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SUSTAINABLE DESIGN OPTIMIZATION TOOL FOR PROTOTYPICAL BUILDINGS IN HOT ARID CLIMATE USING ANALYTICAL HIERARCHY PROCESS

[1*]Muhammad Adel Mahmoud, [1]Medhat Dorra, [2]Khaled Nassar, [3]Ayman H. El Hakea and [4]Hisham Nadim

[1]Architecture Department, Faculty of Engineering Cairo University

[2] Construction Engineering Department, the American University in Cairo

[3] PhD Candidate, Construction and Building Engineering Department, College of Engineering and Technology, Arab Academy for Science, Technology and Maritime Transport

[4] Department of Architecture, Faculty of Engineering Al-Azhar University

*Corresponding Author E-mail: muhammad.adel@hotmail.ca

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ABSTRACT:
New Building Information Modelling (BIM) – enabled performance metrics are gaining importance in Building Performance Simulation (BPS). However, scarce work was published featuring holistic metrics for prototypical designs in hot arid climate. Thus, this research presents a BIM-enabled sustainable early-design decision support tool, whose optimization variables are building orientation and Window-to-Wall Ratio (WWR). The mode's objective is reaching optimum building Sustainability Combined Score (SCS); the holistic value of performance parameters considered by the user. To demonstrate the methodology, the daylighting and thermal comfort metrics are considered: (1) Day-Lit Area (DLA); (2) Daylight Autonomy (DA); (3) Mean Daylight Factor (µDF); (4) Useful Daylight Index (UDI); (5) Temperature Discomfort Hours (TDH); and (6) Humidity Discomfort Hours (HDH). BIM simulation is carried out for various combinations of building orientations and WWR, metrics are converted into percentages then into criteria scores based upon expert-determined criteria rating scales. Next, using the Analytical Hierarchy Process (AHP), Criteria Relative Weights (CRW's) are determined, using a Pairwise Comparison Matrix (PCM). SCS's are computed for each scenario, as a function of criteria scores and CRW's. The verification of the AHP Module is done arithmetically using consistency indices. After screening all valid scenarios considering site constraints, accessibility and design codes, the scenario with optimum SCS is obtained. Three cases of prototypical designs, comprising a school building, a civil defense facility and a congregational building are presented. All cases are located in the hot desert climate of Qatar. The validation of the SCS Module output is carried out using expert survey.

KEYWORDS: Analytical Hierarchy Process, Building Performance Simulation, Hot Climate, Multi-Objective Optimization.

تحقيق أفضل معدلات التصميم المستدام للمنشآت النمطية في المناخ الصحراوي الحار باستخدام التحليل الهرمي

محمد عادل محمود*١ ومدحت درة١ وخالد نصار٢ وأيمن الهاكع٣ وهشام نديم٤

١قسم العمارة، كلية الهندسة، جامعة القاهرة

٢قسم هندسة التشييد، كلية العلوم والهندسة، الجامعة الأمريكية بالقاهرة

٣إدارة تطوير النظم، الشركة الهندسية للإنشاء والتعمير، عضو مجموعة شركات درة

٤قسم العمارة، كلية الهندسة، جامعة الأزهر

*البريد الإلكتروني للباحث الرئيسي: muhammad.adel@hotmail.ca

الملخص

اكتسب قياس معدلات أداء المنشآت باستخدام نمذجة معلومات البناء زخماً كبيراً في كلٍ من التصميم المعماري المستدام ومحاكاة البناء، وبالرغم من ذلك، قلما نُشر من أبحاث تتناول معدلات مجمعة لقياس أداء المنشآت، ولاسيما فيما يتعلق بالتصميمات النمطية في المناطق ذات المناخ الصحراوي الجاف، ومن هذا المنطلق، يقدم هذا البحث أداة مبتكرة لدعم اتخاذ القرار ,والوصول لأفضل المعدلات أثناء مرحلة التصميم المبدئي، حيث تتماشى تلك الأداة المقترحة مع نظم نمذجة معلومات البناء، كما تعتمد تلك الأطروحة على تحليل الحالات الممكنة للمتغيرين: زاوية توجيه المنشأ ونسبة النوافذ إلى الحوائط، بهدف التوصل إلى أفضل قيمة للدرجة الكلية للاستدامة، والتي تمثل قيمة موحدة لكافة مؤشرات الأداء المختارة من قبل المستخدم. وبغرض عرض تلك الأطروحة، تم الاعتماد على هذه المجموعة من مؤشرات أداء الإضاءة الطبيعية والراحة الحرارية: (١) المساحة المضاءة طبيعياً، (٢) متوسط معامل الإضاءة الطبيعية ، (٣) استقلالية الإضاءة الطبيعية، (٤) مؤشر الإضاءة الطبيعية، (٥) ساعات درجة الحرارة السنوية غير المستوفاة، (٦) ساعات الرطوبة النسبية غير المستوفاة. يتم إذاً القيام بالمحاكاة المعتمدة على نمذجة معلومات البناء لكل من السيناريوهات الممكنة لزاوية توجيه المبنى مع نسبة النوافذ إلى الحوائط، ويتم تحويل مخرجات تلك الخطوة، وهي القياسات المنفصلة، إلى نسب مئوية، يتم تحويلها بدروها إلى درجات قياسية استناداً إلى مقياس تم تحديده بواسطة ورشة عمل ضمت مجموعة من الخبراء، وهكذا فإنه باستخدام طريقة التحليل الهرمي يتم التوصل إلى الأوزان النسبية لمعدلات الأداء المختارة، وذلك بتطبيق مصفوفة المقارنة الثنائية على تلك المعدلات، وبناء على ذلك يتم تقدير القيم الخاصة بالدرجة الكلية للاستدامة، والتي تعتمد بالأساس على الدرجات القياسية والأوزان النسبية لمعدلات الأداء، كما يتم التحقق من منظومة التحليل الهرمي رياضياً باستخدام مؤشرات الاتساق، وبالإضافة إلى ذلك، فبعد إتمام عملية التدقيق لكل سيناريو مقترح - من حيث زاوية التوجيه ونسبة النوافذ إلى الحوائط- في ضوء طبيعة الموقع وأكواد البناء المحلية وغيرها من خصائص المشروع، وقد تم تناول ثلاثة مشروعات ذات تصميمات نمطية، تشمل مبنىً تعليمياً ومنشأة للدفاع المدني وداراً للعبادة، كأمثلة لتطبيق الأداة المقترحة، تقع كلها في المنطقة المناخية الصحراوية الحارة بدولة قطر، مع عرض النتائج التي تم التوصل إليها، وقد تم التحقق من المنظومة الخاصة بدرجة الاستدامة الكلية بواسطة استقصاء موجه إلى نخبة من المعماريين المتخصصين في مجال الاستدامة ونمذجة معلومات البناء، وتم التوصل بالأخير إلى أن المنشآت ذات المساحات الكبيرة عكست دقة أكثر في عملية محاكاة مؤشرات الاستدامة، وأظهرت قدراً أكبر من التأثر بالتغيير في القيم المدخلة من زاوية توجيه المنشأ أو نسبة النوافذ إلى الحوائط، مقارنة بالمنشآت الأصغر مساحةً التي لم تتأثر نتائجها بنفس عند تغيير قيم المتغيرات.

الكلمات المفتاحية: عملية التحليل الهرمي، محاكاة أداء المنشآت، المناخ الحار، التحسين متعدد الأغراض.

