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The Impact of Architects' Reasoning on Early Design Decision-Making for Energy-Efficient Buildings

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Abstract: Architects arguably have the greatest influence on the design of buildings. One of the key factors that make it hard to improve the energy efficiency of buildings is the use of architects' reasoning by architects at the early design stage. There is a need to assess the impact of architects' reasoning on the energy performance of the designed building. To this end, this research was conducted in two phases. Firstly, the most influential design parameters, in terms of energy efficiency, were identified and used to develop a design exercise issued to a sample of practising architects in the north of Algeria. Design exercise participants were required to minimise expected energy consumption along with the construction cost. Secondly, computer-generated dynamic design optimisation for the same design task was conducted in DesignBuilder v6. 1 .8. The computer-generated designs decisively outperformed the human-generated designs. The experienced architects achieved the least-performing designs rather than those with less experience.

Keywords: sustainability; architects' reasoning; optimisation; pareto front; optimal design; early design decisions; knowledge repertoire

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1. Introduction

To design energy-efficient buildings that respond to the current challenges of sustainability, particular aspects have to be considered from the early stage of design. Important decisions are made early in the design that significantly affect a building's energy performance over its lifecycle [1–3]. These decisions are in the form of several design variables that that need to be fixed early in the design process. By considering energy efficiency at an early stage, the architect has the greatest influence over the lifecycle performance of a building. Influential energy-efficient design variables such as building orientation and building fabric are usually decided early on. Once these decisions have been made, it is difficult to make subsequent revisions in order to enhance energy efficiency. Although energy performance is of paramount importance, it cannot be considered in isolation without regard for other design priorities.

As energy aspirations become increasingly ambitious, the intricacy of these aspirations and the complexity of building design challenge the architect's built-up experience [4]. Ercan and Elias-Ozkan [5] argue that the integration of energy performance measures needs to start from the conceptual design stage. The architect's reasoning is therefore crucially important during the early design stage to ensure energy-informed decisions are made in a timely manner.

The energy performance gap between design intent and actual performance during operation originates in early design decision-making, arguably due to the cognitive process employed by architects' minds while working on design problems [6]. Commonly, the early design process is controlled by architects alone, usually without prior energy-efficiency expertise [7]. This was supported by Rezaee et al. [8], who reported the wide confidence intervals for performance predictions in thermal building performance during early design stages; they reported confidence levels well below 50%. Lacking expertise in building physics, architects' choices are predominantly guided by intuition and experience that fails to account for the implications of design decisions on building energy performance. Consequently, architects tend to favour conventional solutions (known by practice) even though their energy performance is not optimal. The amount of information humans may consider at a time is limited to a few pieces of information, which can obstruct human design problem-solving.

Such limitations have been observed as humans solve increasingly complex parametric design problems. Hirschi and Frey [9] report experiments showing that human problem-solving performance declines considerably as the number of considered variables increases. Much research has been conducted into the architectural design process and the methods designers use to solve design problems [10–12]. Such work signposts the scope for significant original research to test architects' reasoning concerning energy performance during the early design stage. By reasoning, the knowledge repertoire that is used by architects to make early design decisions is meant to inform and guide their initial creative process.

Within a background of more stringent building energy targets, designers must approach with care the task of designing their buildings. This research aims to assess the tacit reasoning of architects and its role in achieving energy-efficient design. Therefore, the primary building design performance objective considered in this paper is energy consumption. Cost was added as a second objective function, because, in real-world projects, it is hard to imagine a scenario in which the designer is only concerned with energy performance but unconcerned with the cost of the resulting design. The most important design variables that have the highest impact on energy performance (as identified from an online questionnaire survey) were then used to design an exercise activity whereby each participant was given the base case design model and asked to modify it to achieve the two competing objectives.

2. Architects' Reasoning in Design Decision-Making

Much of the knowledge in people's heads is constructed within the system in which they operate, and, therefore, this reasoning mechanism is the property of the system [13]. In the case of building performance, energy simulation and optimisation are typically employed to create design solutions that meet the desired design objectives. As a result, the majority of the simulation software that is generally used supports optimisation tasks that are effective only late in the design process. Energy performance simulation generally requires precise building geometry as well as data about the fabric characteristics of building elements. The early design stage, however, is characterised by high-level activity with regards to the architectural aspects of the design, where such design precision is not yet possible. Petersen [14] suggests concentrating significant effort in the early design stage by handling the design variables that architects can access and control at this early stage. However, the lack of building physics expertise has always hindered design decision-makers [15]. Without being able to investigate design alternatives against performance targets early on in the design process, the resulting design may not be optimal due to the multiple trade-offs to be made. In the absence of precise simulation predictions, architects tend to use their reasoning based on experience to develop a design alternative. Thus, in this research, architects' reasoning is singled out as the factor which differentiates design decision-making by humans versus the precise optimisation of computers. DesignBuilder was used as the optimisation platform, as it has the capability of running optimisation with multiple design objectives, for the following research: energy consumption and construction cost.

3. Method

Our research method adopts a descriptive design models paradigm, which emphasises the process of generating a solution from an early stage. This paradigm emerged as a response to the notion that what many designers do in actual practice does not completely algin with the classical systematic pattern of design activities. De Wilde [6] observes that descriptive decision-making does not always ensure optimum energy performance-based design. Therefore, this research assesses the performance of this naturalistic decision-making driven by architects' reasoning. Two research methods were combined in an attempt to isolate the effect of tacit reasoning by human architects. Firstly, a design exercise experiment was conducted to trigger naturalistic design decision-making in practising architects. Secondly, computational dynamic simulation and optimisation was applied to the same design problem to explore the entire design space thoroughly. Figure 1 outlines the research design.

