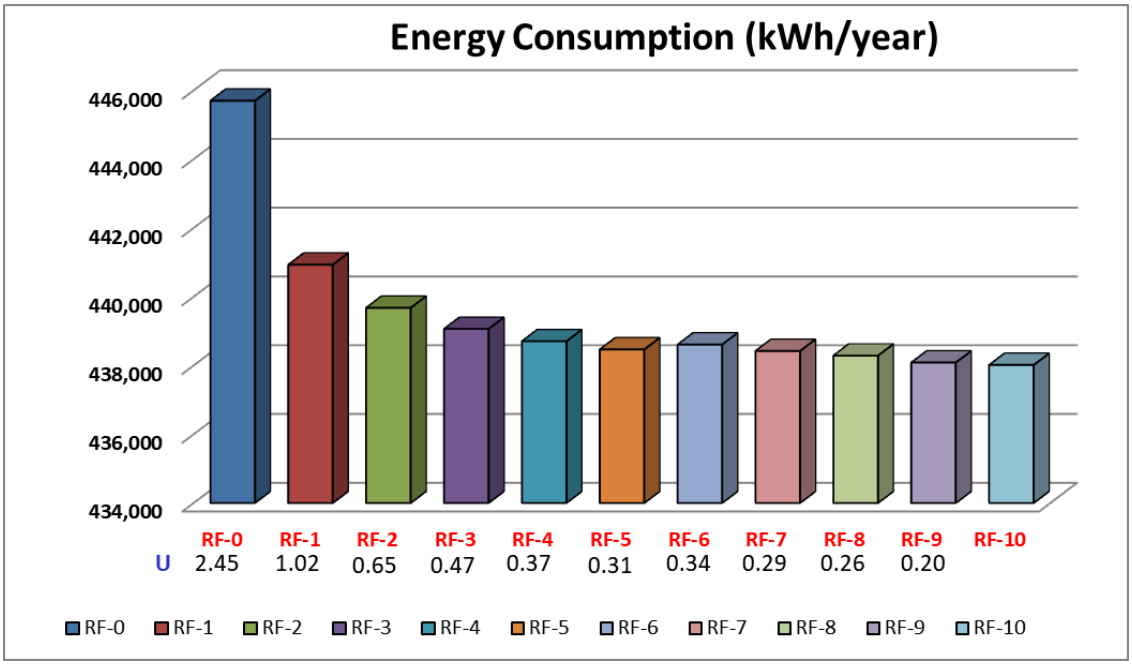
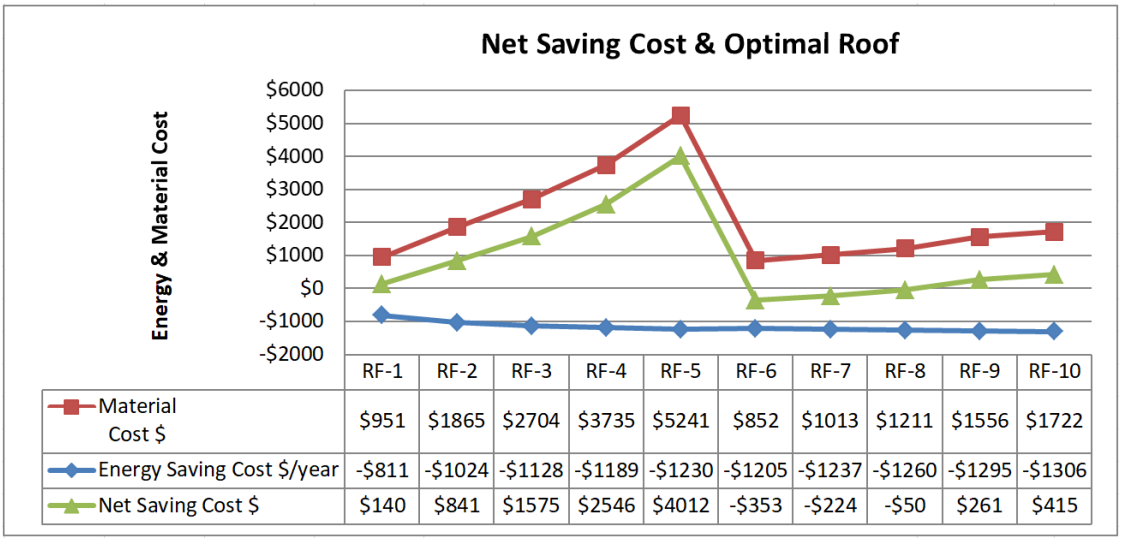