1. INTRODUCTION
1.1 GENERAL BACKGROUND

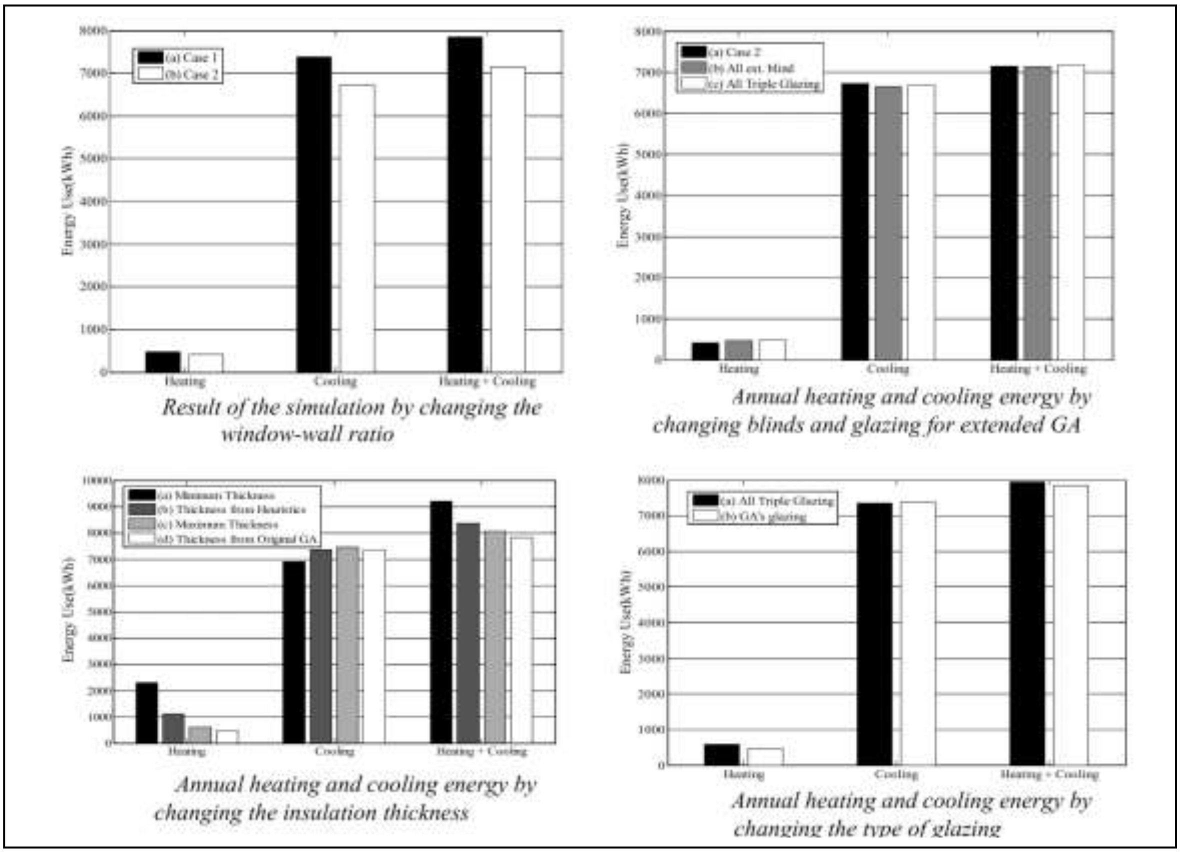
Building sustainable performance measures are usually calculated using a number of physical simulations such as daylighting, thermal, energy and acoustic performance. Yet traditional methods of Building Performance Simulation (BPS) have been blamed for being lengthy in terms of setup and validation. In contrast, modern interactive sustainable design tools and metrics have been moving towards holistic performance indicators and Building Information Modeling (BIM)-aided simulation tools. From this standpoint, this paper proposes a single Sustainability Combined Score (SCS) metric, used to reflect the building sustainability performance. For the purpose of demonstrating this idea, two distinct performance categories are considered: (1) Daylighting; and (2) Thermal comfort. In addition, the suggested Sustainability Combined Score (SCS) metric is used to assess a variety of possible design scenarios for prototypical building designs, as far as the scope of this work is concerned. Thus, examining previous related literature in this particular regard, it was observed that a sizable amount of publications tended to focus either on daylighting or thermal comfort and performance, single-handedly.

Considering daylighting, numerous sources addressed the issue of optimizing design features towards achieving the best daylighting performance. Such design features included: (1) Window and opening design [1-3]; (2) Solar control devices [4]; (3) Optimal positioning and of lighting shelves using scale modelling and computer assessment [5, 6]; and (4) Building shape, including façade and ceiling shape and characteristics [7-9]. Other authors focused around simulation and isolation of daylighting in a wide variety of space types using computer-aided tools, with the aim to assess daylighting performance using software tools [10-16]. Further published works using the same tool considered the simulation using controlled shading devices, parametric workflow, subjective perception and intelligent clustering [17-20]. Rather recent innovative works were published by Carlucci et al. (2015a) involving optimization of daylighting and visual comfort using Genetic Algorithms (GA's) [21]. Moreover, Mahmoud et al. (2016) proposed a new

climate-based BIM metric for daylighting depending on a series of sensors placed inside a prototypical room [22].
As for thermal comfort and performance, Artificial Intelligence (AI) was extensively used for thermal design optimization. GA's were used to this end by Wright el al. (2002) for building thermal design multi-criteria optimization [23]. Nevertheless, Lee (2007) used both GA's and Computational Fluid Dynamics (CFD) for indoor climate conditioning, combined with active and passive methods [24]. Later, Boithias et al. (2012) combined GA's, Artificial Neural Networks (ANN's) and fuzzy controllers using a MATLAB/SIMULINK® model, for building thermal comfort optimization [25]. Nevertheless, Carlucci et al. (2015b) modelled temperature and relative humidity "discomfort" hours also depending on a GA-based framework [26]. Among other AI techniques frequently discussed in the literature came Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). While Wang et al. (2010) using PSO to optimize building cooling, heating and power consumption, Chen et al. (2010) presented a combination of PSO and feed-forward ANN for temperature identification in smart buildings [27, 28]. In 2012, on the other hand, Yuan et al. developed an ACO module to optimize building energy performance [29]. In view of design elements optimization towards better thermal performance, while Prianto & De Pecker (2011) developed an AI-based module for optimizing balcony and window designs, Nguyen (2013) proposed a thermal comfort optimization specifically tailored for climate-responsive design strategies, taking public housing projects in Vietnam as a case study [30-31]. Also in 2013, Ngueyn & Reiter (2013) used passive design techniques for thermal comfort optimization in low-cost housing [32]. Similar to Prianto & De Pecker (2011), Prashant et al. (2017) suggested a building layout selection model based on thermal comfort simulation [33]. From a rather different perspective, Mara & Tarantola (2008) used sensitivity analysis to model building thermal performance metrics are affected by changing various façade shading design features [34].

