Improving Energy Performance and Thermal Comfort for Heritage Buildings: A Case Study Murabaa Palace

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Abstract

Heritage Buildings are significant of their historical and architecture added value, which require in deep and precise preliminary brainstorming when considering upgrade or retrofitting of these valuable buildings. This study opts to spotlight on some passive design architecture interventions to improve the thermal comfort and the required cooling energy for the building. The Murabaa Palace in Riyadh was selected as a case study. The design builder software was used to evaluate the energy performance of four passive architectural design alternatives. The results show that using Low-E double glass in addition to applying double wall with polystyrene thermal insulation can enhance the thermal comfort inside the building and reduce the energy performance and CO_2 emissions to 17% and 9% respectively.

Keywords: Heritage buildings, passive design, energy conservation, and reduction of CO_2 emissions.

I. INTRODUCTION

Heritage buildings are integral parts of modern life, in which they gain their significance from their historical, archeological, and cultural added value [1; 2; 7; 13]. Therefore, improving the energy performance and indoor thermal comfort of an as built building with minimum interventions and preserving its heritage value is a dilemma. This is the role of introducing passive architectural design by precise choice of building materials and additions [9; 14; 18]. Accordingly, this research aims to spotlight on some passive architectural alternatives that can enhance indoor thermal comfort, reduce energy required for cooling and in turn minimize the CO_2 emissions.

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Moreover, heritage buildings inherited from the past are a crucial component of our modern society. Heritage included those buildings, structures, artifacts, and areas that are historically, aesthetically and architecturally significant. Figure 1 below shows the number of world heritage properties inscribed each year per region. As of July 2019, a total of 1,121 World Heritage Sites located in167 States around the globe. Additionally, three key factors determine whether a property worth to be listed as heritage are: historic significance, historic integrity, and historical context. Historic significance is related to how valuable the property to the history, archaeology, engineering or culture of a community. This includes any heritage building that is associated with a past event or an important person in addition to those building that has a distinctive physical characteristic. Historic integrity is relevant to the authenticity of the building identity with existing evidence of its unique physical characteristics during the building's historic period [5].

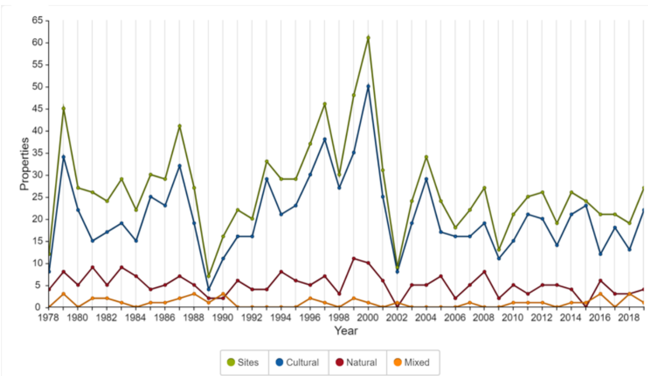

Figure 1. The number of world heritage properties inscribed each year per region [5].

According to Al-Sakkaf et al. [3; 4] the trends of protection and use of heritage buildings and cultural heritage components testify to increasing attention in the study of heritage and legacy. Studies have shown that project life cycle phases have been developed to evaluate the performance of buildings in general. Nevertheless, heritage buildings and their need were not considered. In heritage buildings projects there are six life cycle phases include: a) planning, b) manufacturing, c) transportation, d) construction, e) operation and f) maintenance phases. In addition, there is a lack of a comprehensive rating system that could assess the heritage buildings elements and to study the possibility of passive design architecture interventions to evaluate the thermal comfort interims of energy for heritage buildings. Furthermore, this paper will assist facility managers in their rehabilitation decisions. Therefore, study opts to spotlight on some passive design architecture interventions to improve the thermal comfort and the required cooling energy for the building Accordingly, the case study is applied in this research MP in Saudi Arabia.

