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SMART BUILDING ENERGY MODEL USING ARTIFICIAL INTELLIGENCE

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Abstract

This paper presents a Smart Building Energy Model of Residential Building using Artificial Neural Network model (ANN) to assist architects and engineers in selecting the optimum alternative design of building envelope parameters such that external wall and roof insulation material types and window types that minimizes the cost of energy consumption of a residential building to transform it to a green building.

Up to 1540 Simulations using different material thickness and conductivity values of material insulation properties and windows types are carried out in eQuest software for simulation.. The simulations results are implemented to create an artificial neural network inverse model (ANN) with Matlab/Simulink and the performance is investigated. The results from the artificial neural network outputs and the corresponding eQuest simulation outputs were found very close. In addition, the Mean absolute percentage error (MAPE) is equal to 0.49% , demonstrating a best correlation between outputs and target value, the results show a great solution with good accuracy to predict the energy consumption of residential building for several other building envelope optimization parameters.

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Keywords

Green Building, Energy Modeling, Artificial Neural Network, Machine Learning

1. INTRODUCTION

Because of the lack of oil and other non-renewable energy resources, the world has set out on an uncertain energy crisis since the beginning of twenty-first century. In the mean time, there has been a tremendous increment in the global energy demand due to the population growth and consumption. Building is the one of the biggest energy use sectors, represents almost 40% of global energy use (Cinzia, et al, 2016). Decreasing building energy use by building energy usage prediction significantly reduces the reliance on global energy which attracted many researchers in the past twenty years. Accurate building energy prediction is the best building energy efficiency evaluation. Appropriate building envelope configuration at the design stage can reduce energy consumption in new buildings. The goal of this study is to optimize the design of the building envelope of a new residential building located in Tripoli - Lebanon. The overall goal of the decision-making model is to take in a simplified set of building parameters from the user, and alternative design options which optimize energy savings based on the user's preferences of payback period and project budget. Section 2 presents a comprehensive review of energy modeling with the artificial intelligence application and the existing approaches towards improvement of energy efficiency in green buildings. Section 3 introduce the development of Baseline and Proposed Energy Model for the building to analyse and to represent the most efficient solution that could be applied in the case study context by presenting the simulation results with an economic feasibility study. Section 4 is devoted to the development of Smart Residential Building Energy Model using artificial neural network (ANN) and validation of this ANN model. Section 5 presents the conclusion of this study.

2. STATE OF ART

Green buildings represent the buildings that provide a better life for the human being and take into consideration the environmental standards at every stage of the construction, design, implementation, operation and maintenance, thus reducing the harmful environmental impact of the building on society and the planet through its ability to save energy and water consumption and to increase the life of the building with the preservation of the ecosystem, which reflects positively on the economy and productivity. Under these objectives, number of themes facilitate the monitoring and evaluation of design, construction and operation specifications, and can be summarized in five main themes: Sustainable Site, Energy Efficiency, Water Efficieny, Materials Selection and Indoor Air Quality. In the last two decades, the development of building performance analysis tools for evaluating green buildings performance have been developed under different aspects for evaluation mainly from the perspective of their environmental impacts and sustainable performance and are mandatory for building rating system such as LEED, BREEAM, Estidama, Green Star, etc. These rating tools provide a framework on how to evaluate and improve building energy and environmental performance. Building energy modeling is a powerful method for studying energy performance of buildings and for evaluating architectural design decisions in selecting building materials and components while designing the building envelope (walls, windows, roofs), and different systems (lighting, HVAC, etc). The building envelope has the greatest impact on buildings performance and energy saving; it is a prime focus area to consider when energy efficiency measures are planned for new buildings. The optimization of the design of the building envelope reduce energy consumption and heat loss. Most building heat loss is through the walls, roofs, and windows. Proper insulation of external wall and roof can reduce the heat loss in cold climates and excess heat infiltration in hot climates. The thickness and the conductivity of the insulation material for external wall and roof with the U-value and shading coefficient of the windows should be considered in the architectural design stage. There are several types of insulation material and windows available in the market. The Energy Modeling techniques can be further classified into three types (Figure 1): Engineering models (White Models), Statistical methods "Data-driven approach" (Black Models) and Hybrid models (Grey Models). Engineering models (White models) includes Forward (classical) approach and Calibrated Simulation. Forward (classical) approach includes the analysis of the dynamic energy performance of a building using computer modeling and simulation techniques. There are many building performance simulation programs with different user interfaces and different simulation engines that are capable of these analyses such as eQUEST, Energyplus and DesignBuilder. Calibrated Simulation: this approach implies the use of a simulation computer program that has been calibrated with actual measured data, allowing the model to predict the energy consumption satisfactorily. Statistical methods “Data-driven approach” (Black Models) do not require physical information about the building or systems, but only historical input and output variables governing the performance of the systems have been measured. The known data is used to define a mathematical description of the system. In this category includes Multiple Linear Regression or Conditional Demand Analysis, and Intelligent methods such Artificial Neural Network, Genetic Algorithm and Support Vector Machine to find the relationship between the outputs and inputs parameters such as climate data, occupancy behavior, and operation parameters. Hybrid models (Grey Models) can be used to analyze building energy behavior when there is only incomplete or uncertain data such as the limitations of building physical characteristics, and the limitations of statistical approaches regarding the need of considerable amount of measured data. This category refers to approaches that combine elements of physical approaches and statistical approaches, which are also called “grey box”. First a mathematical model is developed for the physical configuration of the building and/or systems/equipment having relevant impact on energy consumption. Then, statistical analyses are used to identify and quantify the parameters that can allow the model to estimate energy performance satisfactorily (Fumo, 2014).