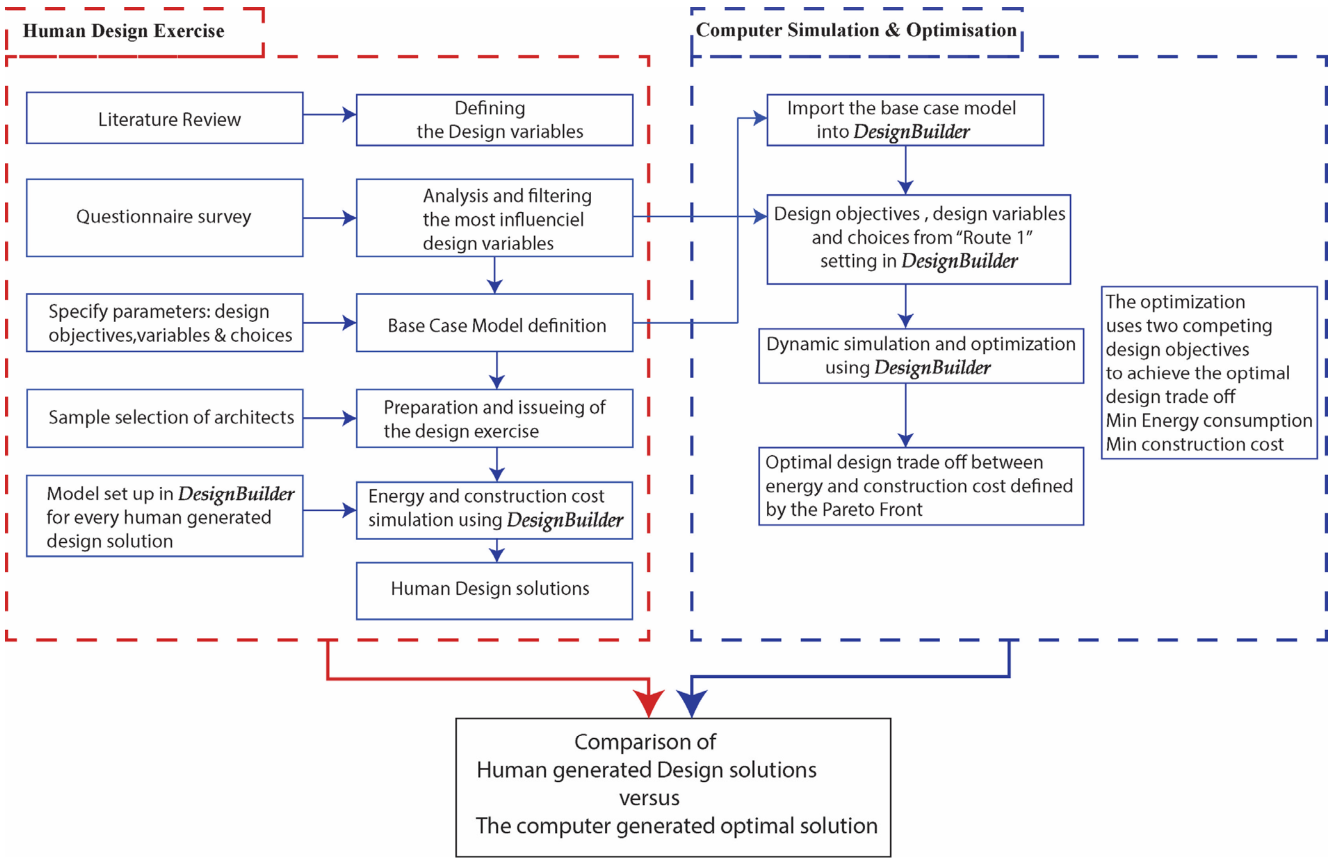

Figure 1. Research method.

3.1. Human Architects Design Experiment

Researchers use several approaches for empirically studying human designers, including verbal protocols, case studies, and design experiments [11]. Design experiments were adopted, because they enable the precise study of specific design processes with rigorous statistical comparisons, rather than case studies and verbal protocols that may contain more conflating contextual variables that obscure the validity of conclusions. Figure 2 presents the experimental procedure for the design experiments.

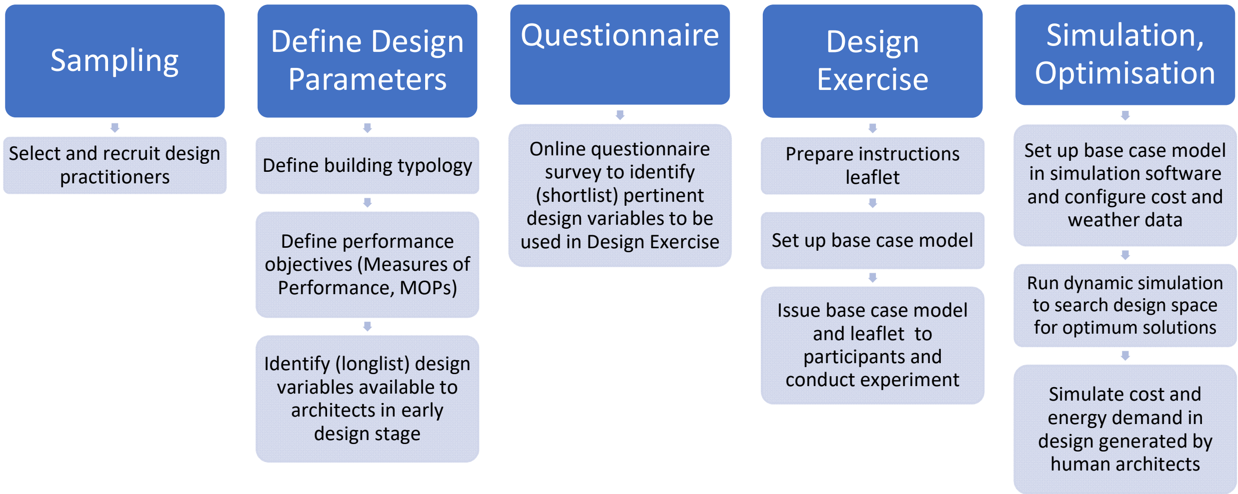

Figure 2. Experimental procedure for design experiments.

In the experiment, practicing architects were asked to complete a design exercise, balancing the two competing objectives of minimising energy consumption and reducing construction cost. Each architect's years of experience was measured as an independent variable in the design experiment. Experimental comparisons of novices and experts are common in design research [16,17].

A design task base case model of a residential building block was created. Designers were asked to modify the base case design considering two design objectives: to minimise energy consumption and to minimise construction cost, with a particular emphasis placed on an energy-efficient design. Measures of performance (MOP) indicators were used to evaluate architects' reasoning in terms of building energy and cost performance.

3.2. Base Case Model Definition

3.2.1. Weather Profile

Weather conditions directly impact the results of any energy performance simulation [18,19]. The location of this study was chosen to be Algeria. Direct access to the Algerian National Council of Architects by the first author facilitated the recruitment of research participants for the design exercise. The location was also chosen due to the importance of the Mediterranean climate and its applicability in many other countries in the region. Furthermore, Algerian public policy prioritises energy efficiency as a matter of urgency [20]. The weather profile from Sahabi Abed and Matzarakis [21] for the region of Algiers was used for the base case model, which was provided to the design experiment participants, in addition to input in DesignBuilder, for the simulations and, subsequently, for the optimisation.