Heritage buildings require reliable restoration, preservation procedures and evaluate the performance of heritage building interims of thermal comfort and user satisfaction. Therefore, it is essential to develop a sustainability rating system that accounts for socio-economic factors, to manage the maintenance of heritage buildings. In the Middle East, for instance, BREEAM and LEED rating systems cannot be employed because of different climatic conditions and local contexts [4; 16]. A sustainability rating tool can be defined as a systematic methodology to examine the overall sustainability assessment of a whole building. This includes economic, environmental, social, cultural, and value-based aspects. Thus, the outcome of such a tool can be used as a means of comparison with other buildings [2]. Around the globe, many rating systems pertain to different areas of sustainable development. By March 2010, there were 382 registered building software tools for sustainability development [3]. Nevertheless, only a few systems are well established and recognized by the World Green Building Council. This comprises Green Globes, Green Building Index, Green Building Program (GBP), Green ship Indonesia, Green Globes, BREEAM, LEED, etc.

Another important aspect that affects building performance is orientation. Building orientation can maximize opportunities for passive solar heating when needed, solar heat gain avoidance during cooling time, natural ventilation, and day lighting throughout the year. For example, southern exposure is the key physical orientation feature for passive solar energy in the northern hemisphere. In general, a south-facing orientation within 30º east or west of true south will provide around 90% of the maximum static solar collection potential. The optimum directional orientation depends on site specific factors and on local landscape features such as trees, hills, or other buildings that may shade the sunspace during certain times of the day. Rectangular buildings should be oriented with the long axis running east-west, so the east and west walls receive less direct sun in the summer. In the winter, passive solar heat gain occurs on the south side of the building [3; 15].

Besides, this research will follow various steps starting with a brief introduction describing the problem statement and the aim. Then the methodology that shows the case study data, the design builder simulation software calibration and data entry, and passive design alternatives and data entry. Ending this research with results and final conclusion.

II. LITERATURE REVIEW

Several previous models were reported in the literature that managed to assess energy consumption in residential buildings, office buildings and commercial buildings. Fayaz et al. [10] utilized back propagation artificial neural networks for the prediction of household energy consumption. They utilized some pre-processing procedures of data normalization and statistical moments for data cleaning and filtering. Results demonstrated that the filtering stages could enhance the prediction accuracies, such that the developed model achieved mean absolute error, mean absolute percentage error and root mean squared error of 4.32, 11.96% and 5.46, respectively. Mohamed Abdelkader et al. [16] studied the implementation of a set of machine learning models in the emulation of heating and cooling loads in residential buildings. The input variables encompassed surface area, roof area, wall area, glazing area, glazing area distribution, overall height and relative compactness. The utilized machine learning models were back propagation artificial neural network, generalized regression neural network, radial basis neural network, radial kernel support vector machines and ANOVA kernel support vector machines. It was argued that radial basis neural network performed better than other machine learning models obtaining mean absolute percentage error, mean absolute error and root mean squared error of 1.01%, 0.53 and 0.21, respectively.

Gassar et al. [12] introduced a set of data-driven models for the sake of simulating electricity and gas consumption in residential buildings in London at the lower supper output areas and middle supper output areas. Their study included the use of multi-layer neural network, multiple regression, random forest and gradient boosting. The input parameters involved average number of rooms per house, number of buildings, household spaces, land area, number of households, population, median house price and annual median household income. It was highlighted that multi –layer neural network outperformed other machine learning models at both levels of lower supper output areas and middle supper output areas yielding a correlation coefficient more than 99%. Gao et al. [11] studied the utilization of a set of machine learning paradigms for designing energy efficient residential buildings. This comprises elastic net, Gaussian process regression, least median of squares regression, multi-layer perceptron, radial basis function regression and others. The outputs of the model were the amounts of heating and cooling loads and they were calculated based on a set of building characteristics. It was inferred that random forest, rules decision table, alternating model tree, lazy k-star yielded less prediction error than other machine learning models.