Figure 5. Energy-consumption simulation results for the roof.



	RF-1	RF-2	RF-3	RF-4	RF-5	RF-6	RF-7	RF-8	RF-9	RF-10
Material Cost $	$951	$1865	$2704	$3735	$5241	$852	$1013	$1211	$1556	$1722
Energy Saving Cost $/year	-$811	-$1024	-$1128	-$1189	-$1230	-$1205	-$1237	-$1260	-$1295	-$1306
Net Saving Cost $	$140	$841	$1575	$2546	$4012	-$353	-$224	-$50	$261	$415

Figure 6. Optimal roof and net savings cost simulation results.

3.4. Building Envelope Combination Simulation Results

Considering a 1540 simulation consisting of a combination of building exteriors (window, exterior wall, and roof) on a large scale: the best combination with the lowest energy consumption, 353.8 MWh/year, and a 20% energy savings, is W8–E9–R10, in which E9 is EPS polystyrene of 14 cm thickness, R10 is 20 cm thick glass wool, and W8 is SC = 0.51, 4-16-4 mm low-e double glazing, and U = 1.3. However, the payback period is not optimal (1.33 years). When considering the payback period, the combination of windows, external walls, and roof that gives the shortest payback period (15 days) is W1–EW0–RF0, in which E0 is the baseline wall without insulation, R0 is the baseline roof without insulation, and W1 is low-e single glazing 4 mm, U = 4.2 and SC = 0.75. However, with this combination, energy consumption (430,026 kWh/year) and energy savings (3.6%) are not ideal. Following the examination of the combination of a building that gives the minimum payback period but a change from the baseline (external wall EW0, roof RF0, and window W0) at

the same time, it is clear that a combination of the building envelope of window, external wall, and roof that gives 0.34 years as the optimum payback period is W2–RF6–EW5, with a 3 cm EPS. This combination results in an annual energy consumption of 383,133 kWh and annual energy savings of about 14%.

Table 7. Alternative window design options.

Input				Output					
ID	Window Name Type	Win. U-Value	Win. SC	Energy Consump.	Energy Saving	Energy-Saving Cost	Material Cost	Net Saving	Payback Period
		$W/m^2.K$		kWh/Year	%	USD/Year	USD	USD	Year
W-0	Clear Single Glazing	6.16	0.95	445,696			Baseline		
W-1	Low-e single glazing, 4 mm	4.2	0.75	430,026	3.6%	−USD 2664	USD 5101	USD 2437	1.91
W-2	Tinted low-e single glazing, 4 mm	4.2	0.62	421,557	5.7%	−USD 4104	USD 5392	USD 1289	1.31
W-3	Clear double glazing, argon-filled, 4-12-4 mm	2.7	0.86	433,062	2.9%	−USD 2148	USD 7218	USD 5070	3.36
W-4	Low-e double glazing, air-filled, 4-12-4 mm	1.6	0.64	416,873	6.9%	−USD 4900	USD 7315	USD 2415	1.493
W-5	Low-e double glazing, air-filled, 4-16-4 mm	1.3	0.64	416,380	7.0%	−USD 4984	USD 7412	USD 2428	1.487
W-6	Low-e double glazing, argon-filled, 4-16-4 mm	1.1	0.64	415,970	7.1%	−USD 5053	USD 7698	USD 2645	1.52
W-7	Tinted low-e double glazing, air-filled, 4-12-4 mm	1.6	0.51	408,347	9.1%	−USD 6349	USD 7698	USD 1349	1.212
W-8	Tinted low-e double glazing, air-filled, 4-16-4 mm	1.3	0.51	407,823	9.3%	−USD 6438	USD 7795	USD 1357	1.211
W-9	Clear triple glazing, air-filled, 4-12-4-12-4 mm	1.1	0.84	429,134	3.9%	−USD 2816	USD 8276	USD 5460	2.94