3.2.2. Base Case Model Description

The distribution of energy usage in Algeria by sector indicates that buildings account for a very high proportion. The residential sector in particular accounts for 43% of the total energy consumption, according to the energy balance released by [22]. For this reason, a design task base case model of a residential building was chosen for this design exercise. The model was a typical five-storey residential block, with each floor comprised of four apartments, as shown in the floorplans of Figures 3 and 4, the latter of which shows a 3D visualisation of the whole building.

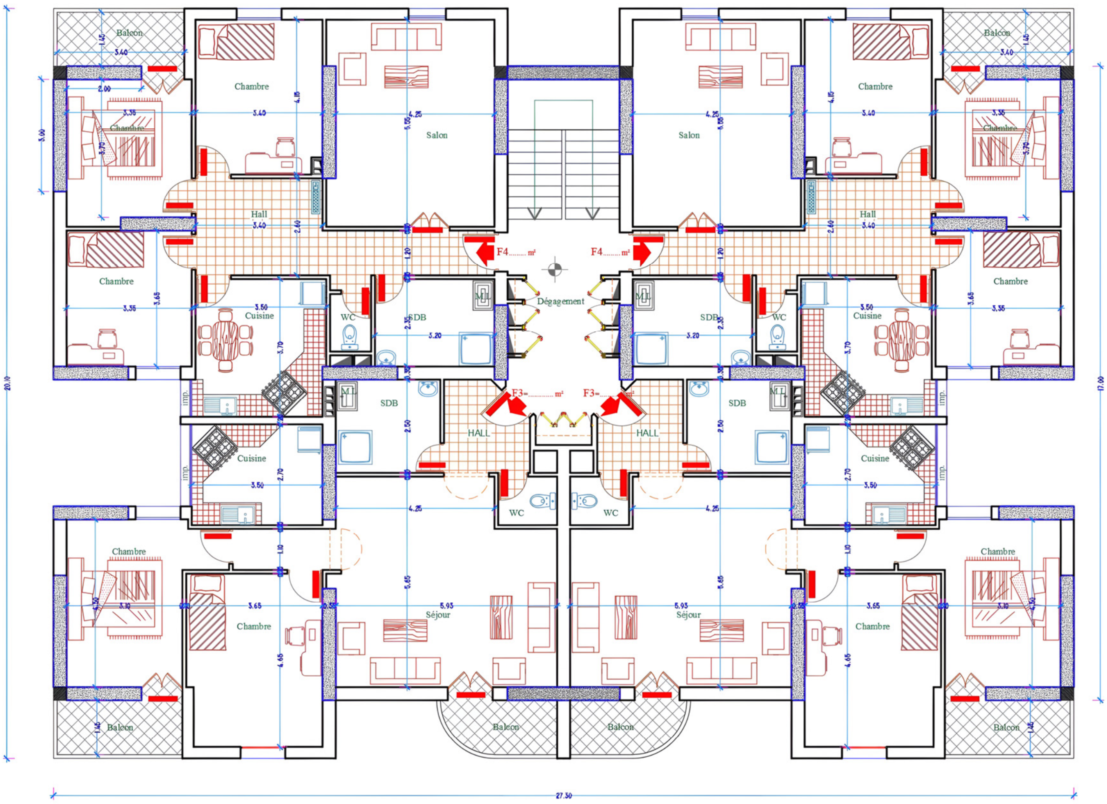

Figure 3. Typical architectural floorplan of the base case model.

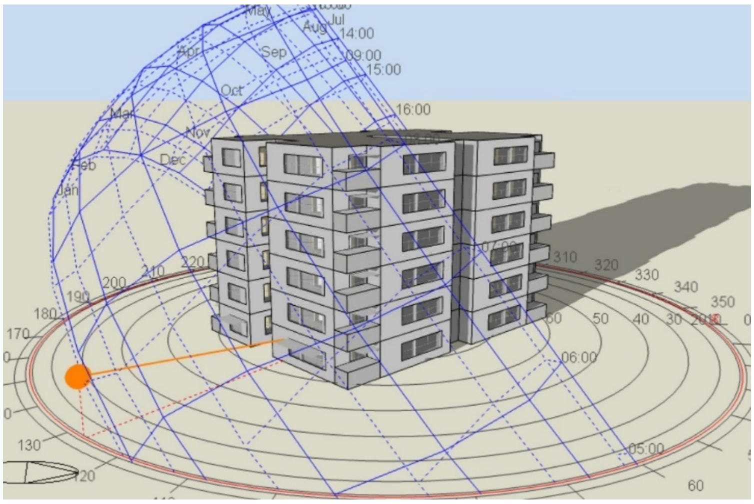

Figure 4. Entire building 3D visualization of the base case model considered for this study.

The floor area of each floor is 511.55 m^2 with a floor-to-ceiling height of 3.0 m. The base case building was assumed to be free from overshadowing from surrounding buildings.

3.2.3. Sampling Strategy

Purposive sampling was used to recruit architects for the design experiment. This approach is suited to understanding aspects of real-world architecture practice. As years of experience was identified as a significant variable, the sample was stratified by recruiting roughly uniform numbers of participants in each of the five-year experience ranges. In Algeria, as is the case for most countries, the architect typically leads the entire building design development process. In early design, architects receive relevant project requirement information from a developer or owner and develop a conceptual building design.

Fundamental decisions are made at this stage, such as 3D massing, building orientation, and materials.

3.2.4. Questionnaire Survey to Identify Pertinent Design Variables

Design experiment participants would be asked to make design decisions about particular building characteristics. For this purpose, it was necessary to identify the most important design variables affecting building energy performance. Therefore, an online questionnaire survey was issued to a separate sample of practising architects to help set up the design experiment. Architects were asked to rank a number of pertinent variables identified from the literature by order of importance to achieving an energy-efficient building and then to rate the potential impact of each variable on final energy performance. A set of 109 questionnaire responses was received, and the data can be found in Figure 5. Based on these assessments of importance and impact by professional architects, the following variables were selected to be incorporated into the design exercise: external wall construction, roof construction, glazing type, window frame type, south/east/west shading, building orientation, and window-to-wall ratio.