It was only in the beginnings of the second decade of the 21st century that BPS research became significantly preoccupied with multi-objective optimization involving daylighting, thermal performance and other BPS measures, for various types of buildings. This research boom has been even made easier thanks to BIM-enabled BPS software packages and solutions. Interestingly, Nguyen et al. (2014) and Zhai et al. (2019) made a thorough review of recent research concerning multi-objective optimization of building sustainable designs, notwithstanding daylighting and thermal performance [35, 36]. Over the past decade, the main research trends identified in the literature were concerned with: (1) Heuristic and meta-heuristic optimization; (2) Leadership in Energy and Environmental Design (LEED) design requirements optimization; and (3) Evolutionary algorithms including GA's and Non-Dominated Sorting Genetic Algorithms (NSGA's). For instance, Suh et al. (2011) combined various energy performance parameters, and used two methods of multi-objective optimization; namely heuristic and meta-heuristic approaches. They considered a post office building in the Republic of Korea, characterized by the hot summer humid climate (Following the Köppen-Geiger Climate Classification [37]), as their case study, and tried to examine the change in building heating and cooling energy upon changing the Window-to-Wall Ratio (WWR), insulation thickness, glazing type and addition of blinds [38]. Results of these tradeoffs are shown in Figure 1. As cited from Suh et al. (2011). As for evolutionary algorithms, while Hamdy et al. (2012) used an NSGA II algorithm to achieve zero-energy building optimization, Salminen et al. (2012) used the same concept to simulate and optimize the performance of a LEED-certified building. Both papers addressed the subarctic climate regions of Finland [39, 40]. A year later, Wright et al. (2013) used an evolutionary algorithm to select the optimal cellular window design corresponding to the best building performance metrics. In doing so, the authors considered the temperate oceanic climate conditions of the United Kingdom (UK) [41]. Similarly, Zhang et al. (2016: 2017), used a GA-based multi-objective optimization methodology to carry out tradeoffs between: (1) Daylighting and thermal performance; and (2) Shape of free-form buildings based, solar radiation gains and space efficiency. The case study comprised residential and educational buildings in the cold climate of the Tibet and Manchuria regions, China [42, 43]. Similar works, on design optimization was carried out by Ochoa et al. (2012) and Rathi (2012) envisioning optimum window design for energy consumption and visual comfort, considering various climatic zones in the United States (US) [44, 45]. Subsequently, Zhai et al. (2019) and Goia et al. (2013) built upon these concepts to optimize window design versus energy consumption, thermal comfort and visual performance of residential naturally-ventilated buildings in humid subtropical regions of China, and to optimize office building façades in Italy and Norway climates, respectively [36, 46]. On a similar perspective, Mahmoud et al. (2016) suggested a climate-based metric for the optimization of WWR to get the best tradeoff between daylighting and thermal comfort for a prototypical room [22]. An example of the model findings illustrated in Figure 2.

Figure 1: BPS multi-objective optimization model output by Suh et al. (2011) [37].



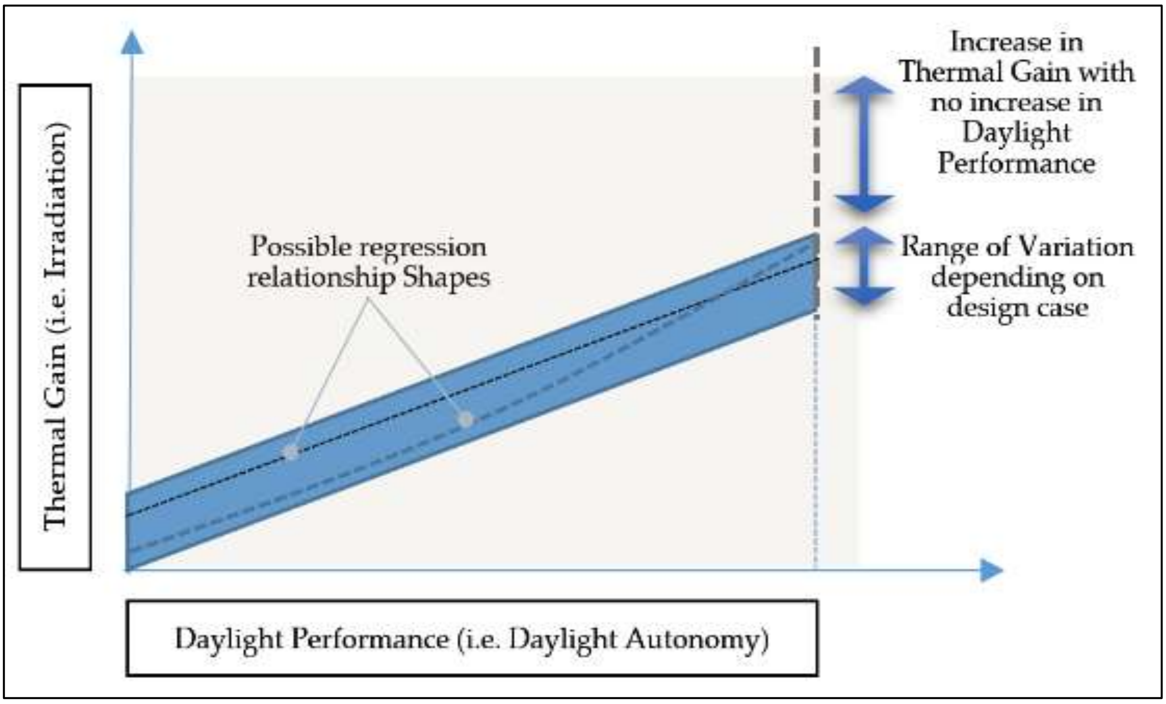


Figure 2: Proposed relationship between daylighting and thermal gain (Mahmoud et al., 2016) [22].

1.2 PROBLEM STATEMENT

As discussed in the General Background Section, it was observed that previous studies often lacked holistic sustainability performance metrics, reflecting collective performance measures, including daylighting and thermal comfort, most notably. While recent attempts have been made to combine daylighting and thermal comfort, under a single optimization process, they tended to addressed tools that were rather too complex [36, 47]. The need for simpler metrics representing the overall efficiency of sustainable design parameters, mandated the move to simpler optimization tools, such as linear programming and Analytical Hierarchy Process (AHP). In an attempt to fill this research gap, this paper proposes a BIM and AHP-based sustainable design decision-support tool, which considers real time feedback to the end user, in interactive design media. Alternatively, while there was ample literature discussing either daylighting improvement or thermal comfort enhancement in residential and educational buildings, similar work on civil defense and congregational buildings was scarce [36]. Nevertheless, none of the previous work tackling any of these two metric categories considered hot arid climate regions. Thus, after conducting the literature review, the topic that was not discussed before could be expressed as the early design decision support tool, capable of holistically representing a multitude of given building sustainability performance metrics, using a simple linear technique, for a wide variety of prototypical designs, while being specifically tailored for hot arid climate.

1.3 GOAL AND OBJECTIVES

The end goal of this paper is to present a multi-objective optimization framework for a wide variety of prototypical building designs, in hot desert climate, depending on a single holistic sustainability performance measure. Such prototypical buildings include educational buildings, firefighting stations and houses of worship (mosques). The model's optimization variables are: (1) Building orientation angle; and (2) WWR. The objective functions of the optimization is reaching the optimum (i.e. maximum) SCS, given a set of possible design scenarios. To demonstrate this concept, the SCS in this paper is indicative of the following building performance metrics (Chosen to be all daylighting and thermal comfort indicators): (1) Daylit Area (DLA); (2) Daylight Autonomy (DA); (3) Mean Daylight Factor (μDF); (4) Useful Daylight Index (UDI); (5) Temperature Discomfort Hours (TDH); and (6) Humidity Discomfort Hours (HDH). Therefore, the objectives of the research is to: (1) Develop a comprehensive Design Database (DD); (2) Compile a Performance Criteria Database (PCD) comprising first, a pool of criteria from which the user can select the desired metrics to be considered in the optimization, and second, a set of expert-determined criteria rating scales; (3) Develop an Analytical Hierarchy Weighing Module (AHWM) where Criteria Relative Weights (CRW's) are determined using the AHP technique, based upon expert-provided Pairwise Comparison Matrices (PCM's); (4) Construct a SCS Module, where all possible building orientation and WWR scenarios are considered, and where SCS output values are validated and the optimum scenarios are recommended.