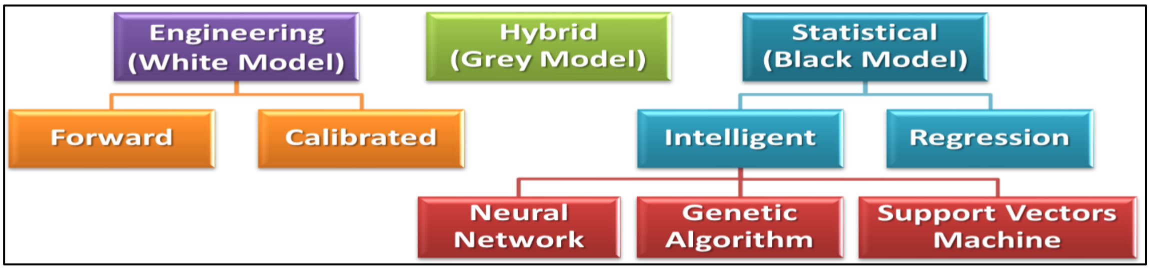

Fig.1: Energy Modeling Techniques

A large number of studies have been developed over the last few decades in the fields cited above. Some important studies and comparisons were previously done are discussed below.

Monah et al (2017) worked on predicting the future load (in KW) consumption for the Technology Tower Block located in VIT University, using time series Artificial Neural networks and MATLAB software. The neural network was trained with the real time recorded training data. Time in hours was the input and recorded ‘power consumption’ in Kilowatts was the target. These data were obtained from the power-house located in VIT University and we have fed these sets into the neural net so that it is trained due to the presence of a pattern over in the long run of data set. Hence the prediction is done with less accuracy and error. Such a prediction can aid us to know about the power needed to meet the demand in the Technology Tower Block. Whenever, the load necessity is less we can then switch into renewable energy sources as mentioned above.

Olanrewaju et al (2017) in his study predicted the United States residential sector energy consumption from 1984 to 2010. The factors having impact on the way energy is consumed were assessed using the connection weight approach while the energy is being predicted. Artificial Neural Network was successfully applied in the prediction with a correlation coefficient of 0.97903. It was observed that the median household income was the most important factor in the consumption of residential sector energy consumption with a percentage of 93% followed by household size and cost of residential natural gas with 90% and 56.5% respectively.

Naji et al (2015) worked in their study in order to estimate building energy consumption based on the general thermal performance of a residential building, using different wall material insulation properties. 180 building simulations were done using EnergyPlus software. A systematic approach for attaining a building's heating and cooling energy needs by means of ANFIS was investigated. A Simulink model was developed in MATLAB with the ANFIS network for the estimation of building cooling and heating. The ANFIS approach performance was compared against the results of ANN and GP. The ANFIS predictions were superior to ANN and GP in terms of root-mean-square error, Pearson coefficient and coefficient error for building cooling energy estimation. The ANFIS results were also more accurate than the ANN and GP results.

Royapoor et al (2015) conduct an energy calibration using a set of two calibrated environmental sensors together with a weather station are deployed in a 5-storey office building to examine the accuracy of an EnergyPlus virtual building model. Using American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Guide 14 indices the model was calibrated to achieve Mean Bias Error (MBE) values within ±5% and Cumulative Variation of Root Mean Square Error (CV(RMSE)) values below 10%. The calibrated EnergyPlus model was able to predict annual hourly space

Magnier et al (2010) present a simulation-based Artificial Neural Network (ANN) to characterize building behaviour, and then combines this ANN with a multiobjective Genetic Algorithm (NSGA-II) for optimization. The methodology has been used in the current study for the optimization of thermal comfort and energy consumption in a residential house. The decision variables were: heating and cooling set points, Rh set point, starting and stopping delay, supply airflow rate, windows and thickness of concrete. TRNSYS was used to generate the ANN training data. Results of ANN training and validation are first discussed. Two optimizations were then conducted taking variables from HVAC system settings, thermostat programming, and passive solar design. By integrating ANN into optimization the total simulation time was considerably reduced compared to classical optimization methodology. Results of the optimizations showed significant reduction in terms of energy consumption as well as improvement in thermal comfort.