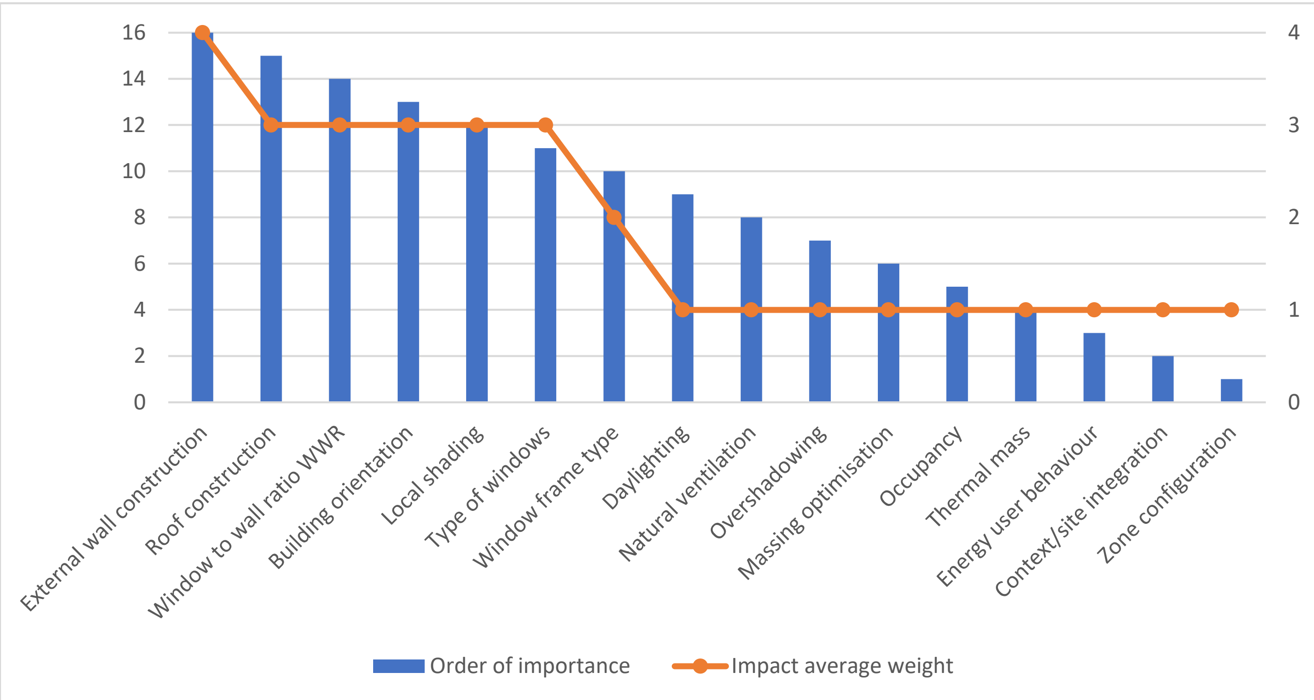

Figure 5. Design variable ranking by order of importance in bars and impact average weight by line design exercise.

Once the base case model was fully developed and pertinent design variables were identified, a design exercise was developed in which professional architects as research participants were asked to modify the base design by altering the pertinent design variables in order to balance the two objectives of construction cost and energy efficiency. Each design generated by a participant had to be assessed for its achievement of the two design objectives. DesignBuilder was selected as the design simulation application, as it has an interface for a leading global simulation engine, EnergyPlus 9.6.0.

Two hundred participants were issued a design exercise leaflet along with the base case model of the residential building block in RVT (Autodesk Revit 2019) format. The data were collected in dual format: in-person visits to architectural offices, where possible, and online, where in-person visits were not feasible.

Participants were instructed to improve the base case model's performance against the two design objectives by reconsidering the pertinent design variables. The list of the design variables was created as a database within Autodesk Revit. The term 'design variables' in this study refers to those variables that the designer can change. This is consistent with other studies, such as Hamdy et al., [23], and Sasena et al. [24]. The term 'design choices' refers to the values that each design variable (in this case, window type) may take, e.g., single glazing, double, grazing, and triple glazing. Each design variable had a number of design choices associated with it, and the architects had to manually apply the design choices in the Revit model provided. These parameters are laid out in Tables 1–3. The types of external wall construction were sourced from the study of Baglivo et al. [25] on optimised external walls in the Mediterranean climate. Each type of wall has predefined layers in which different materials (in the layer thickness range column) are allowed to vary according to the design variables and choices that architects think are the most appropriate. The thermal specifications of insulation materials, in terms of thermal conductivity, heat capacity, and density, have been identified based on the standard EN ISO 10456 [26].

Table 1. Building fabric variables.

Choices for Building Envelope Variable	Layers	Choices for Layer Thickness Choices (mm)
Types of external walls; the choice of internal/external insulation was left to the participants		
External heavyweight wall Type 1	Concrete	90/100/110/120/130/140/150
	Polyurethane foam 1	20/30/40/50/60/70/80/90/100/120
	Concrete exp. clay	50
	Polyurethane foam 2	20/30/40/50/60/70/80/90/100/110/120/130/140
	Concrete	100
External heavyweight wall Type 2	Concrete	10/20/30/40/50/60/70/80/90/100/110/120/130/140/150
	Cork panel exp.	10/20/30/40/50/60/80/100/120/140/160
	Cellulose fibre	30/40/50/60/80/100/120/140/160/180
	Brick	120
	Polyethylene exp.	2/3/4/5/6/8/10/12/15/20/25/30
External heavyweight wall Type 3	Concrete	90/100/110/120/130/140/150
	Polyurethane foam 1	20/30/40/50/60/70/80/90/100/120
	Cross-laminated timber panels	60/78/95/128/146/162/202
	Polyurethane foam 2	20/30/40/50/60/70/80/90/100/110/120/130/140
	Plaster	15
External lightweight wall Type 4	Concrete	90/100/110/120/130/140/150
	Hemp fibre	30/40/50/60/80/100/120/140/160/180/200/220/240
	Air	5/10/15/20/25/30/35/40/45/50
	Cross-laminated timber panels	60/78/95/128/146/162/202
	Cork panel exp.	10/20/30/40/50/60/80/100/120/140/160
External lightweight wall Type 5	Concrete	90/100/110/120/130/140/150
	Fibreboard	20/40/60/80/100/120/140/160
	Polyethene exp.	2/3/4/5/8/10/12/15/20/25/30
	Cork panel exp.	10/20/30/40/50/60/80/100/120/140/160
	Plaster	15