2. RESREARCH METHODOLOGY

2.1 GENERAL FRAMEWORK

The research general framework and modules are illustrated using the flowchart shown in Figure 3. Each of the respective modules are explained, in order, over the next sub-sections.

2.2 DESIGN DATABASE (DD)

The basis of simulation is laid using the DD tool. It is there where all design information pertaining to the project under study are logged in by the user. These data include the BIM model, which in its turn incorporates a multitude of design information such as: (1) Building materials; (2) Opening characteristics; (3) Finishing materials and their properties; (4) Space characteristics; (5) Zoning definition; (6) Occupancy schedules and occupant behavior; (7) Weather information; (8) Site attributes and accessibility constraints; and (9) Limits imposed by relevant design codes.

2.3 PERFORMANCE CRITERIA DATABASE (PCD)

Equally important to the DD tool, comes the PCD. It is here where users can select from a preset pool of sustainability performance metrics, as needed, to be considered for the simulation and optimization process. For the purpose of demonstrating this methodology, the authors considered the following daylighting and thermal comfort parameters:

- DLA;
- DA;
- µDF;
- UDI;
- TDH; and
- HDH.

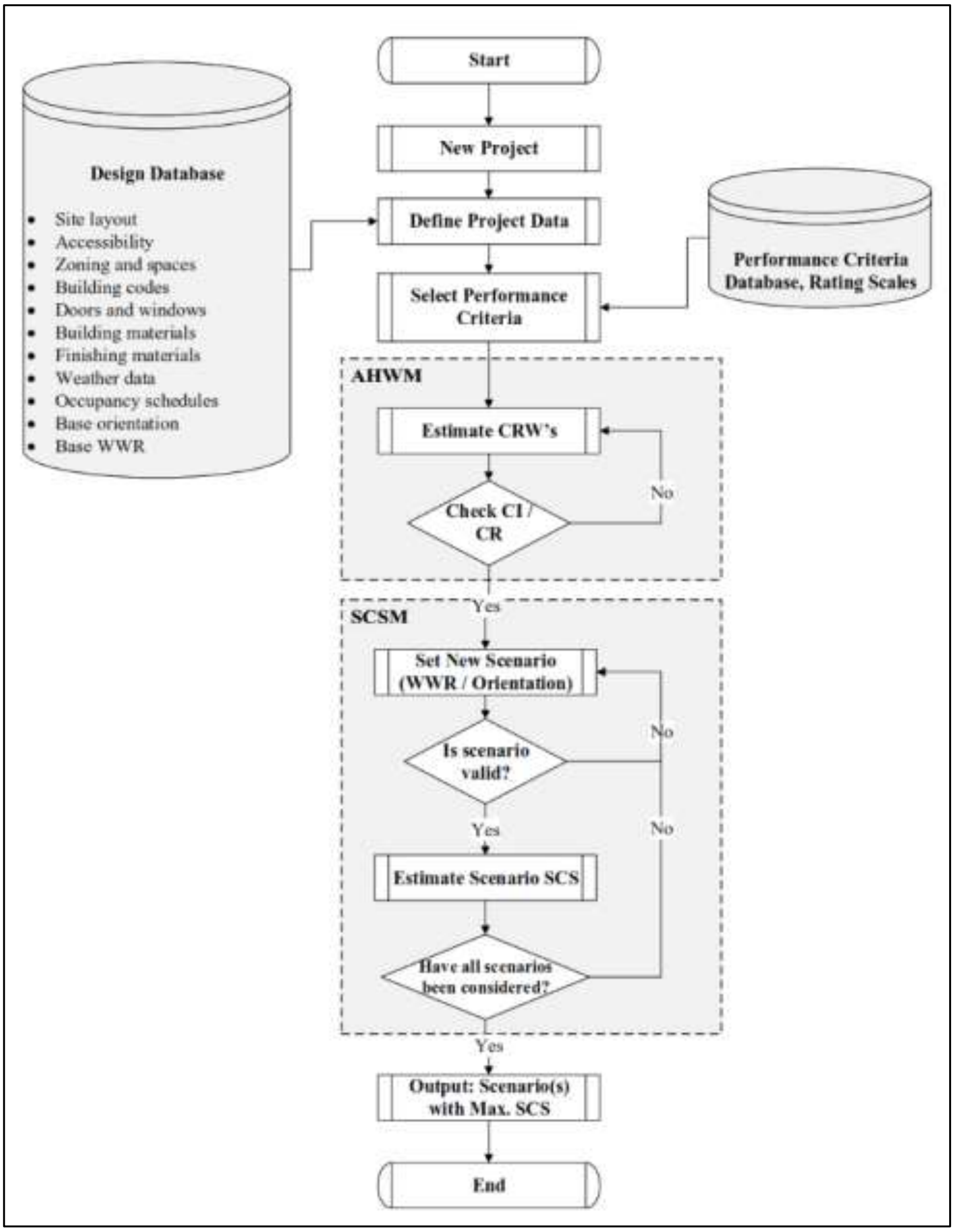


Figure 3: Research methodology framework diagram.

The PCD comprises a group of performance criteria rating scales based upon preset ranges and thresholds. These rating scales are displayed in Tables 1, 2 and 3; for DLA, DA, µDF, UDI, TDH and HDH, respectively, and were based on the consensus of an expert panel workshop, consisting of 16 experts in the field, with proven experience in architectural design and practice in the hot arid climate region of the Middle East and North Africa. Experts have been nevertheless presented with the corresponding design and climate data peculiar to the considered case studies, as well as a model demonstration, prior to developing such rating scales. While BIM simulations are carried out using DIVA® and EnergyPlus® software tools, the output is converted to a percent figure. Then, percent figures falling within each range are in their turn simplified to their corresponding 1-integer rating, in order to facilitate linear modelling using the AHWM.

Table 1: DLA performance rating scale.

DLA Ranges	Rating by Range
0% ≤ DLA < 10%	1
10% ≤ DLA < 20%	2
20% ≤ DLA < 30%	3
30% ≤ DLA < 40%	4
40% ≤ DLA < 60%	5
60% ≤ DLA < 70%	4
70% ≤ DLA < 80%	3
80% ≤ DLA < 90%	2
90% ≤ DLA	1

Table 2: µDF, DA and UDI performance rating scales.

Measure	Ranges	Rating by Range
µDF	0% ≤ µDF < 2%	0
	2% ≤ µDF	5
DA	0% ≤ DA < 50 %	0
	50% ≤ DA	5
UDI	0% ≤ UDI < 50 %	0
	50% ≤ UDI	5

Table 3: TDH and HDH performance rating scales.