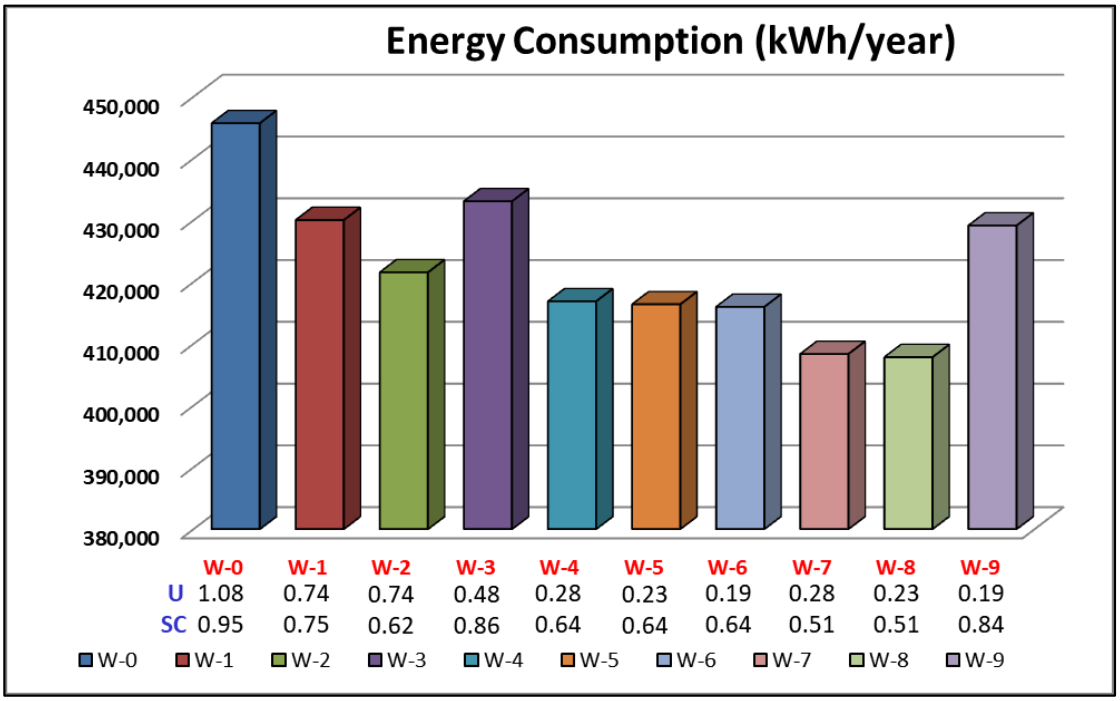
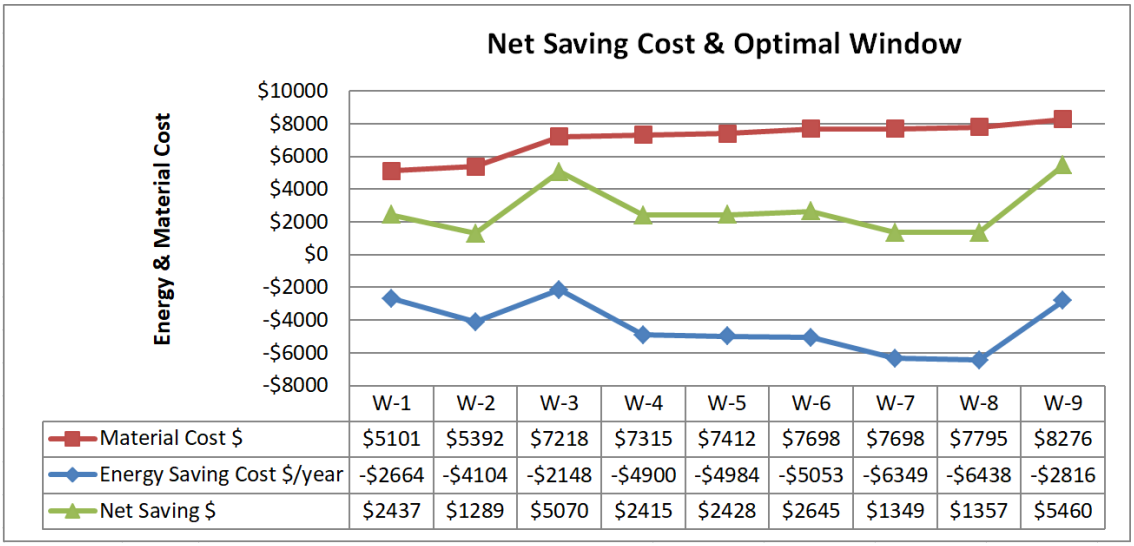