Turhan et al. [17] compared the results of an energy simulation software called "KEP-IYTE-ESS" and artificial neural network in forecasting heating loads of buildings. The input variables of the developed artificial neural network model were width\length ratio, area/volume ratio, wall overall height transfer coefficient, total external surface area, and total window area/total external surface area ratio. Simulation results showed good similarity between the predicted and observed predicted values. In this regard, the developed artificial neural network attained mean absolute percentage error of 5.06% and successful predication rate of 97.7%. Amber et al. [6] compared the prediction capabilities of five intelligent techniques for forecasting electricity consumption in an administrative building. The deployed artificial intelligence models were artificial neural network, deep neural network, support vector machines, genetic programming and multiple regression. The electricity consumption was simulated according to the solar radiation, temperature, wind speed, humidify and weekly index. It was stated that the developed artificial neural network surpassed other artificial intelligence models accomplishing mean absolute percentage error of 6%.

Chae et al. [19] proposed artificial neural network model for emulating sub-hourly electricity consumption in commercial buildings. The input predictors were environmental, operational and time factors. The environmental factors included sky condition, wind speed, rain indicator, precipitation probability, outdoor relative humidity and outdoor dry-bulb temperature. The developed Bayesian regularized neural network with Levenberg–Marquart back propagation algorithm was found to provide a good predictive model that can minimize energy costs in buildings. Yu et al. [21] employed decision tree for simulating future building energy demand. The predicted loads were obtained according to annual average air temperature, house type, construction type, floor area, heat loss equivalent, equivalent leakage area, number of occupants, space heating, hot water supply and type of kitchen. It was projected that the developed decision tree model could accomplish accuracies of 93% and 92% for the training and testing datasets, respectively.

Jovanovic et al. [20] studied the implementation of an ensemble of artificial neural networks in forecasting heating energy consumption. This encompassed feedforward backpropagation neural network, radial basis function network and adaptive neuro-fuzzy interference system. The input parameters involved mean daily outside temperature, mean daily wind speed, total daily solar radiation, minimum daily temperature, maximum daily temperature, relative humidity, day of the year, month of the year and heating consumption of the previous day. Results showed that the three different types of artificial neural networks accomplished a perfect agreement between the actual and predicted values. In the view of the above, it can be derived that most of the reported models evaluate energy consumption in typical residential, office and commercial buildings. In this context, the literature lacks models which can look at the energy consumption of heritage buildings, and the environmental implications of their different architectural design alternatives.

III. METHODOLOGY

The methodology of this research that was followed to enhance the energy performance of the Murabaa palace heritage building is divided into two main parts as will be described below in detail: 1) the case study description; 2) Design Builder software calibration and data entry; and 3) Passive design alternatives and energy simulation.

A. Case Study Data

Murabba Palace is in Riyadh, Kingdom of Saudi Arabia. It was built around 150 years ago. Murabba Palace is one of the most popular historic buildings in the Kingdom with an area of 9,844.64 m^2. The building gets its name from its square shape. It is one of the museums in the city and is comprised of 12 designated areas with conference rooms, meeting rooms, and administrative offices. The main materials used in its construction were bricks, indigenous stones, tamarisk trunk and palm-leaf stalks. The walls of the building were built using straw reinforced adobe with engraved ornaments on coating as shown in Figure 2.

Figure 2. 3 D model for Murabaa Palace.

B. Design Builder Calibration and Data Entry

Design Builder software [8] version 4.5.0.148 was utilized to perform the energy simulations for the selected passive design insulation retrofitting for the Murabaa Palace. The location of the building is Riyadh and the selected weather data form the software template is SAU_RIYADH_IWEC. The activity template was set to Generic Office Area. The building has no lighting control. The used HVAC system is central unit VAV Air cooled chiller. The mechanical ventilation is turned on. No heating system is utilized. Moreover, natural ventilation and mixed mode are both set in action in the software. The windows in the building are composed of single layer 6mm clear glass.