TDH Ranges	HDH Ranges	Rating by Range
0% ≤ TDH < 30%	0% ≤ HDH < 30%	5
30% ≤ TDH < 40%	30% ≤ HDH < 40%	4
40% ≤ TDH < 50%	40% ≤ HDH < 50%	3
50% ≤ TDH < 60%	50% ≤ HDH < 60%	2
60% ≤ TDH < 70%	60% ≤ HDH < 70%	1
70% ≤ TDH	70% ≤ HDH	0

2.4 ANALYTICAL HIERARCHY WEIGHING MODULE (AHWM)

Upon selecting the desired performance criteria rating scales, based upon the user's experience and engineering judgment, as dictated by the considered case, the AHWM tool enables the user to reach sound and valid CRW's. However, this end is reachable through the multi-stage linear concept of AHP, based on the work published by Anderson et al. (2014) [58]. Table 4 indicates the standard scale of criteria relative importance, as per Anderson et al. (2014) explanation of the AHP method [48]:

Table 4: Criteria relative importance rating scale.

Rating	Relative Importance
1	Equally important
3	Moderately Important
5	Strongly Important

7	Very Strongly Important
9	Extremely Important
2, 4, 6, 8	Intermediate Values
1/3, 1/5, 1/7, 1/9	Values of inverse comparison

Next, a Pairwise Comparison Matrix (PCM) is constructed to compare these criteria arithmetically with each other. The matrix is constructed as explained in Anderson et al. (2014) [48]. In this research, after presenting the expert panel with a demonstration of the research methodology and project data, the expert panel workshop was able to develop the PCM based on the sequence shown in Tables 5 and 6, respectively. In Table 5, if DLA on the left column as an example, was chosen by the expert panel to be "Moderately Important" than µDF, thus the value indicated is 3, based upon Table 4 rating for "Moderately Important". Hence, starting by the left column criteria, the PCM is populated as shown in Table 5. Nevertheless, diagonal values should be equal to 1.

Table 5: Development of the Pairwise Comparison Matrix (PCM).

	DLA	**µDF**	**DA**	**UDI**	**TDH**	**HDH**
DLA	**1**	3				
µDF		**1**	1			
DA	3	1	**1**			
UDI	5	2	2	**1**		
TDH	9	5	3	2	**1**	1
HDH	7	5	3	2	1	**1**

Next, all that remains is to complete the entries for the remaining cells of the matrix. To illustrate how these values are obtained, consider the numerical rating of 9 for the TDH-DLA pairwise comparison. This rating implies that the DLA-TDH pairwise comparison is thus 1⁄9. Since the expert panel had indicated that TDH is extremely more important than DLA, it is inferred that the reciprocal comparison value is 1⁄9. Hence, the complete PCM is expressed in Table 6:

Table 6: PCM completion.

	DLA	**µDF**	**DA**	**UDI**	**TDH**	**HDH**
DLA	1	3	1/3	1/5	1/9	1/7
µDF	1/3	1	1	1/2	1/5	1/5
DA	3	1	1	1/2	1/3	1/3
UDI	5	2	2	1	1/2	1/2
TDH	9	5	3	2	1	1
HDH	7	5	3	2	1	1
Total	**25.3**	**17.0**	**10.3**	**6.2**	**3.1**	**3.2**

Based upon the PCM, the AHWM then generates the Normalized PCM by dividing each value in the PCM by the summation of its corresponding column in the original PCM, as displayed in Table 7. Criteria Weights (CW's) are then calculated by taking the average of each row of the Normalized PCM.

Table 7: Normalized PCM.

	DLA	µDF	DA	UDI	TDH	HDH	CW
DLA	0.04	0.18	0.03	0.03	0.04	0.05	**0.06**
µDF	0.01	0.06	0.10	0.08	0.06	0.06	**0.06**
DA	0.12	0.06	0.10	0.08	0.11	0.11	**0.09**
UDI	0.20	0.12	0.19	0.16	0.16	0.16	**0.16**
TDH	0.36	0.29	0.29	0.32	0.32	0.32	**0.32**
HDH	0.28	0.29	0.29	0.32	0.32	0.32	**0.30**

Then, each value in each column of the original PCM is multiplied by its own CW obtained from the Normalized CPM. At this stage, and as shown in Table 8, the sum of each row is expressed as the CRW, which is the quotient of dividing the Weighted Sum Value (WSV) –*which is the summation of all row values*- by CW.

Table 8: WSV and CRW values.

	DLA	µDF	DA	UDI	TDH	HDH	WSV	CRW
DLA	0.06	0.19	0.03	0.03	0.04	0.04	0.39	**6.50**
µDF	0.02	0.06	0.09	0.08	0.06	0.06	0.38	**6.11**
DA	0.18	0.06	0.09	0.08	0.11	0.10	0.63	**6.64**
UDI	0.30	0.13	0.19	0.16	0.16	0.15	1.09	**6.62**
TDH	0.54	0.31	0.28	0.33	0.32	0.30	2.09	**6.60**
HDH	0.42	0.31	0.28	0.33	0.32	0.30	1.97	**6.49**

Henceforth, and for the purpose of simulation in this research, the generated CRW values of Table 8 are those that shall be regarded. Furthermore, Anderson et al. (2014) described the mathematical verification method of CRW's, by performing a consistency check on the PCM itself. In doing so, they expressed the average CRW using Equation (1) [48]:

$$\lambda_{max} = \frac{\sum \frac{WSV}{CW}}{N} \qquad (1)$$

Where:

- "λ_{max}" is the total of WSV's divided by CW's; and
- "N" is the number of performance criteria.

Applying Equation (1) on the example given in Tables 8 to 10, λ_{max} is going to be equal to 6.492. Thus, the Consistency Index (CI) is expressed using Equation (2):

$$CI = \frac{(\lambda_{max} - N)}{(N-1)} \qquad (2)$$

Accordingly, upon substituting λ_{max} with 6.492 and N with 6 in Equation (2), CI becomes equal to 0.098. Next, this CI value is substituted in Equation (3) in order to obtain the Consistency Ratio (CR) of the AHP PCM:

$$CR = \frac{CI}{RI} \qquad (3)$$

Where:

- *RI* is a Random Index, whose typical values are provided in Anderson et al. (2014), and are used for calculating the consistency of randomly-generated PCM's, as shown in Table 9 [48].

All while considering a given standard numbers of performance criteria (In this case N=6 and RI=1.24). Subsequently, when the RI value is substituted in Equation (3), CR becomes equal to 0.079, and since CR<0.10, then, the PCM is said to of reasonable consistence, and thus the CRW's consequently.

Table 9: Number of criteria vs. Random Indices (RI's) [48].

N	1	2	3	4	5	6	7	8
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41

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2.5 SUSTAINABILITY COMBINED SCORE MODULE (SCSM)

After generating a set of all possible building orientation angle combined with WWR value, the SCSM first checks the validity of each scenario in the set based upon the input constraints. Invalid scenarios are filtered and only valid combinations are considered. For the purpose of making the model rather simple, only four building orientation options are considered: 0º, 90º, 180º and 270º. As for WWR values, they pretty much depended on the range provided in local building codes with regard to the considered case studies. Taking the above into account, daylighting and thermal comfort simulations are done, albeit separately onto two stages, using two distinct software packages. For daylighting, the authors utilized Rhinoceros® package for data input, while opting for DIVA® for BIM simulation. Whereas for thermal comfort, this research features OpenStudio® for data input and EnergyPlus® for thermal BIM simulation. This separate two-stage simulation is attributed to the relation governing both daylighting and thermal comfort in hot arid sunny climate, where thermal comfort is adversely impacted with DF values surpassing the 10,000 lux threshold; a condition peculiar to the case studies' region [22, 49].