Figure 7. Results of the window energy-consumption simulation.



	W-1	W-2	W-3	W-4	W-5	W-6	W-7	W-8	W-9
Material Cost $	$5101	$5392	$7218	$7315	$7412	$7698	$7698	$7795	$8276
Energy Saving Cost $/year	-$2664	-$4104	-$2148	-$4900	-$4984	-$5053	-$6349	-$6438	-$2816
Net Saving $	$2437	$1289	$5070	$2415	$2428	$2645	$1349	$1357	$5460

Figure 8. Net savings cost and simulation results for the optimal window.

Finally, after the previous results for four scenarios, using 1540 simulation results from the combination of the building envelope parameters (taking time about 16 days), it was determined that we could not cover all possible combinations of parameters because the simulations would take a very long time; thus, we needed to construct a fast, easy, time-saving tool (digital tool) to predict the annual energy consumption, assessing all possible combinations of the building envelope parameters range, as shown in Table 8. The aim was to convert the building into a green one by assisting the engineers in their calculations of the required renewable energy resources such as solar panels, wind turbines, and corresponding storage batteries.

Table 8. Input parameter ranges used in ANN training model.

Code	Input Parameters	Unit	Data Used in Anns Model	
			Minimum	Maximum
×1	Thickness of Material Insulation for External Wall	cm	0	14
×2	Conductivity of Material Insulation for External Wall	W/m.K	0.035	0.039
×3	Thickness of Material Insulation for Roof	cm	0	20
×4	Conductivity of Material Insulation for Roof	W/m.K	0.035	0.04
×5	U-value of Window	$W/m^2.K$	1.1	6.16
×6	Shading Coefficient SC of Window	-	0.51	0.95
Code	Output Parameters		Minimum	Maximum
y1	Building Energy Consumption	kWh/year	353,875	445,696

3.5. ANN Smart Building Energy Model

The neural fitting tool function (NFTOOL) in MATLAB was used to construct and train an ANN using a total of 1540 cases that were simulated using eQuest software. The input parameter ranges used to build the ANN model are shown in the following table.

The selected ANN model consisted of input, hidden, and output layers. The ANN input parameters represented six decision variables, namely:

- U-value.
- SC of glass.
- Insulation of external wall material, conductivity, and thickness.
- Roof material insulation conductivity and thickness.