Table 1. *Cont.*

Choices for Building Envelope Variable	Layers	Choices for Layer Thickness Choices (mm)
External lightweight wall Type 6	Concrete	90/100/110/120/130/140/150
	Wood fibre hardboard	20/40/60/80/100/120/140/160
	Wood fibre hardboard	20/40/60/80/100/120/140/160
	Polyurethane foam 1	20/30/40/50/60/70/80/90/100/120
	OSB (Oriented Strand Board)	15/18/22/25
Roof type		
Ground floor This part is fixed	Ceramic finishing	7
	Cement mortar	50
	Polystyrene	0 to 50
	Reinforced concrete slab	200
Roof type 1-hollow core	Plasterboard	15
	Hollow concrete slab	160
	Compression slab	40
	Polystyrene	0 to 180
	Sealing layer	20
Roof type 2-prestressed reinforced concrete	Plasterboard	15
	Solid slab	150
	Vapour barrier	20
	Polystyrene	0 to 180
	Sealing layer	20

Table 2. Characteristics of glazing typologies.

Window Variables	Window Layer Thickness (mm)	U-Value (W/m^2 K)	SHGC	Solar Transmission	Solar Reflectance	Visual Transmission
Single glazing (Glz1)	2.5	5.74	0.87	0.85	0.075	0.901
Double glazing filled with air (Glz2)	2.5/12.7/2.5	2.95	0.777	0.727	0.129	0.817
Triple glazing filled with air (Glz3)	2.5/12.7/2.5/12.7/2.5	2	0.7	0.624	0.168	0.744
Double glazing filled with air +1 low emissivity layers facing inward (Glz4)	3/12.7/2.5	1.76	0.597	0.544	0.22	0.769
Double glazing filled with argon +1 low emissivity layers facing inward (Glz5)	3/12.7/2.5	1.43	0.596	0.544	0.22	0.769

Table 3. Different levels of selected parameters.

Other Variables	Symbol	Lower Limit	Upper Limit	Unit
Shading coefficient of windows facing south	SCs	0	1	-
Shading coefficient of windows facing east	SCe	0	1	-
Shading coefficient of windows facing west	SCw	0	1	-
Glazing	Glz	Glz1, Glz2, Glz3, Glz4, Glz5	-	-
Type of window frame	WF	Aluminium, Wood, UPVC	-	-
Building Orientation	BO	±45°, ±90°	-	Degrees from North
Window-to-wall ratio	WWR	20	90	%

All the architects' generated designs were simulated in DesignBuilder, taking into account all the configurations decided by the participants; this includes the type of wall, insulation thickness layers, type of roof, type of glazing and window frame, building orientation, window-to-wall ratio, air change rate and local shading devices, and the size. The purpose of this sub-task was to evaluate the two MOPs of each design, which were energy consumption in kWh/m^2 and total construction cost in DZD, as shown in Figure 6.

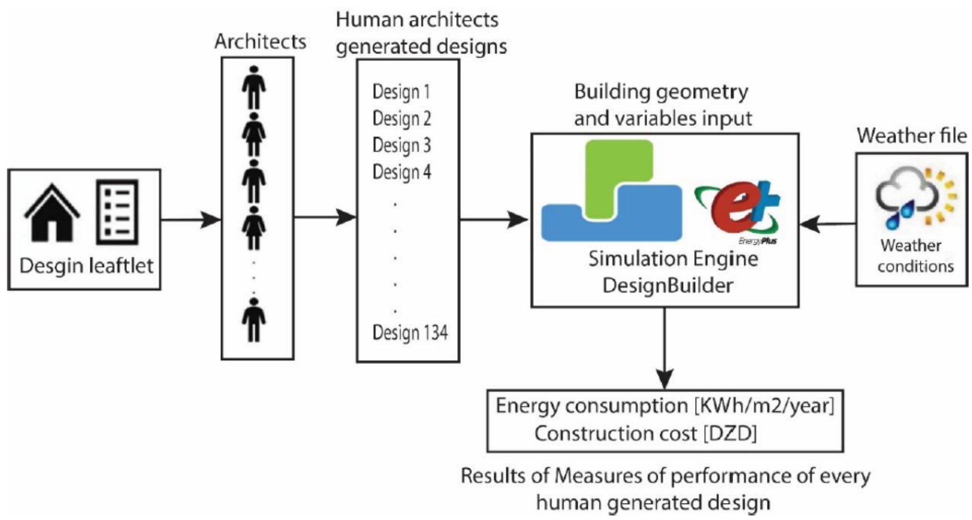

Figure 6. Workflow of model's preparation for energy and cost performance simulation in DesignBuilder.

Following the selection by each architect of alternative design options in line with the two design objectives, the resulting design was assessed by using DesignBuilder to predict its energy consumption and construction cost, as measures of performance (MOP). The gbXML standard was used to export the models from Revit and import them into DesignBuilder. A simulation was run to calculate the expected lifecycle energy consumption in kWh/m^2 and total construction cost in DZD (Algerian dinar).

A few assumptions had to be made in DesignBuilder when entering the simulation input settings:

- Activity: The average occupancy for residential apartments in Algeria is four people per apartment. A typical family would consist of a father, mother, and two to three children. From the building layout, the total occupancy area of each flat is approximately 90 m^2. Therefore, the occupancy density specified in the simulation was 0.055 people/m^2. Furthermore, DesignBuilder's default metabolic factors were used:

1.00 for men, 0.85 for women, and 0.75 for children or an average value if there is a mix of occupants.

- The lighting heat gain was set to 7 W/m^2 from the CIBSE energy code of practice [27]. The default diversity factor of 70% was used for the lighting heat gain, since it is unlikely that all lights will be on simultaneously. From the assumed occupancy schedule, lighting in the base case model was set to be used daily from 12:00 to 23:00.
- The heating and cooling setpoint temperatures were selected as default values; 21 °C for heating and 25 °C for cooling.
- Minimum fresh air was assumed to be 10 L/s–person, as suggested in the CIBSE 2015 guide [27]
- Depending on the nature of the treated zone in the energy simulation model, the internal gains, such as from occupants and equipment, were left at their default values from DesignBuilder, depending on the nature of the occupant activity schedule and metabolic rate.

Weather data that are used in DesignBuilder are based on EnergyPlus weather files that define external conditions during simulation. Each location has a separate weather file describing the external temperature, atmospheric conditions, solar radiation, etc., for every hour of the year at that location. The file location of this research was set in the North African region of Algeria and specifically in the capital Algiers.