ASHRAE (2010) was used as being the primary reference for choosing the temperature and humidity acceptable ranges in various thermal zones of studied buildings, against which the TDH and HDH are measured [50]. For each valid design parameters combination, the SCSM estimates the SCS, whose maximum value corresponds with the optimum design combination scenario of building orientation and WWR. The SCS is expressed using Equation (4):

$$SCS = \prod_n CRW_k \, C_{ijk} \qquad (4)$$

Where:

- CRW_k is the criteria relative weight of criterion k; and
- C_{ijk} is the Performance Score of criterion k for building orientation angle i and WWR j.

3. CASE STUDIES

For the purpose of demonstrating the model, three case studies comprising a school building, a civil defense (firefighting) facility and congregational facility, are discussed in this paper. The three case studies –all located in Qatar- are, respectively: (1) EIA Academy, Lusail; (2) Main Fire and Rescue Station at Mesaeid Insdustrial City (MIS); and (3) MIC Mosque. The preliminary information pertaining to these case studies is displayed in Table 12.

Table 9: Preliminary information on case studies.

Case Study	Owner	Coordinates	Location
EIA Academy	EIA Academy	25°23'15.2"N 51°31'32.0"E	Lusail
Main Fire and Rescue Station	MIC Municipality	24°95'33.7"N 51°53'94.7"E	MIC
MIC Mosque	MIC Municipality	25°00'13.3"N 51°32'17.4"E	MIC

Other design details such as the Built-Up Area (BUA), Foot Print Area (FPA), number of floors, and occupancy attributes, are illustrated in Table 13. The case study BIM models were provided by EGEC Qatar for Engineering Consultations WLL [51-53].

Table 10: Case studies' space and occupancy attributes.

Case Study	BUA (m^2)	FPA (m^2)	Number of Floors	Number of Occupants	Yearly Occupied Hours
EIA Academy	8,028	3,117	2Bs., Gr.+2	2,109	3,650
Main Fire and Rescue Station	3,795	3,396	Gr.+1	26	3,650
MIC Mosque	710	710	Gr.	412	3,650

4. RESULTS AND ANALYSIS

With the exception of the MIC Mosque whose building orientation only valid scenario was 0º, as dictated by the direction of the *qibla*, simulations were carried out on all case studies considering the four-quadrant configuration of building orientations, and various WWR scenarios. Thus, while the MIC Mosque was simulated for 4 scenarios, the other two case studies underwent 16 possible scenarios. Starting by EIA Academy, Figure 4 displays a screenshot of the DA simulation using DIVA® tool. Furthermore, the preliminary results prior to simplification are shown in Table 11, then after applying the criteria rating scale simplification, the results are presented in Table 12.

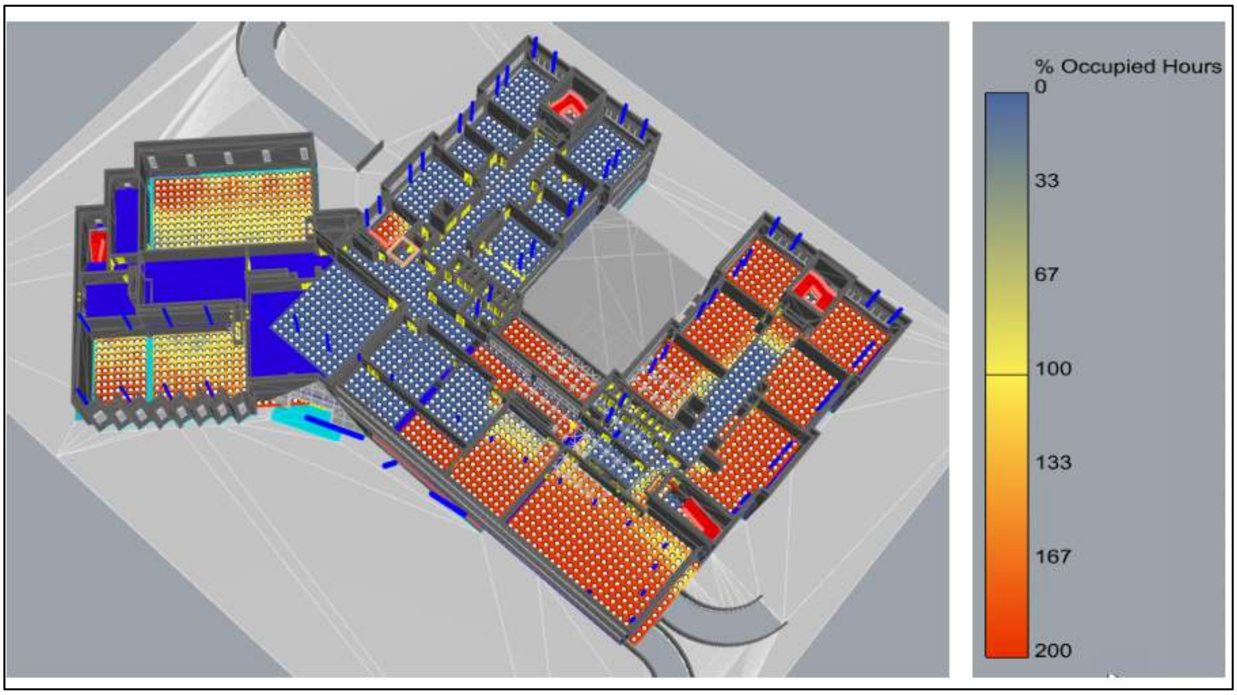

Figure 4: 3D View of the EIA Academy building DA simulation using DIVA®

Table 14: EIA Academy simulation results expressed as % figures.

Scenario No.	**Orientation**	**WWR**	**DLA**	**µDF**	**DA**	**UDI**	**TDH**	**HDH**
1	0º	6%	11%	1.9%	20%	18%	37.3%	26.0%
2	90º	6%	6%	1.6%	14%	13%	37.2%	26.5%
3	180º	6%	6%	2.1%	16%	16%	37.2%	25.9%
4	270º	6%	7%	2.1%	16%	15%	37.2%	35.5%
5	0º	8%	36%	3.3%	34%	53%	37.5%	34.8%
6	90º	8%	7%	1.9%	26%	35%	37.4%	35.5%
7	180º	8%	9%	2.3%	28%	38%	37.3%	35.1%
8	270º	8%	10%	2.4%	29%	39%	37.1%	35.6%
9	0º	15%	0%	0.5%	16%	0%	37.6%	36.7%
10	90º	15%	18%	2.2%	38%	51%	37.7%	35.9%
11	180º	15%	26%	3.0%	44%	52%	37.6%	35.7%
12	270º	15%	40%	4.0%	37%	53%	37.5%	35.7%
13	0º	29%	36%	2.5%	40%	35%	37.6%	35.4%
14	90º	29%	44%	3.5%	58%	56%	37.6%	35.7%
15	180º	29%	41%	3.5%	56%	55%	37.5%	35.5%
16	270º	29%	47%	4.5%	58%	50%	37.5%	35.6%

Table 14: EIA Academy SCS simulation results after applying the rating scales and CRW's.