The output parameters representing building energy consumption in the construction of the ANN are as follows:

- The hidden layers have a sigmoidal activation function (tansig), while the output layers have a linear activation function (purelin).
- The training algorithm is (Trainlm) backpropagation based on a Levenberg–Marquardt minimization method.
- The mean squared error (MSE) expresses the difference between the outputs and those provided by the network.
- Pearson's correlation coefficient (R) measures the correlation between the output and those provided by the network; since R is closer to 1, the approximation is better.

After the construction of the neural network model, the main parameter that was affected was the number of neurons in the hidden layer. The optimum number of neurons in the hidden layer was 17 after several training trials (by changing the number of neurons in a hidden layer from 7 up to 30) to obtain the minimum value of error between target output and outputs. The ANN model is shown in Figure 9, and the details are in Figure 10.

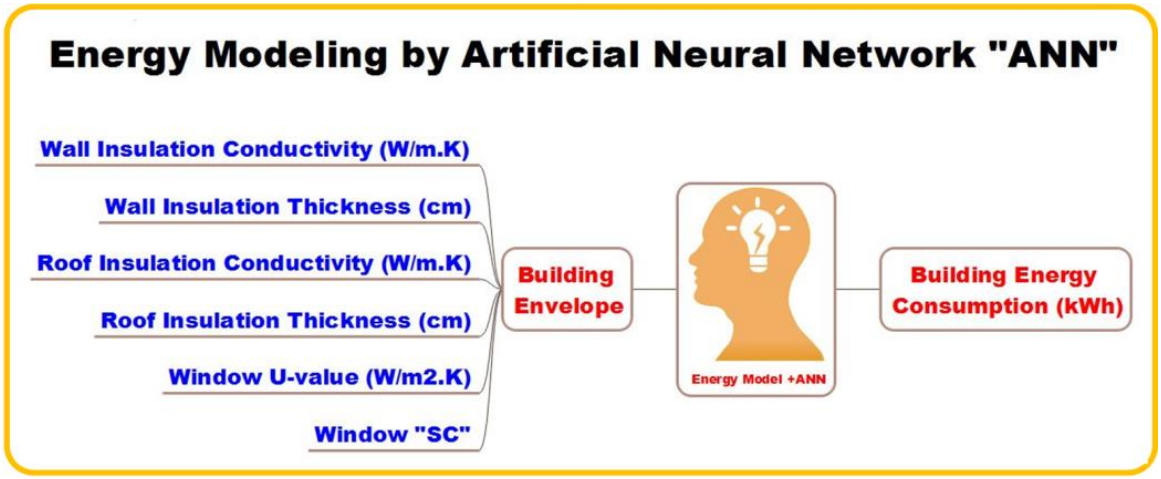


Figure 9. ANN model diagram.

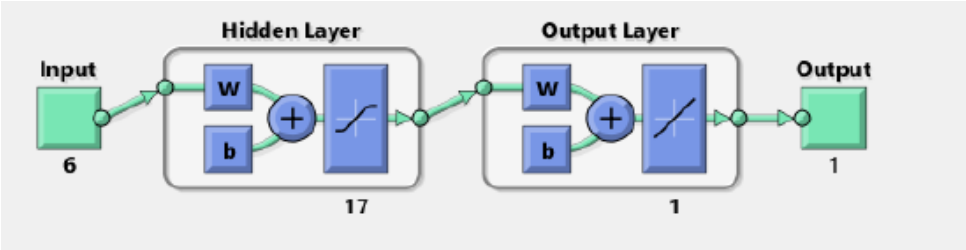


Figure 10. ANN detailed model.