3. BUILDING ENERGY MODEL DEVELOPMENT

3.1 Baseline Model

A medium residential building located in Tripoli, Lebanon (34°26'47.44" N, 35°49'38.39" E) as shown in figure 2. The longer axis of this building is oriented North West/South Est. This residential building has ten storey building (2 apartments in each floor) with a total of 2540 m² floor area and 2.80 m in floor height. The ground floor compose of retails. From 1st floor to 10th floor are similar and each floor consists of two apartments. This building is very similar as internal partition and rooms comparing to other residential building construction in Lebanon which it will be considered as an ideal case for analysis in this study. The 3-dimensional view of this building is represented in the figure 3. An Energy Model is created using "eQuest" software to be able to analyse some energy conservation measures. The building energy model (BEM) is represented in figure 3 and modeled without a lot of details to be as simple as possible because the objective is to make a comparison between a conventional building and another one with several energy conservation measures for building envelope improvement that will be detailed in the following paragraphs. The base-case building energy model was simulated for the weather file of Tripoli was used in the energy analysis of the baseline model case. The general building informations of baseline model are presented in the Table 1. Each apartment is modeled as one thermal zone as per ASHRAE 90.1 requirements for residential building. In the other hand, each building core (stair and lifts) in each floor is also modeled as one thermal zone. The building envelope is selected to represent construction standards applicable in Lebanon. It is built of concrete slabs, concrete slabs and is plastered inside and out, and has an uninsulated flat roof. No insulation layer exists on any part of the building envelope to ensure that the baseline model case does not meet the minimum obligatory energy performance requirements in Lebanon as per Lebanese thermal standard for buildings (2010). The details of the construction, materials, fenestration insulated for the baseline building model are described in in detail in the table 2. The walls are composed of 20 cm of hollow concrete blocks and 1 cm of plaster on each side. The roof consists of 20 cm of reinforced concrete slab, 1 cm of plaster on one side and 4 mm of bitumen for another side with 6 cm of sand with gravel, 2 cm of cement mortar and 2cm of concrete tiles. The calculated U values of the exterior walls, roof and windows are 3.02 W/ m².°K, 2.45 W/ m².°K and 6.16 W/ m².°K, respectively. All windows with aluminium frames have single glazing with high shading coefficient SC value (0.95) and there is no shading component on any façade of the building. The windows are uniformly distributed and the glazing ratio is 33 %. As for HVAC system, for each apartment a single zone heat pump package system with a coefficient of performance (COP) of the cooling system is 2.92. The lights and electric equipment in individual zones contribute to internal gains and they respectively have power densities of 6.7 W/m² and 7.5 W/m² as per ASHRAE 90.1 standard. The occupancy in each apartment is 6 persons. The heating set point is 21°C and the cooling set point is 24°C, while the setback temperatures are 20°C and 25°C, respectively. The schedules of lighting, equipments, occupant and HVAC set points are according to ASHRAE 90.1 standard. The baseline model was simulated over a one-year period (01-01-2019 to 31-12-2019). As per baseline model case simulation results, the energy consumption per year is 445696 kWh/year.

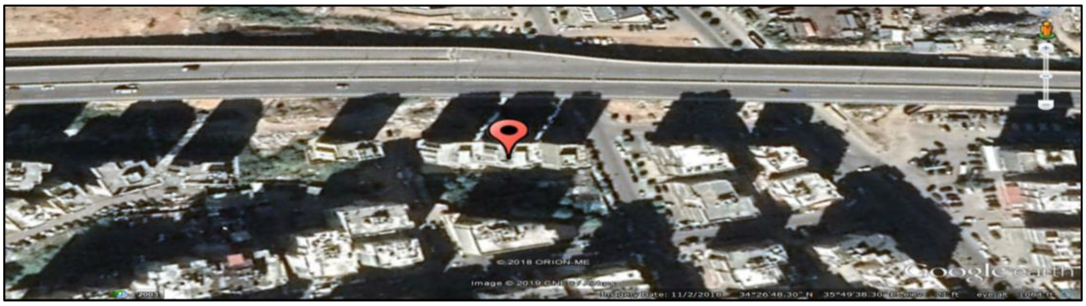

Fig.2: Building Location in Tripoli, Lebanon according to Google Earth

Fig.3: 3D Dimensional view and Energy Model of the building located in Tripoli

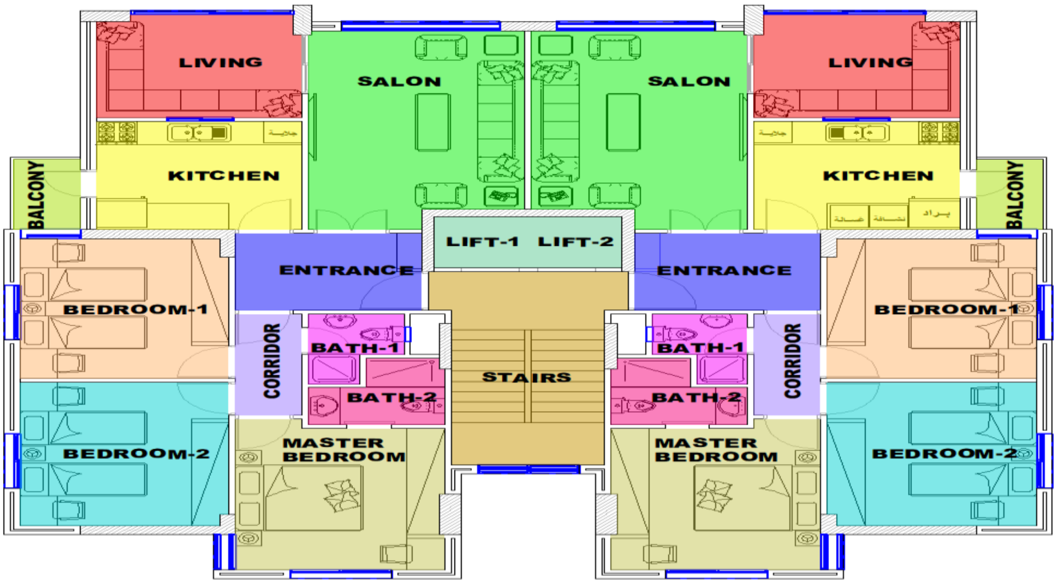

Fig.4: Interior architecture of the building located in Tripoli

Table 1: General building information for Baseline Energy Model

Building type		**Residential building**
Areas	Gross Floor Area	2540 [m²]
	External Walls Area	1997 [m²]
	Windows Area	422 [m²]
	Roof Area	448 [m²]
Dimension and Heights	Average floor height	2.80 [m]
	Window height	1.25 [m]
	Window-to-wall ratio	33%
Construction Envelope	External Walls	1cm Cement Plaster + 20cm Parapaing + 1cm Cement Plaster
	Roof	2cm Concrete Tiles + 2cm Cement Mortar + 6cm Sand + 4mm Bitumen + 20cm Reinforced Concrete + 1cm Cement
	Windows	Single-pane simple glass (U = 6.16 W/m².°K, SC = 0.95)
Operating Hours	Monday to Sunday	24h
HVAC Parameters	Total number of persons	130
	Lighting Load	6.7 W/m²
	Equipment Load	7.5 W/m²
	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 Envelope Informations of Baseline Model