3.3. Computer Optimisation

DesignBuilder's dynamic simulation and optimisation was used to compare the performance of the human-generated designs to those from computer-generated optimum design. Computer optimisation was conducted to benchmark the quality of the human designs, highlighting the role of human reasoning. Optimisation in design is a process where design variables and objectives need to be clearly defined in the early stages of the design process [28]. The variation and the number of design variables make it possible to identify a large number of possible designs including the interactions of the design variables that eventually determine how buildings are constructed and use energy [29]. The more design variables there are and the more choices available for each design variable, the larger the design search space (the set of all possible designs). DesignBuilder has a built-in genetic algorithm in its optimisation engine called r It is widely used as a multi-objective method that supports the search for a good trade-off between a well-converged and well-distributed solution set. This method is used in this research to search for optimal design solutions. The same entire set of design variables and design choices that were used for the human architect design experiment were also used in the optimisation exercise to allow a robust comparison between the human architects' generated design and the computation. The design variables were taken through a wide range to ensure that the optimum design could be found in that range. The design variables were incremented in sufficiently small steps through their respective ranges to avoid missing optimum values. The variables used in this experiment fall into two categories: variables with numerical design choices and those with non-numerical design choices. The ranges and incremental step values for the numerical variables were set heuristically, informed by best practice in design. For non-numerical variables such as building floor and roof, only one design alternative option was set to limit the sheer number of design possibilities.

4. Results and Discussion

The results of the preliminary survey are shown in Figure 5. These design variables emerged from the literature and are assumed to be within the architect's control. The aim was to rank the variables by order of importance, as a precursor to including the most important variables in the subsequent design experiment. However, it is recognised that architects might not have full freedom to make early-stage decisions due to high uncertainty and the complexity of stakeholders. Therefore, architects were also asked to rate the impact on energy performance of the variables [7]. External wall construction was ranked as the most important variable with an impact factor of four, followed by roof construction and window-to-wall ratio (*WWR*), each with an impact weight factor of three. The variables included in the design exercise (Tables 1–3) were carefully selected to represent the top ranked variables from Figure 5. The design exercise was delivered to a sample of 200 professional architects. A total of 134 valid design solutions out of 200 were received. The location of the study had a direct effect on the results due to prevalent common design practices and design culture.

The building was modelled in DesignBuilder, considering all the configurations decided by the participants based on Tables 1–3. The DesignBuilder platform has a construction cost component which was used to calculate the initial construction cost of each design variant provided by the architects. The cost model used in the calculation is based on per unit area averages from a published database linked to DesignBuilder. The prices of materials and labour cost were sourced from ©CYPE Ingenieros, S.A [30]. The price generator is an engine that allows a calculation of the real cost of construction materials and labour in Algeria, where the experiment was carried out. It provides an updated real-time construction cost adjusted to the market in which the project is built. A cost correction factor was applied specifically for Algeria. The accuracy of absolute cost estimates is unimportant here, but rather the relative costs used to compare design alternatives and identify optimum solutions were used instead. Table 4 shows the results of the two performance indicators, energy consumption in kWh/m^2/year and construction cost in *DZD* for the 134 designs submitted by the architects.

Table 4. Simulation results of energy consumption and construction cost for architects' designs.

Human Designs	Energy kWh/m^2/Year	Construction Cost in Euros
Architect 1	143.07	260,210,000.00
Architect 2	151.67	257,351,000.00
Architect 3	150.01	253,508,000.00
Architect 4	173.47	253,367,000.00
Architect 5	172.64	262,919,000.00
Architect 6	157.38	257,025,000.00
Architect 7	182.19	254,735,000.00
Architect 8	174.04	260,942,000.00
Architect 9	156.81	261,224,000.00
Architect 10	214.39	232,977,000.00
Architect 11	215.87	232,580,000.00
Architect 12	190.56	235,461,000.00
Architect 13	163.46	260,451,000.00
Architect 14	190.37	235,731,000.00
Architect 15	215.61	232,501,000.00
Architect 16	136.03	260,651,000.00
Architect 17	137.92	260,965,000.00
Architect 18	215.85	232,117,000.00
Architect 19	213.73	236,004,000.00
Architect 20	170.91	260,738,000.00
Architect 21	213.09	235,553,000.00
Architect 22	169.02	262,370,000.00
Architect 23	169.5	261,038,000.00

Table 4. *Cont.*

Human Designs	Energy kWh/m^2/Year	Construction Cost in Euros
Architect 24	169.98	260,500,000.00
Architect 25	215.3	232,201,000.00
Architect 26	156.01	261,224,000.00
Architect 27	173.29	260,320,000.00
Architect 28	146.72	257,943,000.00
Architect 29	215.37	232,820,000.00
Architect 30	143.01	260,222,000.00
Architect 31	143.02	260,222,000.00
Architect 32	151.1	252,390,000.00
Architect 33	173.1	253,239,000.00
Architect 34	170.7	262,200,000.00
Architect 35	161.04	257,285,000.00
Architect 36	171.3	262,416,000.00
Architect 37	155.23	257,001,000.00
Architect 38	214.85	232,773,000.00
Architect 39	143.1	230,201,000.00
Architect 40	153.69	254,490,000.00
Architect 41	150.29	252,309,000.00
Architect 42	172.96	254,765,000.00
Architect 43	173.79	262,919,000.00
Architect 44	156.1	289,391,000.00
Architect 45	180.2	250,731,000.00
Architect 46	169.04	259,840,000.00
Architect 47	154.82	250,443,000.00
Architect 48	214.2	232,983,000.00
Architect 49	215.9	232,490,000.00
Architect 50	196.8	239,309,000.00
Architect 51	160.01	259,099,000.00
Architect 52	193.4	234,870,000.00
Architect 53	213.21	232,601,000.00
Architect 54	132.1	261,390,000.00
Architect 55	137.92	260,965,000.00
Architect 56	215.7	232,877,000.00
Architect 57	213.73	232,004,000.00
Architect 58	170.91	260,738,000.00
Architect 59	213.09	232,553,000.00
Architect 60	169.02	262,370,000.00
Architect 61	167.6	261,038,000.00
Architect 62	140.1	260,210,000.00
Architect 63	149.9	256,781,000.00
Architect 64	151.57	256,951,000.00