The construction material data entry was divided into four categories: 1) roof floor layers; 2) ground floor layers; 3) typical floor levels; and 4) external wall layers. As shown in Figure 3, the roof comprises 15-20 cm diameter wooden athel beam, 3 cm palm bot layer, 1cm date palm leaves, non-woven layer, 20 cm stabilized soil layer. Furthermore, the ground floor consists of compacted filling material, polyethylene layer for thermal insulation, 10 cm reinforced concrete, 2 cm cement mortar, 6 cm Riyadh stone stones as shown in Figure 4. Additionally, as shown in Figure 5, the first-floor layers are divided into 15 cm wooden athel tree trunk beam, 3 mm palm bot, 1 cm palm leaves layers, non-woven polyester layer, 10 cm mud soil and 10 cm stabilized earth. Finally, the external wall is 40 cm stabilized earth bricks with 3 cm thick external and internal stabilized earth render. The total U-values for roof floor, ground floor, first floor, and external wall layers are 0.441 W/m^2.K, 0.779 W/m^2.K, 0.406 W/m^2.K, and 1.737 respectively.

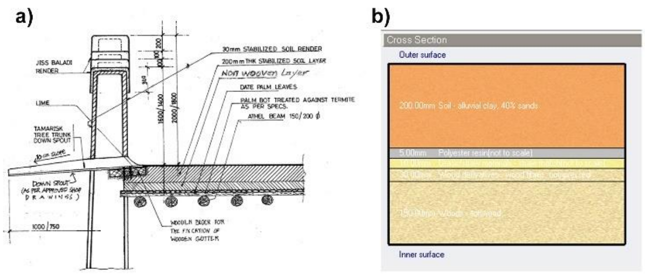

Figure 2. Roof floor layer: a) as built detail, b) design builder data entry roof layer.

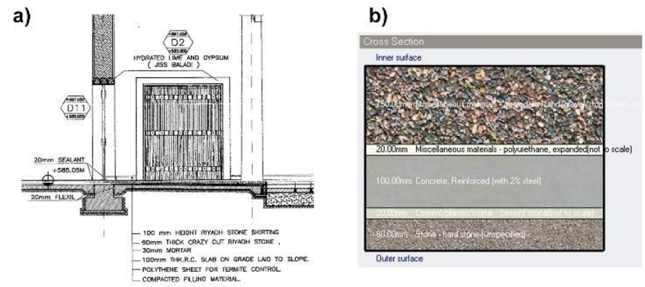

Figure 3. Ground floor layer: a) as built detail, b) design builder data entry ground layer.

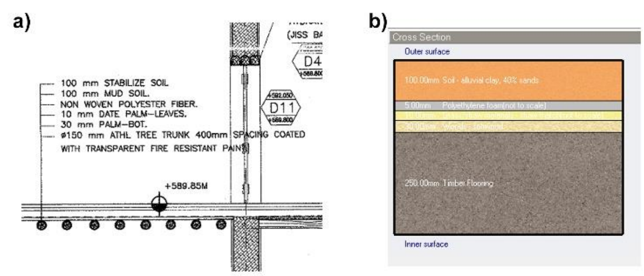

Figure 4. First floor layer: a) as built detail, b) design builder data entry ground layer.

C. Passive Design Alternatives and Energy Simulations

According to the heritage character of the building, the selected passive interventions were taken place to improve the energy performance of the building and the indoor thermal comfort with minimum intervention and retrofitting actions to preserve the heritage entity of the building exterior shape and the internal character of the building as much as possible. There are four scenarios that were utilized as follows: 1) replacing the existing single glass with double reflected glass with 13 mm gas filled gap that decreases the U-value from 5.360 W/m^2.K, as in the base case, to be 2.294 W/m^2.K; 2) replacing the existing single glass with double reflected glass with 13 mm gas filled gap that decreases the U-value from 5.360 W/m^2.K to be 1.622 W/m^2.K; 3) using the loE-glass as in the second scenario in addition to 5 cm air-gap and 12 cm rammed earth brick that makes the U-value 1.614 W/m^2.K as shown in Figure 5 (a); and 4) using the loE-glass as in the second scenario in addition to 5 cm expanded polystyrene thermal insulation and 12 cm rammed earth brick which achieves U-value 0.568 W/m^2.K as shown in Figure 5 (b).