Envelope Components	**Materials**	**Thickness (mm)**	**Conductivity (W/m.°K)**	**Density (Kg/m³)**	**Specific Heat (J/Kg.°K)**	**Resistance (m².°K/W)**	**U Value (W/m².°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	
	Concrete Tiles	20	1.1	2100	1000	0.018	2.45
	Cement Mortar	20	1.4	2200	1000	0.014	
	Sand & 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	Aluminium Frame+Single Glazing	6	-	2500	750	**U =**	6.16
						SC =	0.95

3.2 Proposed Model

Proposed Model has been created using "eQuest" Software to be able to analyse different energy conservation measures concerning building envelope optimisation. The input parameters of the energy model are represented in Figure 5. The details of the construction, materials, fenestration insulated for the proposed building model are described in the table 3 - 4. The proposed model will be run parametrically with incremental improvement in building envelope parameters compared to the baseline model. Each strategy used for building envelope optimization was analysed, on the other hand, all other input parameters and schedules (geometry, weather, lighting, equipment, occupancy, internal load and HVAC, etc) will remain the same between proposel model and baseline model because the aim being to represent building energy efficiency measures of the building envelope. The design variables subjected to the optimization procedures are: thermal insulation materials of external walls (conductivity and thickness), thermal insulation materials of roof (conductivity and thickness), window types with varying U values and the Shading Coefficient (SC). The set of energy efficiency solutions refers to the combination of alternatives with such design variables. While generating material alternatives for each decision variable, it was decided that material alternatives should describe the materials that are currently available on the market.

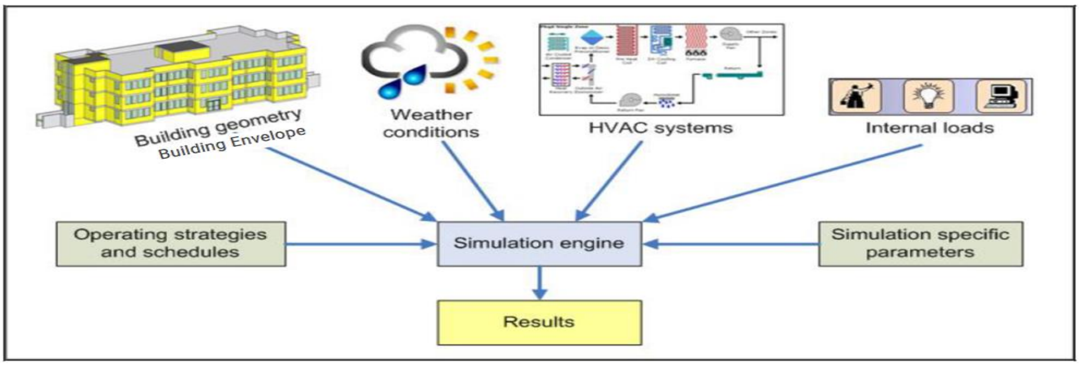

Fig.5: Input parameters of the Energy Model

Therefore, several material alternatives with their thermo-physical properties and unit cost values, including labour and value-added tax (VAT), were defined based on the materials commonly used in the building sector in Lebanon, in order to create the decision space for optimization process. Nine (9) alternative windows ranging from low-e single glazing to triple glazing with different thermo-physical properties were selected from table 3. As per table 4, five (5) XPS extruded polystyrene foam board materials, and five (5) glass wool materials with different thickness were generated for the roof thermal insulation. Similarly, thirteen (13) different exterior wall insulation materials. Combining the different design options with baseline also, a total of 1540 combinations have been obtained. Each simulation run needs 15 min. The total run time of this Scenario took around 16 days for 24 hours/day using a laptop with Intel Core i7 Quad Core CPU 2.8 GHz, 16GB Ram, 256 SSD and 2 TB hardrive. The simulation model of this building, will be run parametrically with incremental improvement in envelope parameters according to the following scenarios:

- The external wall material insulation types and parameters for different values (conductivity and thickness) with fixing the roof and window parameter values as per baseline model which give the minimum energy consumption then minimum payback period.
- The roof material insulation types and parameters for different values (conductivity and thickness) with fixing the external walls and windows parameter values as per baseline model which give the minimum energy consumption then minimum payback period.
- Window types and parameters for different values (U-value and SC) with fixing the external wall and roof parameter values as per baseline model which give the minimum energy consumption then minimum payback period.
- The combination of building envelope (external wall, roof and window) which give the minimum energy consumption and then minimum payback period.

In this section, the results will be interpreted and discussed according to the scenarios noticed in the previous section. The results will be arranged and presented in point of view: Energy Consumption, Energy Saving %, Material Cost $, Net Saving cost and Payback Period. The equations (1) (2) (3) represent for Net Cost, Payback period and Energy saving cost.

$$\text{Net Cost (\$)} = \text{Material Cost (\$)} - \text{Energy Saving Cost (\$)} \quad (1)$$

$$\text{Payback Period (year)} = \text{Material Cost (\$)} / \text{Energy Saving Cost (\$} \quad (2)$$

$$\text{Energy Saving Cost (\$)} = \text{Energy Consumption (kWh/year)} \times \text{Energy Cost Rate (\$/kWh)} \quad (3)$$

Where material cost is the cost for insulation used for insulated wall/roof and energy cost rate is equal to 0.17$/kWh (Including Electricity of Lebanon (EDL) and generator supply cost rate).