The total data (1540 simulation results obtained from eQuest) were divided into three parts: 85% for training, 20% for testing (selecting randomly from 85% of training data), and 15% for validation and evaluation of the forecast capabilities of the ANN model. As a training method, the Levenberg–Marquardt learning algorithm was utilized using the mean square error performance function. Following ANN model training, the predictive performance of the proposed model is reported as the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute percentage error (MAPE) to examine the acquired results and the model precision. The regression correlation coefficients, "R^2", were found to be extremely close to 0.98 between the simulation results (target) and the network output (Figure 11). However, the RMSE was 4186, and the MAPE was 0.49%, suggesting an excellent correlation between the results and target values. After that, the

ANN model can be implemented using a Simulink diagram (see Figure 12). This diagram can be used to forecast the output results for any selection values of input data that are within the range of training data, as shown in Table 7. With the parallel computation capability of the ANN developed by Simulink (MATLAB) to anticipate the building's energy usage, the simulation time was cut down to 5 s, which produced an excellent answer with good accuracy. As a result, it could be a more expedient and cost-effective approach to calculate buildings' energy consumption based on several design options for building envelope optimization. This ANN model is an excellent tool for estimating and forecasting building energy consumption and developing engineering to convert buildings into green structures through various design alternatives, such as optimizing the main building envelope parameters.

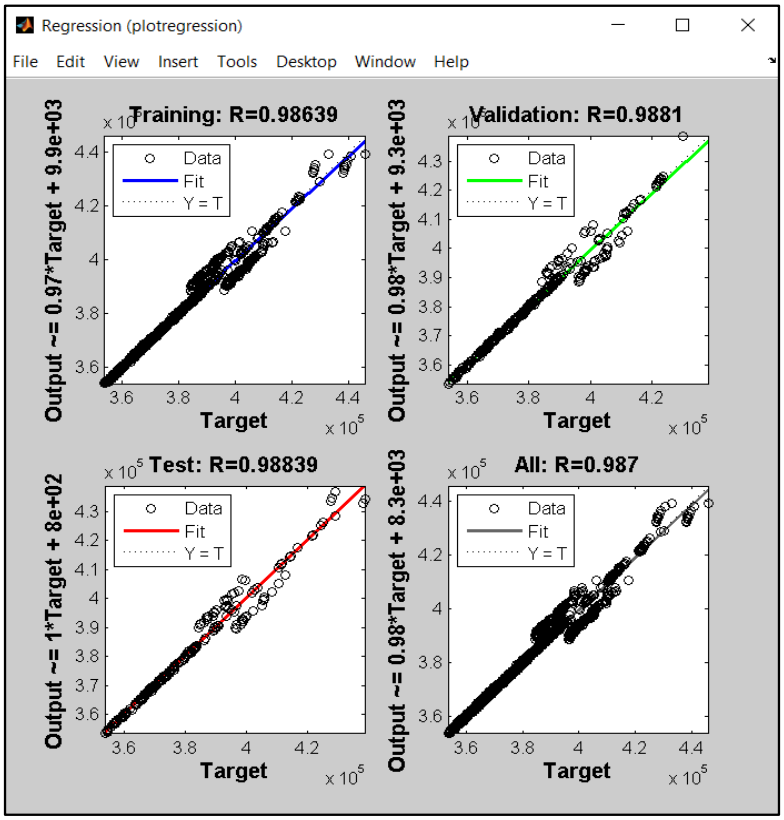


Figure 11. ANN regression plots.

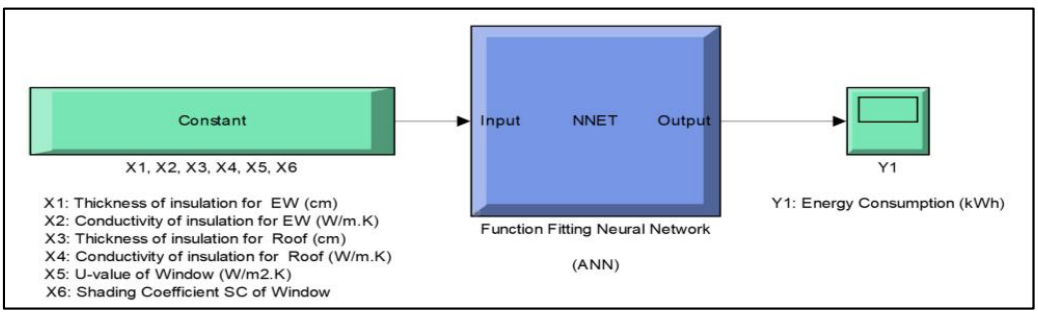


Figure 12. Simulink diagram for the ANN model.