Table 4. *Cont.*

Human Designs	Energy kWh/m^2/Year	Construction Cost in Euros
Architect 65	170.91	255,547,000.00
Architect 66	171.15	262,919,000.00
Architect 67	159.4	253,580,000.00
Architect 68	180.92	252,635,000.00
Architect 69	173.89	259,998,000.00
Architect 70	156.5	260,359,000.00
Architect 71	215.28	232,500,000.00
Architect 72	214.9	232,821,000.00
Architect 73	191.12	235,461,000.00
Architect 74	164.45	261,451,000.00
Architect 75	190.37	235,319,000.00
Architect 76	213.05	232,835,000.00
Architect 77	130.94	261,903,000.00
Architect 78	136.64	259,376,000.00
Architect 79	213.58	232,769,000.00
Architect 80	170.87	261,378,000.00
Architect 81	142.64	256,644,000.00
Architect 82	213.75	233,853,000.00
Architect 83	141.52	261,913,000.00
Architect 84	141.06	261,733,000.00
Architect 85	214.83	232,809,000.00
Architect 86	121.76	240,907,000.00
Architect 87	159.3	264,600,000.00
Architect 88	155.09	234,102,000.00
Architect 89	169.51	260,333,000.00
Architect 90	155.4	261,203,000.00
Architect 91	159.41	258,901,000.00
Architect 92	179.29	232,433,000.00
Architect 93	170.09	261,222,000.00
Architect 94	157.61	260,453,000.00
Architect 95	215.31	232,430,000.00
Architect 96	214.97	232,321,000.00
Architect 97	187.69	234,200,000.00
Architect 98	158.53	258,285,000.00
Architect 99	187.43	235,416,000.00
Architect 100	213.7	232,001,000.00
Architect 101	134.79	234,773,000.00
Architect 102	137.01	231,201,000.00
Architect 103	213.92	232,490,000.00
Architect 104	213.64	232,309,000.00
Architect 105	171.03	252,765,000.00

Table 4. *Cont.*

Human Designs	Energy kWh/m^2/Year	Construction Cost in Euros
Architect 106	213.11	232,919,000.00
Architect 107	170.03	285,391,000.00
Architect 108	171.11	251,731,000.00
Architect 109	139.94	260,840,000.00
Architect 110	166.83	255,443,000.00
Architect 111	214.48	231,983,000.00
Architect 112	151.95	230,490,000.00
Architect 113	176.19	240,309,000.00
Architect 114	141.08	257,099,000.00
Architect 115	213.74	235,870,000.00
Architect 116	145.96	235,601,000.00
Architect 117	141.95	262,390,000.00
Architect 118	159.13	259,965,000.00
Architect 119	179.19	234,877,000.00
Architect 120	168.58	234,004,000.00
Architect 121	156.19	258,738,000.00
Architect 122	173.95	236,553,000.00
Architect 123	144.02	262,370,000.00
Architect 124	213.57	234,038,000.00
Architect 125	149.21	258,210,000.00
Architect 126	157.73	257,781,000.00
Architect 127	149.28	253,951,000.00
Architect 128	173.94	254,547,000.00
Architect 129	167.02	261,919,000.00
Architect 130	150.14	254,580,000.00
Architect 131	179.21	251,635,000.00
Architect 132	170.03	260,998,000.00
Architect 133	151.82	261,359,000.00
Architect 134	213.41	235,500,000.00

The results for the designs generated by DesignBuilder's optimisation engine are shown in the optimisation converged at 309 model iterations, of which 13 were identified as optimal and formed a Pareto front, as shown in red in Figure 7. The Pareto front is identified with DesignBuilder optimisation automatically, and it uses equal weights for each of the design objectives. In design, there is always a trade-off between competing design objectives. Some of these design objectives need to be given a certain priority weight, each of which makes those objectives that are given a higher priority in order to drive the design. Wang et al. [31] reported that, in practice, the use of equal weights (50/50) is the most popular weighting method.

Table 5 summarises the Pareto front solutions.

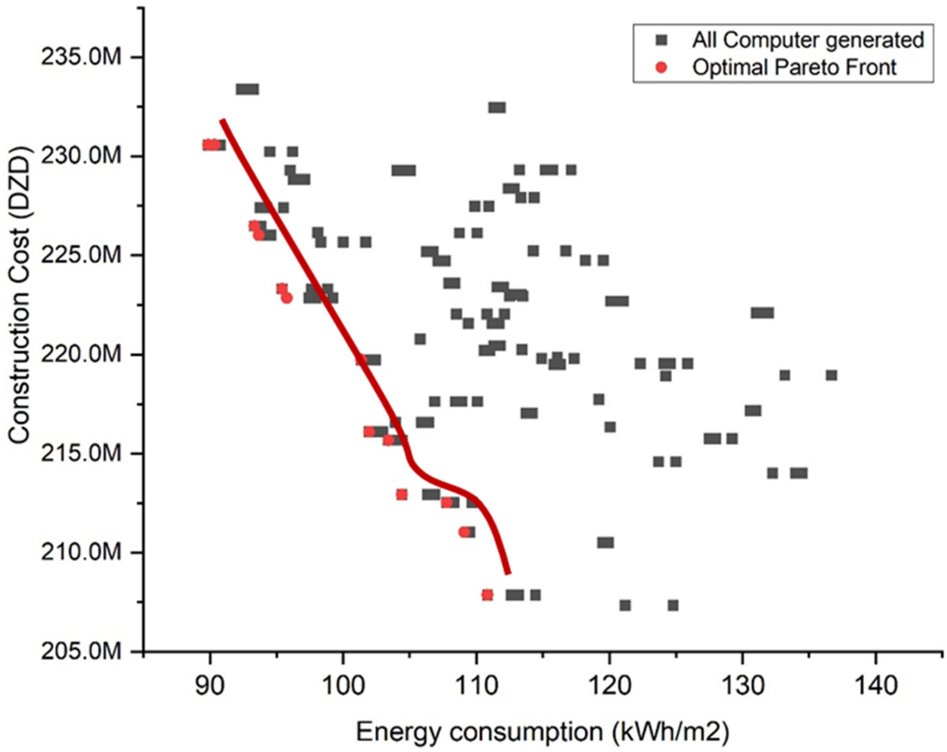

Figure 7. Trade-off between energy consumption and cost using computer optimisation (The red represent the front that is referred to as Pareto Front to distinguish the best trade off design options from the rest of the design population).

Table 5. Energy consumption and construction cost for the optimal designs from the Pareto front.