Table 3: Characteristics of alternative Window types
Reference: (Senel Solmaz, et al, 2018)

	ID	Material name	U value [W/m².°K]	SC	Visible transmittance	Cost [$/m²]
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

Table 4: Characteristics of alternative insulation materials for Roof & Exterior Wall
Reference: (Senel Solmaz, et al, 2018)

Envelope component	ID	Material name	Thickness [mm]	Conductivity [W/m.°K]	U-value [W/m².°K]	Specific heat [J/kgK]	Density [kg/m3]	Cost [$/m2]
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

3.3 External Wall Simulation Results

The results of simulations for external wall material insulations parameters (conductivity and thickness) with fixing the roof and window parameter values as per baseline model are summarized in the table 5 and Figure 6-7. From the results of alternative design options for external walls comparative study from energy consumption and energy saving point of view is evident that EW-9 (Wall with 14cm EPS Polystyrene material Insulation) is the less energy consuming about 404,411 kWh/year with energy saving 9.3%. The U-value for this type is 0.25 W/m².°K. For greater transparency and clarity, it's ideal to compare the studied alternative design options of external walls through multi-criteria decision-making in addition to energy consumption and energy saving, three other indicators were considered: material cost, net saving cost and payback period. This procedure will give the optimal external wall between alternative design options for external walls. As per table 5, It's evident that despite external wall EW-9 is the less energy consuming but in the same time it's not the optimal selection in payback period point of view due that the payback period is 1.6 years. In the other hand, it's clear from the table 8, through multi-criteria decision-making the optimal selection of external wall type is EW-5 (Wall with 3cm EPS Polystyrene Insulation). The U-value for this type is 0.91 W/m².°K, the Energy Consumption is 417625 kWh/year with Energy Saving 6.3% and payback period = 0.5 years which give an attractive option for the client to go through it because of the least cost in case no change for baseline roof and window.

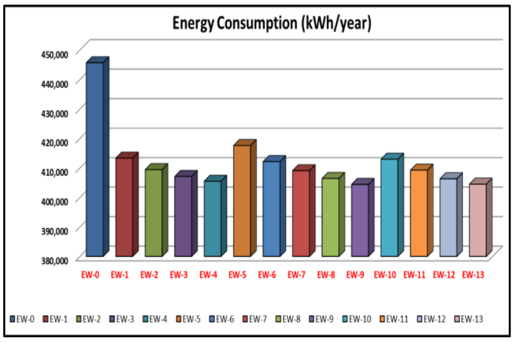

Fig.6: External Wall Simulation Results for Energy Consumption

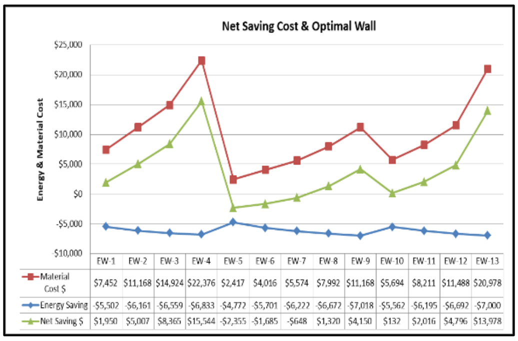

Fig.7: External Wall Simulation Results for Net Saving Cost and Optimal Wall

Table 3: Alternative Design options of External Wall Types

INPUT			OUPUT					
ID	Wall Name Type	Wall U-value W/m².°K	Energy Consumption kWh/year	Energy Saving %	Energy Saving Cost $/year	Material Cost $	Net Saving $	Payback period year
EW-0	Wall- No Insulation	3.01	445,696	Baseline				
EW-1	Wall- 4cm Rockwool	0.71	413,331	7.3%	-$5,502	$7,452	$1,950	1.4
EW-2	Wall- 6cm Rockwool	0.51	409,452	8.1%	-$6,161	$11,168	$5,007	1.8
EW-3	Wall- 8cm Rockwool	0.40	407,113	8.7%	-$6,559	$14,924	$8,365	2.3
EW-4	Wall- 12cm Rockwool	0.28	405,504	9.0%	-$6,833	$22,376	$15,544	3.3
EW-5	Wall- 3cm EPS Polystyrene	0.91	417,625	6.3%	-$4,772	$2,417	-$2,355	0.5
EW-6	Wall- 5cm EPS Polystyrene	0.62	412,160	7.5%	-$5,701	$4,016	-$1,685	0.7
EW-7	Wall- 7cm EPS Polystyrene	0.47	409,098	8.2%	-$6,222	$5,574	-$648	0.9
EW-8	Wall- 10cm EPS Polystyrene	0.35	406,450	8.8%	-$6,672	$7,992	$1,320	1.2
EW-9	Wall- 14cm EPS Polystyrene	0.25	404,411	9.3%	-$7,018	$11,168	$4,150	1.6
EW-10	Wall- 4cm XPS Polystyrene	0.68	412,977	7.3%	-$5,562	$5,694	$132	1.0

EW-11	Wall- 6cm XPS Polystyrene	0.49	409,255	8.2%	-$6,195	$8,211	$2,016	1.3
EW-12	Wall- 8cm XPS Polystyrene	0.38	406,332	8.8%	-$6,692	$11,488	$4,796	1.7
EW-13	Wall - 12cm XPS Polystyrene	0.27	404,521	9.2%	-$7,000	$20,978	$13,978	3.0