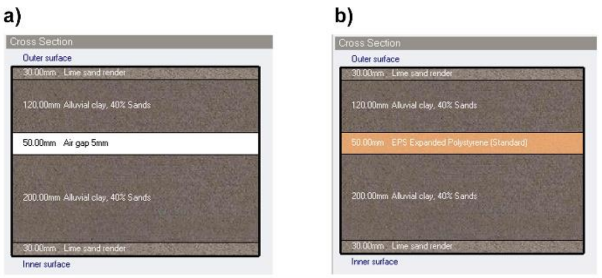

Figure 5. Proposed double wall layers: a) double wall with air-gap, b) double wall with polystyrene.

IV. RESULTS AND DISCUSSION

According to the simulations performed using design builder software the fourth case (low E double glass with double wall enclosing thermal insulation) achieves the minimum cooling energy consumption of 96779 Wh/m^2 annually, which is attributed to the minimum U-value. The other three cases consume 112129 Wh/m^2, 114908 Wh/m^2, 112718 Wh/m^2 respectively as illustrated in Table 1. Hence, the four cases achieve reduction in cooling energy consumption than the base case as follows: (case_1) 4%; (case_2) 2%; (case_3) 4%; and (case_4) 17%. Moreover, although the annual cooling energy consumption in case of using reflective glass case is lower than that when applying double wall with air cavity, but in the summer peak months (June, July, August, and September) it can be recognized, based on Table 1, the double wall achieves more reduction than using reflective glass only.

Accordingly, the carbon emissions inherit the same reduction characteristics in the four passive intervention cases as shown in table 2. Using double reflective glass possesses 132176 Kg CO_2 equ that represents 2% reduction than the base case. Applying double low-E glass emits 132532 Kg CO_2 equ, which is equal to 1.8% reduction than the base case. Utilizing both double low-E glass and double wall with air gap represents 1% reduction with 133860 Kg CO_2 equ. Finally, applying both double low-E glass and double wall with thermal insulation emits 122873 Kg CO_2 equ, which is equal to 9 % reduction than the base case.

The predictive mean value (PMV) is a metric used to indicate the degree thermal comfort achieved in a certain space. The value of this metric ranges from value of 3 to -3, and improvement in this metric takes place when its value tends to zero. Therefore, based on Table 3 and Figure 6, case 4 has the best PMV values than the other three cases and it improves the indoor thermal comfort than the base case through the twelve months of the year. Moreover, it can be recognized that applying double low-E glass achieves more improvement than using double reflective glass in the winter months.

Table 1. Monthly and annual cooling electricity.

	As Built	Case1 Wh/m^2	Case2 Wh/m^2	Case3 Wh/m^2	Case4 Wh/m^2
January	51	44	70	77	129
February	535	504	587	598	687
March	1692	1635	1813	1835	1994
April	6958	6704	7061	7020	6556
May	15711	15151	15482	15201	12929
June	17362	16699	16961	16579	13824
July	21015	20151	20441	20000	16619
August	20596	19798	20033	19577	16190
September	16924	16310	16623	16253	13648
October	11370	10973	11377	11158	9788
November	3976	3848	4105	4059	3988
December	323	312	356	360	428
Total	116513	112129	114908	112718	96779

Table 2. Monthly and annual CO_2 emissions equivalent.

	As Built	Case1 Kg equ.	Case2 Kg equ.	Case3 Kg equ.	Case4 Kg equ.
January	5680	5676	5696	5691	5727
February	5246	5227	5284	5277	5338
March	6208	6173	6295	6281	6391
April	9623	9469	9661	9686	9379
May	15170	14831	14861	15031	13484
June	15462	15060	14987	15219	13317
July	18384	17861	17769	18036	15720
August	17897	17414	17279	17556	15227
September	15430	15057	15023	15247	13444
October	12539	12299	12411	12543	11581
November	7583	7505	7633	7661	7590
December	5612	5605	5634	5631	5675
Total	134833	132176	132532	133860	122873

Table 3. Monthly Fanger PMV.