Scenario No.	**Orientation**	**WWR**	**DLA**	**µDF**	**DA**	**UDI**	**TDH**	**HDH**	**SCS**
1	0º	6%	13.0	0.0	0.0	0.0	26.4	32.4	71.8
2	90º	6%	6.5	0.0	0.0	0.0	26.4	32.4	65.3
3	180º	6%	6.5	30.6	0.0	0.0	26.4	32.4	95.9
4	270º	6%	6.5	30.6	0.0	0.0	26.4	26.0	89.4
5	0º	8%	19.5	30.6	0.0	33.1	26.4	26.0	135.5
6	90º	8%	6.5	0.0	0.0	0.0	26.4	26.0	58.8
7	180º	8%	6.5	30.6	0.0	0.0	26.4	26.0	89.4
8	270º	8%	13.0	30.6	0.0	0.0	26.4	26.0	95.9
9	0º	15%	6.5	0.0	0.0	0.0	26.4	26.0	58.8
10	90º	15%	13.0	30.6	0.0	33.1	26.4	26.0	129.0
11	180º	15%	19.5	30.6	0.0	33.1	26.4	26.0	135.5
12	270º	15%	19.5	30.6	0.0	33.1	26.4	26.0	135.5
13	0º	29%	26.0	30.6	0.0	0.0	26.4	26.0	108.9
14	**90º**	**29%**	**32.5**	**30.6**	**33.2**	**33.1**	**26.4**	**26.0**	**181.7**
15	**180º**	**29%**	**32.5**	**30.6**	**33.2**	**33.1**	**26.4**	**26.0**	**181.7**
16	**270º**	**29%**	**32.5**	**30.6**	**33.2**	**33.1**	**26.4**	**26.0**	**181.7**

Thus, it was observed that the maximum SCS value corresponded with a WWR of 29%, considering all orientation except 0º. This design configuration produced a SCS value that is 153% higher than the base scenario (Orientation angle of 0º with a WWR of 6%). By the same token, the SCS simulation results for all scenarios pertaining to the MIC Main Fire and Rescue Station are shown in Tables 15 and 16, respectively, similar to the previous case study. Meanwhile, an extract of the daylighting simulation software DIVA® of the facility is shown in Figure 5. It was observed that the maximum SCS value corresponded with a WWR of 12%, considering and orientation angle of 270º. This result corresponds to a SCS values that is 151% higher than the base scenario (Orientation angle of 0º with a WWR of 6%).

Table 15: MIC Main Fire and Rescue Station SCS simulation results expressed as % figures.

Scenario No.	Orientation	WWR	DLA	μDF	DA	UDI	TDH	HDH
1	0º	49.0%	2.8%	45.0%	43.0%	49.0%	25.7%	28.9%
2	90º	51.0%	4.6%	54.0%	39.0%	51.0%	25.4%	29.1%
3	180º	51.0%	4.8%	53.0%	37.0%	51.0%	25.7%	28.6%
4	270º	51.0%	4.6%	53.0%	37.0%	51.0%	26.1%	28.7%
5	0º	51.0%	3.9%	54.0%	45.0%	51.0%	25.6%	29.0%
6	90º	50.0%	3.8%	53.0%	44.0%	50.0%	25.5%	29.0%
7	180º	50.0%	4.0%	53.0%	42.0%	50.0%	25.9%	28.4%
8	270º	51.0%	3.9%	49.0%	43.0%	51.0%	26.3%	28.5%
9	0º	54.0%	4.6%	52.0%	46.0%	54.0%	25.7%	28.8%
10	90º	53.0%	4.8%	51.0%	46.0%	53.0%	25.7%	28.9%
11	180º	53.0%	4.5%	53.0%	28.0%	53.0%	26.2%	28.1%
12	270º	53.0%	4.6%	52.0%	44.0%	53.0%	26.6%	28.4%
13	0º	56.0%	4.1%	53.0%	48.0%	56.0%	26.2%	28.6%
14	90º	56.0%	5.3%	54.0%	46.0%	56.0%	26.0%	27.5%
15	180º	52.0%	3.5%	56.0%	46.0%	52.0%	26.7%	27.5%
16	270º	53.0%	5.8%	51.0%	53.0%	53.0%	27.2%	28.0%

Table 16: MIC Main Fire and Rescue Station results after applying the rating scales and CRW's.

Scenario No.	Orientation	WWR	DLA	μDF	DA	UDI	TDH	HDH	SCS
1	0º	6%	32.5	30.6	0.0	0.0	33.0	32.4	128.5
2	90º	6%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
3	180º	6%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
4	270º	6%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
5	0º	8%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
6	90º	8%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
7	180º	8%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
8	270º	8%	32.5	30.6	0.0	0.0	33.0	32.4	128.5
9	0º	10%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
10	90º	10%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
11	180º	10%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
12	270º	10%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
13	0º	12%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
14	90º	12%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
15	180º	12%	32.5	30.6	33.2	0.0	33.0	32.4	161.7
16	**270º**	**12%**	**32.5**	**30.6**	**33.2**	**33.1**	**33.0**	**32.4**	**194.8**

As for the MIC Mosque, a screenshot of the EnergyPlus® thermal simulation is displayed in Figure 6, while the simulation results are presented in Tables 17 and 18 using the two-step preciously-explained methodology. It was observed that the base design, with orientation angle being 0º and the WWR set as 8% corresponded with the optimum SCS score.

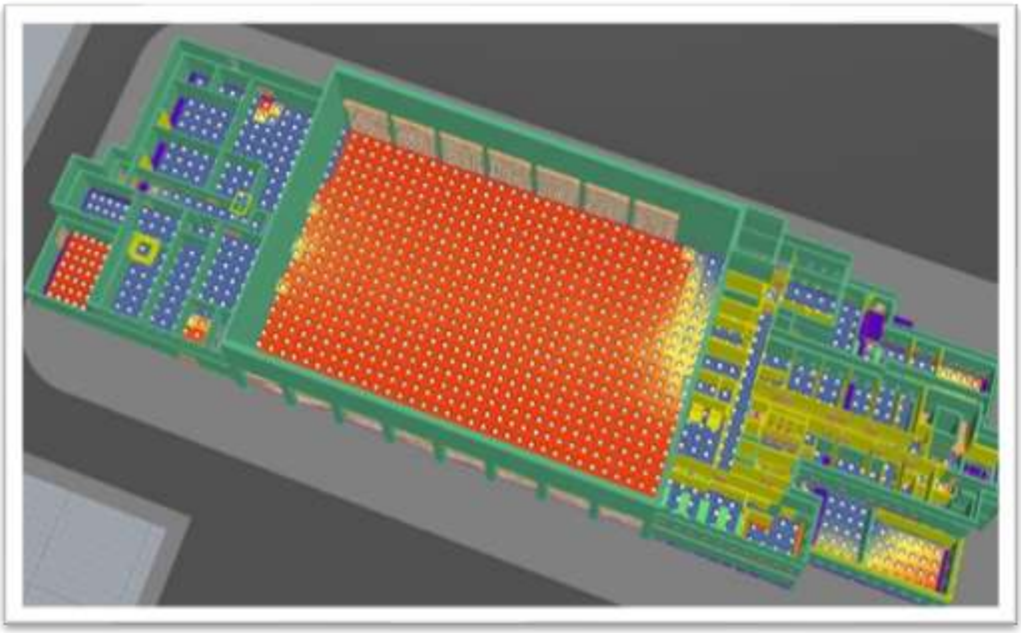

Figure 5: DA screenshot for MIC Main Fire and Rescue Station using DIVA® package [52].