3.4 Roof Simulation Results

The results of roof simulations are summarized in the table 6 and figure 8-9. From the results of alternative design options for roof comparative study from energy consumption and energy saving point of view is evident that RF-10 (Roof with 20cm Glasswool material Insulation) is the less energy consuming about 438,011 kWh/year with Energy Saving 1.72%. The U-value for this type is 0.19 W/m².°K. For greater transparency and clarity, it’s ideal to compare the studied alternative design options of roofs through multi-criteria decision-making in addition to energy consumption and energy saving, three other indicators were considered: material cost, net saving cost and payback period. This procedure will give the optimal roof between alternative design options. All the mentioned evaluation criteria are summarized in the Table 8. It’s evident that despite external wall RF-10 is the less energy consuming but in the same time it’s not the optimal selection in payback period point of view. In the other hand, it’s clear from the table 8 and through the multi-criteria decision-making, the optimal selection of roof type is RF-6 (Roof with 10cm Glasswool material Insulation). The U-value for this type is 0.34 W/m².°K, the Energy Consumption is 438,606 kWh/year, Energy Saving 1.59% and payback period 0.71 years which give an attractive option for the client in case no change for baseline wall and window.

Table 4: Alternative Design options for Roof Types

INPUT			**OUPUT**					
ID	**Roof Type Name**	**Roof U-value W/m².°K**	**Energy Consumption kWh/year**	**Energy Saving %**	**Energy Saving Cost $/year**	**Material Cost $**	**Net Saving $**	**Payback period year**
RF-0	Uninsulated Roof Baseline)	2.45	445,696	Baseline				
RF-1	Roof - 2cm XPS Polystyrene	1.02	440,927	1.07%	-$811	$951	$140	1.17
RF-2	Roof - 4cm XPS Polystyrene	0.65	439,674	1.35%	-$1,024	$1,865	$841	1.82
RF-3	Roof - 6cm XPS Polystyrene	0.47	439,060	1.49%	-$1,128	$2,704	$1,575	2.40
RF-4	Roof - 8cm XPS Polystyrene	0.37	438,701	1.57%	-$1,189	$3,735	$2,546	3.14
RF-5	Roof - 10cm XPS Polystyrene	0.31	438,463	1.62%	-$1,230	$5,241	$4,012	4.26
RF-6	Roof - 10cm Glasswool	0.34	438,606	1.59%	-$1,205	$852	-$353	0.71
RF-7	Roof - 12cm Glasswool	0.29	438,419	1.63%	-$1,237	$1,013	-$224	0.82
RF-8	Roof - 14cm Glasswool	0.26	438,283	1.66%	-$1,260	$1,211	-$50	0.96
RF-9	Roof - 18cm Glasswool	0.20	438,081	1.71%	-$1,295	$1,556	$261	1.20
RF-10	Roof - 20cm Glasswool	0.19	438,011	1.72%	-$1,306	$1,722	$415	1.32

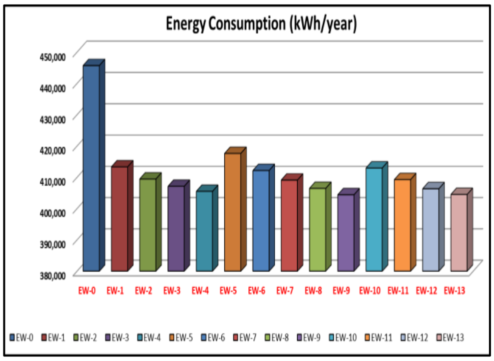

Fig.8: Roof Simulation Results for Energy Consumption

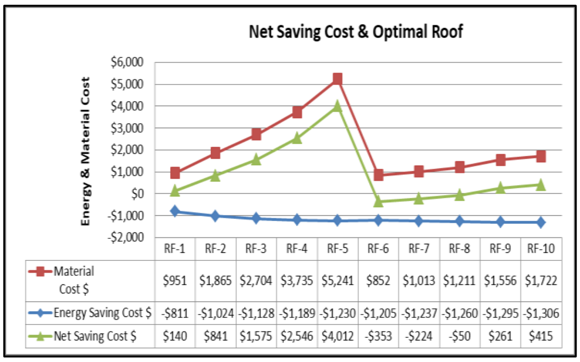

Fig.9: Roof Simulation Results for Net Saving Cost and Optimal Roof

3.5 Window Simulation Results

The results of window simulations are summarized in the table 7 and figure 10-11. This table summarizes the results of alternative design options for windows comparative study. From energy consumption and energy saving point of view is evident that W-8 (Window with tinted low-e double glazing air filled 4-16-4mm) is the least energy consuming about 407,823 kWh/year with Energy Saving 9.3%. The U-value for this type is 1.3 W/m².°K and SC equal to 0.51 and in the same time it's the optimal selection also in payback period point of view (Payback period = 1.211).

Table 5: Alternative Design options for Window Types

INPUT				OUPUT						
ID	**Window Name Type**	**Win. U-value W/m².°K**	**Win. SC**	**Energy Consump kWh/year**	**Energy Saving %**	**Energy Saving Cost $/year**	**Material Cost $**	**Net Saving $**	**Payback period 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%	-$2,664	$5,101	$2,437	1.91
W-2	Tinted low-e single glazing, 4 mm	4.2	0.62	421,557	5.7%	-$4,104	$5,392	$1,289	1.31
W-3	Clear double glazing, argon-filled, 4-12-4 mm	2.7	0.86	433,062	2.9%	-$2,148	$7,218	$5,070	3.36
W-4	Low-e double glazing, air-filled, 4-12-4 mm	1.6	0.64	416,873	6.9%	-$4,900	$7,315	$2,415	1.493
W-5	Low-e double glazing, air-filled, 4-16-4 mm	1.3	0.64	416,380	7.0%	-$4,984	$7,412	$2,428	1.487
W-6	Low-e double glazing, argon-filled, 4-16-4 mm	1.1	0.64	415,970	7.1%	-$5,053	$7,698	$2,645	1.52
W-7	Tinted low-e double glazing, air-filled,4-12-4 mm	1.6	0.51	408,347	9.1%	-$6,349	$7,698	$1,349	1.212
W-8	Tinted low-e double glazing, air-filled,4-16-4 mm	1.3	0.51	407,823	9.3%	-$6,438	$7,795	$1,357	1.211
W-9	Clear triple glazing, air-filled, 4-12-4-12-4 mm	1.1	0.84	429,134	3.9%	-$2,816	$8,276	$5,460	2.94