	As Built	Case1	Case2	Case3	Case4
January	-1.02	-0.99	-0.88	-0.85	-0.60
February	-0.57	-0.55	-0.46	-0.44	-0.30
March	-0.10	-0.09	-0.02	-0.02	0.04
April	-0.32	-0.33	-0.27	-0.27	-0.34
May	0.38	0.35	0.39	0.37	0.13
June	0.82	0.78	0.81	0.78	0.45
July	0.76	0.72	0.75	0.72	0.38
August	0.88	0.83	0.86	0.83	0.47
September	0.67	0.63	0.67	0.64	0.34
October	0.74	0.73	0.76	0.75	0.63
November	0.17	0.17	0.22	0.22	0.20
December	-0.68	-0.64	-0.56	-0.55	-0.34

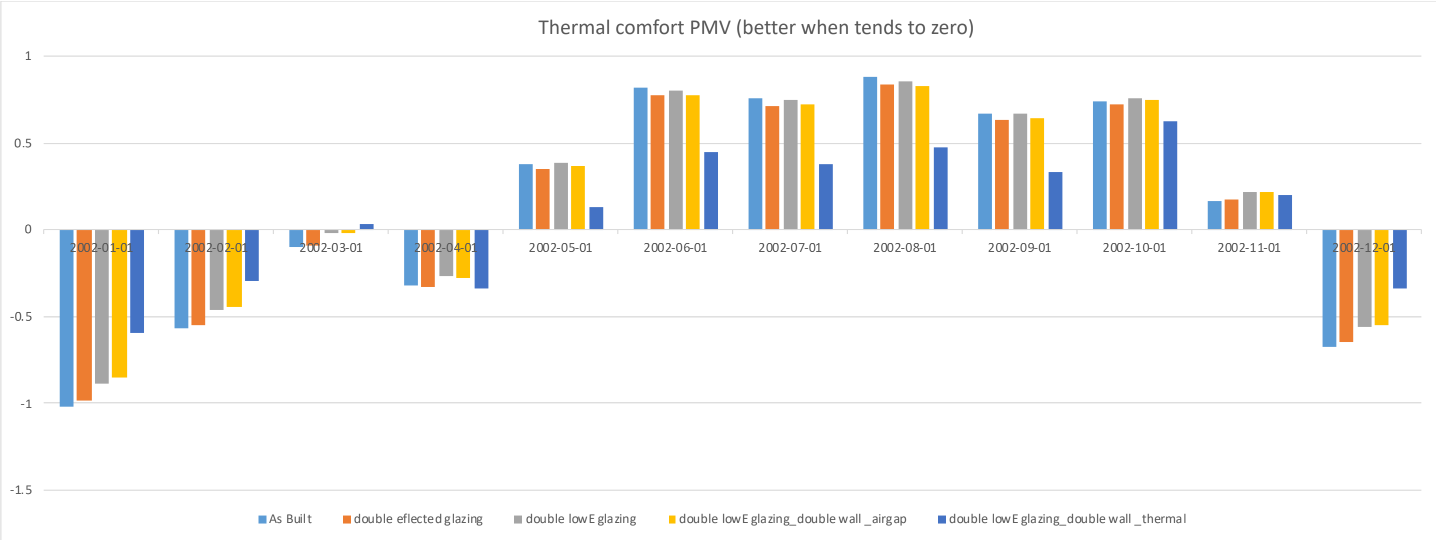

Figure 6. Fanger PMV thermal comfort.

V. CONCLUSION

As the heritage buildings has their significant character and added value to our today's architecture, also as the whole world stands hand in hand to achieve sustainability through our daily practices especially in building sector, the heritage buildings possess certain difficulties when they are required to conserve energy and enhance their indoor thermal comfort while preserving their architecture materials and character. Accordingly, this research introduced few passive architecture treatments to enhance the indoor thermal comfort, reduce energy consumption and minimize CO_2 emission. The four selected alternatives are 1) using double reflective glass, 2) using double low-R glass, 3) using double low-E glass with double wall and air gap, and 4) using double low-E glass with double wall and thermal insulation. The fourth alternative was able to achieve reduction in both required cooling energy and CO_2 emissions with percentages 17% and 9% better than the as built base case. However, these findings should be require in deep life cycle cost analysis to stand for the economic worth of these passive designs compared to the improvements in energy and thermal comfort.

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