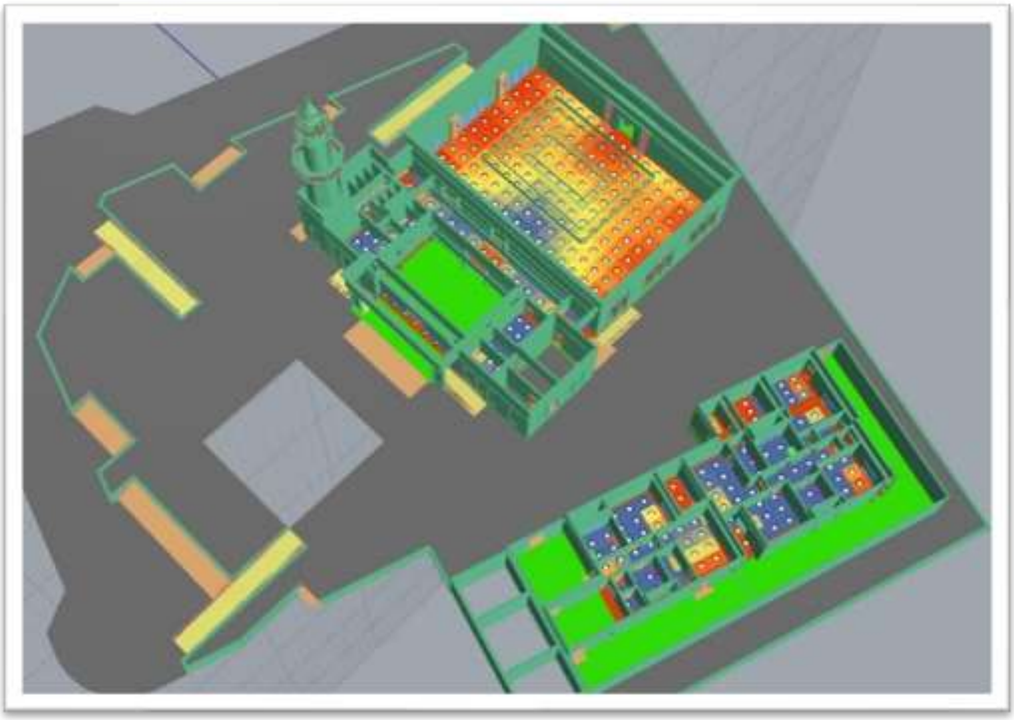

Figure 6: DA simulation screenshot for the MIC Mosque using DIVA®.

Table 17: MIC Mosque SCS simulation results *expressed as % figures.*

Scenario No.	Orientation Angle	WWR	DLA	µDF	DA	UDI	TDH	HDH
1	0º	8%	43.0%	2.5%	57.0%	25.4%	14.2%	25.4%
2	0º	10%	45.0%	4.6%	43.0%	24.7%	15.1%	24.7%
3	0º	12%	15.0%	1.9%	41.0%	23.3%	16.4%	23.3%
4	0º	15%	18.0%	3.8%	42.0%	22.9%	16.8%	22.9%

Table 18: MIC Mosque SCS simulation results after applying the rating scales and CRW's.

Scenario No.	Orientation Angle	WWR	DLA	μDF	DA	UDI	TDH	HDH	SCS
1	**0º**	**8%**	**31**	**33**	**33**	**33**	**19**	**0**	**149**
2	0º	10%	31	33	0	33	19	0	116
3	0º	12%	12	0	0	33	19	0	65
4	0º	15%	12	33	0	33	19	0	98

Results were then verified by virtue of expert questionnaires, which were responded by a group of 16 industry experts having an average experience per expert amounting to 17 years. Nevertheless, the targeted group of industry experts included design consultants, architectural engineering professors, BIM specialists and architectural engineering working in the field of construction. The response rate of the survey was 100%, where 91% of the experts on average either agreed or strongly agreed with the model's significance, rationale and validity of its results. Moreover, 93% of the surveyed sample either agreed or strongly agreed with the adopted rating scales for performance criteria scores, pertaining to daylighting and thermal comfort metrics. The same percentage also either agreed or strongly agreed with using the AHP method for obtaining of CRW's.

5. CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORK

The proposed BIM and AHP-based early design multi-objective optimization tool was used to estimate the optimum design combination featuring building orientation angle and WWR, considering three case studies, all located in hot arid climate. The case studies represented a school building, a firefighting station and a house of worship. While the model optimum output for the school and fire station case studies provided significantly higher SCS values (153% and 151%, respectively) compared to base designs, the mosque's base design proved to be the most optimal as opposed to the other scenarios considered in the model. Needless to mention that while 16 building orientation and WWR scenarios were considered for the school and fire station, only 4 scenarios were attempted for the mosque, as it was not allowable to change the building orientation to respect the direction of the *qibla*.

Some areas were identified as new contributions to the body of knowledge: (1) This work is an early attempt to combine various performance simulation metrics into a single holistic measure; SCS; (2) This concept was applied for three types of prototypical buildings: Educational, civil defense and congregational facilities; (3) This paper offers an attempt to bridge the research gap observed in BPS (especially daylighting and thermal comfort) in hot arid climate; (4) This paper features expert-based performance criteria rating scales, upon which it establishes a non-complex linear AHP-based methodology for estimating CRW's; (5) This work may be applied to a wider variety of prototypical designs, such as residential, commercial, medical and administrative office buildings.

On the other hand, some aspects were defined by the authors as areas for potential improvement. For instance, while the verification of the AHP PCM depended on arithmetic consistency indices and ratios, there could be still a need to verify these findings against other more complex non-linear AI methods and techniques. Among such suggested methods come heuristic, stochastic and statistical multi-objective optimization. Another limitation lies in the negligence of mechanical HVAC systems in all of the considered case studies, making the methodology more suited to naturally-ventilated buildings. As such, further work is suggested for similar cases, while including mechanical acclimatization systems and their associated properties in thermal performance simulation and modelling. Meanwhile, recent research such as Attia el al. (2012) and Wang et al. (2020) strongly advocate the use of non-traditional BPS metrics, such as Spatial Daylight Autonomy (sDA), Annual Sunlight Exposure (ASE), and subjective thermal metrics [54, 55]. Nevertheless, according to ASÉ (1989), Darula & Kittler (2002), CEN (2011) and Reinhart (2014), DF was primarily developed as a daylighting metric under overcast sky conditions, and is calculated for standard CIE overcast sky as well as 20 different CIE clear skies [49] [56-58]. On the contrary, sDA and ASE have gained significant momentum in assessing the performance of daylit spaces by numerous illuminating engineering societies [56] [58]. In light of these recent research advances, further work is recommended to consider such new daylighting and thermal comfort metrics in the holistic SCS estimation, specifically in lieu of DF, TDH and HDH. Nevertheless, other BPS parameters might also be considered in the holistic measure such as energy and acoustic performance. An equally important observation lies in the slight difference between CRW values (±2.5%, except for μDF: ~5%), suggesting marginal CRW impact on the SCS value that on the SCS. However, the door remains wide open for the inclusion of more sustainability performance criteria, where RCW may exhibit larger variance. The variances between CRW values while being marginal, they were obtained through an arithmetically-verified AHP calculation method. This is in fact posed a challenging limitation while carrying out the simulation. While four daylighting metrics were used only two thermal performance metrics were considered. Thus, achieving a better degree of differentiation between the overall performance of case studies, lies in a more balanced representation of thermal performance metrics as opposed to daylighting measures. This representation begins by considering a wider range of thermal performance parameters by the expert panel. This is foreseen to provide more varying levels of CRW's as a result of the variance that could be obtained in relative importance values determined by the expert panel. Nevertheless, had the methodology been verified arithmetically, the opportunity to mitigate this limitation constitutes in itself an invitation for future work on improving the results.

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