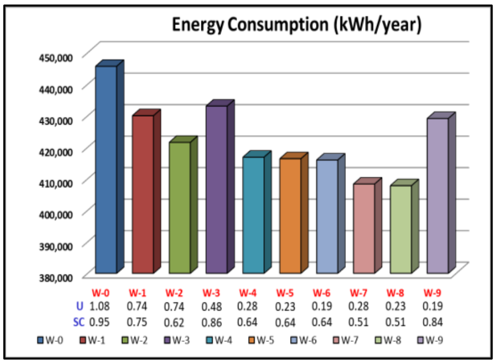

Fig.10: Window Simulation Results for Energy Consumption

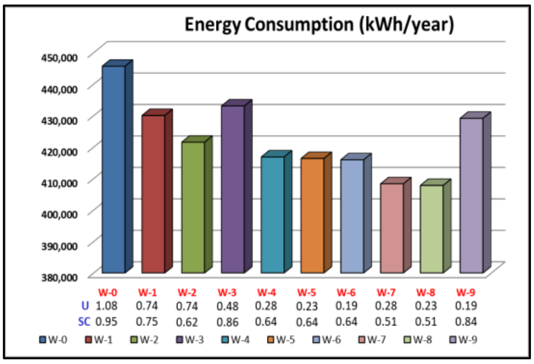

Fig.11: Window Simulation Results for Net Saving Cost and Optimal Window

3.6 Combination of building envelope Simulation Results

At large scale, considering 1540 simulation generated by the combination of building envelope (Wall, Roof and Window). The best combination which give the minimum Energy Consumption (353,875 kWh/year and Energy saving of 20.6%) is [E9, R10, W8] which E9 (14cm EPS Polystyrene), R10 (20cm Glasswool), W8 (low-e Double glazing 4-16-4mm) but the payback period is not the ideal one (payback period = 1.33 year). In the other hand, for payback period point of view, the combination of building envelope (Wall, Roof and Window) which give the minimum payback period (payback period = 0.34 years) is [EW-5, RF-6, W-2] which EW-5 (3cm EPS Polystyrene), RF-6 (10cm Glasswool), W-2 (Tinted low-e single glazing 4mm). This combination give Energy Consumption (383,133 kWh/year) and Energy Saving (14%).

Table 6: Range of Parameters used for ANN model creation

			INPUT								OUPUT		
			Wall Insulation			Roof Insulation			Window		eQuest	ANN	PE
Wall ID	Roof ID	Win ID	Type cm	e_{Wall} cm	λ_{Wall} W/m.°K	Type	e_{Roof} cm	λ_{Roof} W/m.°K	Uvalue W/m2.°K	SC	EC1 kWh	EC2 kWh	%
EW_0	R_0	W_0	N/A	0	-	N/A	0	-	6.16	0.95	445,696	440,794	1.10%
EW_9	R_{10}	W_8	EPS	14	0.039	Glass.	20	0.04	1.3	0.51	353,875	353,535	0.10%
EW_5	R_6	W_2	EPS	3	0.039	Glass.	10	0.04	4.2	0.62	383,133	383,514	0.10%

4. SMART BUILDING ENERGY MODEL USING ANN

In this section, 1540 cases simulated with eQuest software will be used for ANN creation and training using the "nftool" neural network fitting tool in MATLAB. The range of the input parameters to use it for ANN model creation is presented in Table 9.

Table 7: Range of Parameters used for ANN model creation

Code	Imput Parameters	Unit	Data used in ANNs Model	
			Minimum	Maximum
x1	Thickness of Material Insulation for External Wall	cm	0	14
x2	Conductivity of Material Insulation for External Wall	W/m.°K	0.035	0.039
x3	Tickness of Material Insulation for Roof	cm	0	20
x4	Conductivity of Material Insulation for Roof	W/m.°K	0.035	0.04
x5	U-value of Window	$W/m^2.°K$	1.1	6.16
x6	Shading Coefficient SC of Window	-	0.51	0.95
Code	**Ouput Parameters**		**Minimum**	**Maximum**
y1	Building Energy Consumption	kWh/year	353,875	445,696

The ANN model adopted in this study was composed of one input layer representing the six decision variables (different energy conservation measures of building envelope optimization), i.e. (conductivity and thickness of wall and roof material Insulation, U-value and SC of window), one hidden layer composed of 17 neurons which produced the best results after trained and tested using several networks each, putting through trial and error a different number of neurons (up to 30) in their hidden layer, and one output layer composed of the energy consumption (Figure 12).