After building a valid ANN model with an acceptable overall R-value, as shown in Figure 11 (R = 0.987), and converting it to the Simulink model, as shown in Figure 12, we have achieved the simple concept of a static digital twin by replacing the physical

model with a digital model (constructed using eQuest). The static digital twin model demonstrated the following advantages:

- The ANN model (digital twin model) can cover infinite combination values of the range of building envelope parameters, as shown in Table 7 (i.e., not only limited to the 1540 simulations in this study); therefore, we can derive the best possible results for reducing the annual energy consumption of buildings according to the materials available on the market.
- As an easy and rapid tool, the simulation time on the Simulink model (digital twin model) took only a few seconds (less than 3 s), compared with the 15 min required for each simulation on eQuest.

4. Conclusions

In this study, the modeling and simulation of an energy model of residential buildings is presented; a digital twin using artificial intelligence is also presented to assist engineers and architects in selecting the optimum alternative building envelope design parameters to minimize and predict the energy consumption of residential buildings, and hence, the cost of energy. eQuest software allows up to 1540 simulations utilizing various parameters, including the U-values of insulation material characteristics, material thickness, and window types. Each simulation experiment took about 15 min to complete. In total, 384 h, or nearly 16 days, were required to perform all scenarios. There were 1540 simulations performed in all, and using an ANN model, all the results were used to construct a digital twin model. The performance of the digital twin was examined using the NFTOOL in the MATLAB/Simulink package. After numerous training sessions in which the numbers of neurons in the hidden layers were varied, the regression correlation coefficients, "R^2", between the eQuest simulation results and the ANN output results were very close to 0.98. The best relationship between outputs and targets was demonstrated by the MAPE being reduced to 0.49% through multiple training cycles. As a result, we have developed an alternative tool to estimate the energy consumption for various envelope design options. This tool can be used to optimize and predict energy consumption and, therefore, cost. The digital twin using the ANN prediction model is a perfect tool for creating green buildings by selecting different design alternatives to optimize the characteristics of the primary building envelope, including external wall conductivity, roof material conductivity, λ, thickness, and the window shading coefficient and U-value.

The objective of this study was to perform a comparison between a baseline building model (a real case in Lebanon) and a proposed building model depending on several energy conservation measures of building envelope thermal performance improvements. The objective of this paper is to be clear and understandable for researchers, engineers, and architects. The overall goal of the decision-making model is to take in a simplified set of building parameters from the user and present alternative design options that optimize energy savings based on the user's preferences for the payback period and project budget. As a recommendation, future research should consider the life cycle cost benefits.

The suggested methodology is based on the ANN approach, which has several limitations. Future research should take into account the various climatic zones in Lebanon, the different geometries and shapes of residential buildings, the life cycle cost analysis, the automatic selection of multi-objective optimization solutions, and online optimization applications.

Author Contributions: M.E.-G. and O.O. proposed the main idea of the article, methodology, M.E.-G. and O.O.; software, M.E.-G. and R.E.-A.; validation, M.E.-G. and R.E.-A. and O.O.; formal analysis, M.E.-G. and R.E.-A.; investigation, M.E.-G. and O.O.; resources, M.E.-G. and O.O.; data curation, M.E.-G. and O.O.; writing—original draft preparation, M.E.-G. and O.O.; writing—review and editing, M.E.-G. and O.O.; visualization, M.E.-G. and O.O.; supervision, M.E.-G. and O.O. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare that they have no conflict of interest.

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