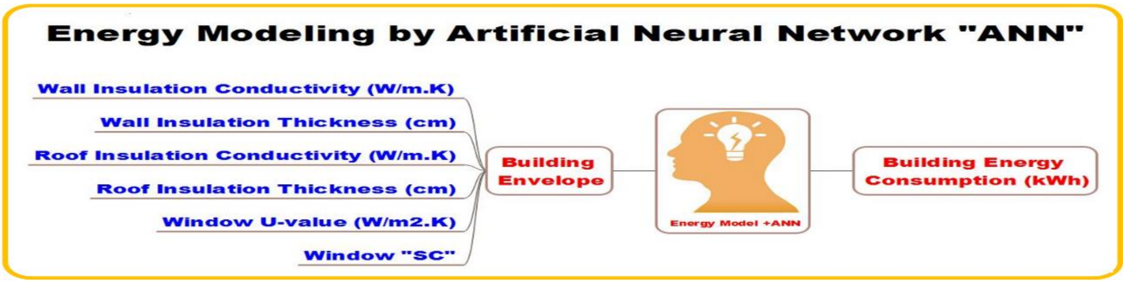

Fig.12: Artificial Neural Network ANN Smart Energy Model Diagram

For ANN training 65% of the data from 1540 simulations was taken, 20% to validate that the network is generalizing and to stop training before overfitting and 15% was used to evaluate and for testing of the forecast capacity of the developed ANN model. The learning Levenberg-Marquardt algorithm has been used as training method. After the training of this ANN model, to evaluate the obtained results and the proposed model's accuracy, the Regression correlation coefficients "R^2" between the network outputs and the corresponding eQuest simulation outputs were found very close to 0.98 (Figure 14). In the other hand, the root-mean-square error for this trained ANN is 4186 and the Mean absolute percentage error (MAPE) is equal to 0.49%, demonstrating a very good correlation between outputs and target values. Finally, the ANN Network can be deployed in form of Simulink diagram (Figure 13) to predict another ouput data for other input data values from table 9.

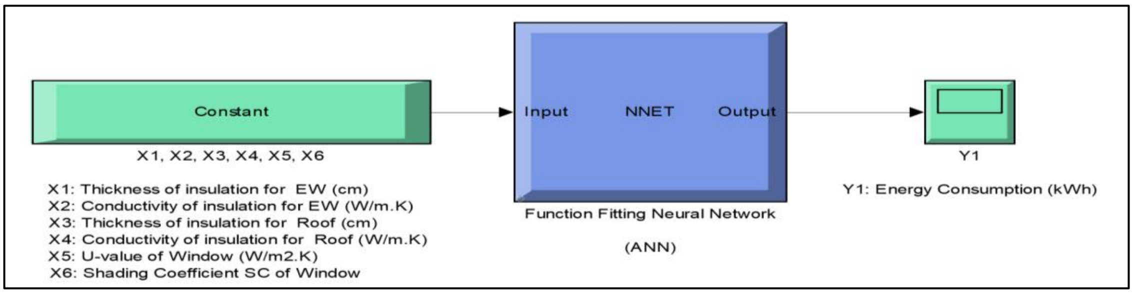

Fig.13: ANN Energy Model Simulink Diagram

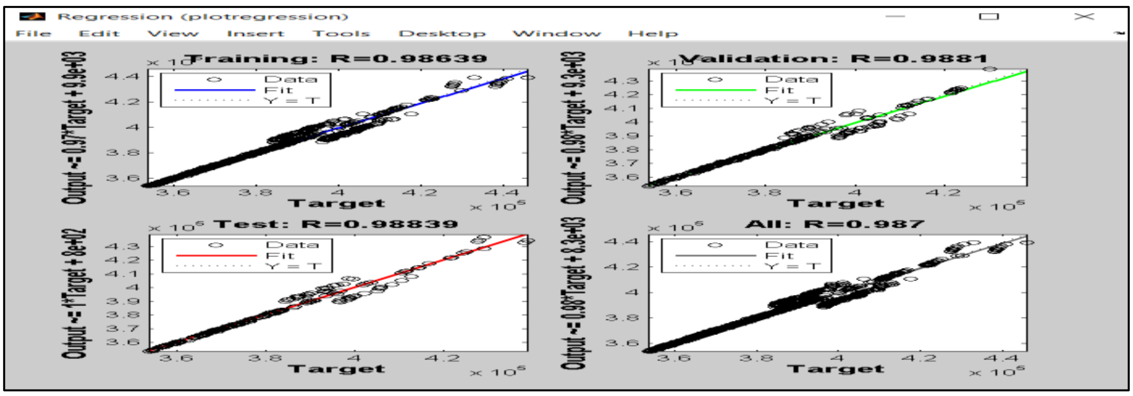

Fig.14: Regression Plots for Artificial Neural Network Trained

5. CONCLUSION

This paper presents a modeling and simulation of Smart Residential Building Energy Model using Artificial Intelligence to assist architects and engineers in selecting the optimum alternative design of building envelope that minimises the cost of energy consumption of residential buildings in Tripoli. Up to 1540 Simulations using different material thickness and conductivity values of material insulation properties and windows types are carried out in eQuest software for simulation. Each simulation run was approximately 15 min and the total run time of this scenario took around 16 days for 24 hours/day. These 1540 simulations results are implemented to create an artificial neural networl model (ANN) with Matlab/Simulink and the performance is investigated. The simulation time was reduced to 5 seconds with a regression correlation coefficients "R^2" between the artificial neural network outputs and the corresponding eQuest simulation outputs were found very close to 0.98 and the Mean absolute percentage error (MAPE) is equal to 0.49%, demonstrating a best correlation between outputs and target value. Therefore, it can be an alternative tool for predicting the energy consumption of residential buildings according to the alternative design options of building envelope optimisation with an important time and money saving. This artificial neural network model (ANN) is very good tool to estimate the energy consumption of residential building in Tripoli by transforming it to a green building for different design alternatives for the optimization of the main building envelope parameters of external wall and roof insulation material types (thickness and conductivity λ) and window types (U-value and SC).

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