Pareto Design Iteration	Energy (kWh/m^2/Year)	Cost (DZD)
Pareto 01	107.79	DZD 212,521,000.00
Pareto 02	95.43	DZD 223,319,000.00
Pareto 03	104.41	DZD 212,935,000.00
Pareto 04	103.4	DZD 215,679,000.00
Pareto 05	90.35	DZD 230,570,000.00
Pareto 06	101.37	DZD 219,733,000.00
Pareto 07	93.34	DZD 226,477,000.00
Pareto 08	89.86	DZD 230,570,000.00
Pareto 09	110.84	DZD 207,874,000.00
Pareto 10	95.77	DZD 222,855,000.00
Pareto 11	93.66	DZD 226,012,000.00
Pareto 12	101.95	DZD 216,092,000.00
Pareto 13	109.09	DZD 211,031,000.00

The optimisation analysis was carried out on the basis of cross-referencing all design variables from Tables 1–3. The Pareto solutions represent the designs that achieved the minimum values for the energy and cost objectives, and neither objective could be improved without harming the other. For both design objectives, minimisation is desired.

Among all the solutions generated by the optimisation, the Pareto curve comprises 13 solutions, as shown in Figure 7. For each Pareto optimum, the performance in the energy consumption objective could only be improved by decreasing the performance in construction cost.

When examining the Pareto front curve more closely, there are optimal solutions that can comparatively be more favourable than others. For instance, from Table 5, Pareto 08 achieved the most energy-efficient design with 89.86 kWh/m^2/year. This Pareto optimal is also the most expensive design on the Pareto front. Given that Pareto 08 offers better outcomes at the same cost, we can confidently state that it dominates Pareto 05. In the language of Pareto efficiency, this means that Pareto 08 is strictly preferred over Pareto 05. Therefore, Pareto 08 is used as the baseline, against which the results from test subjects are compared.

Figure 8 shows a comparison of the architects' designs versus the designs that were generated with multi-objective optimisation in DesignBuilder. The first observation is that the bulk majority of architects who took part in this study are far from the range of the optimal designs generated by the optimisation. The human-generated designs can be considered failed designs as they do not achieve a trade-off between the two competing design objectives. The primary energy consumption target was set to 100 kWh/m^2/yr in the design exercise, yet almost none of the architects were able to come close this energy figure.

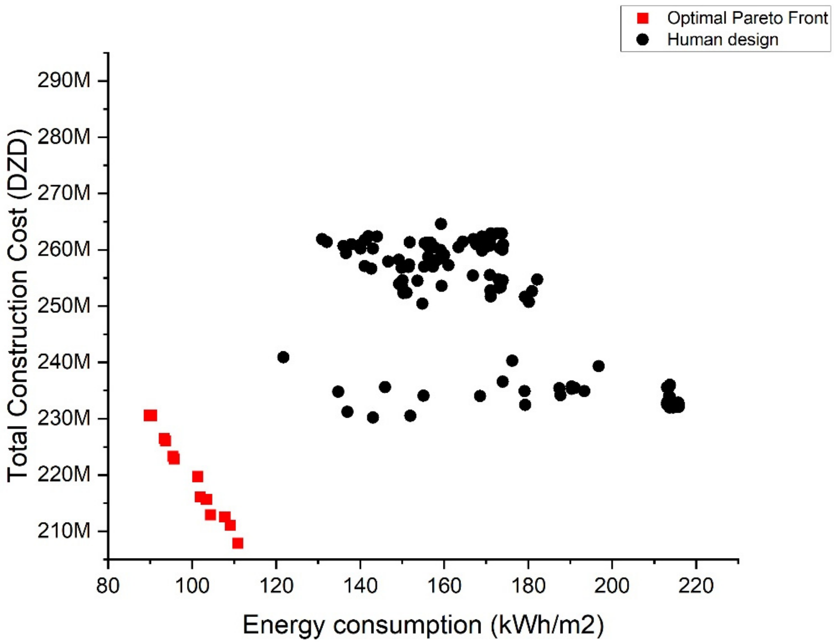

Figure 8. Computer-generated Pareto optimal designs versus human designs, plotted by two competing design objectives of construction cost and energy consumption.

Computer optimisation clearly outperforms humans when searching for the best trade-off between energy performance and construction cost. The architects had generated various designs at substantially different performance levels when a considerably cheaper design at a much lower energy consumption was found using optimisation. The analysis of the human designs suggests that the architects are, to a certain extent, not concerned with energy efficiency. Architects seem to struggle to position energy efficiency within their professional boundaries. Figure 9 categorises architects' performance by years of experience and suggests that the relationship between design performance and experience is not decisive. The relationship is a little clearer from Figures 10 and 11. Figure 10 shows that the energy consumption of human-generated designs rises slightly as the architects' years of experience rises. Figure 11 shows that more experienced architects generated cheaper designs. The error bars shown in the charts suggest that these differences might not be statistically significant.

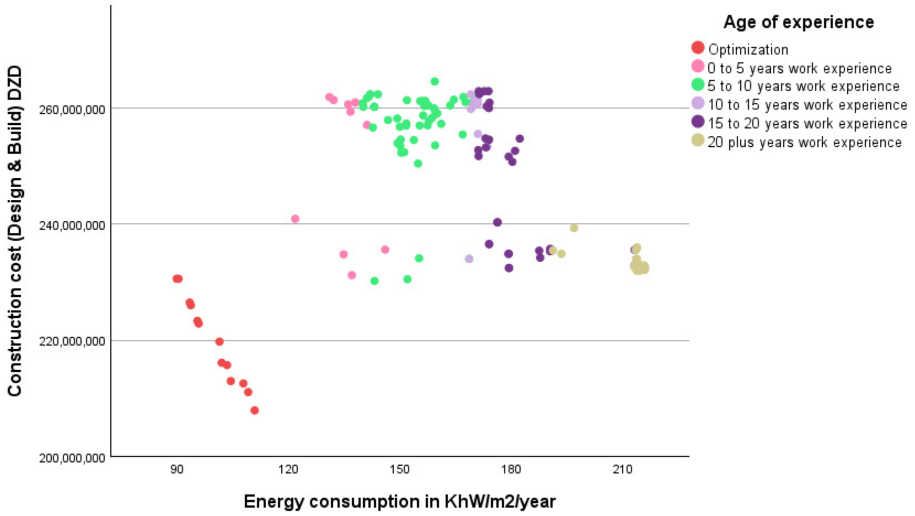

Figure 9. Trade-off between energy consumption and construction cost according for architects with various years of experience of the architects.

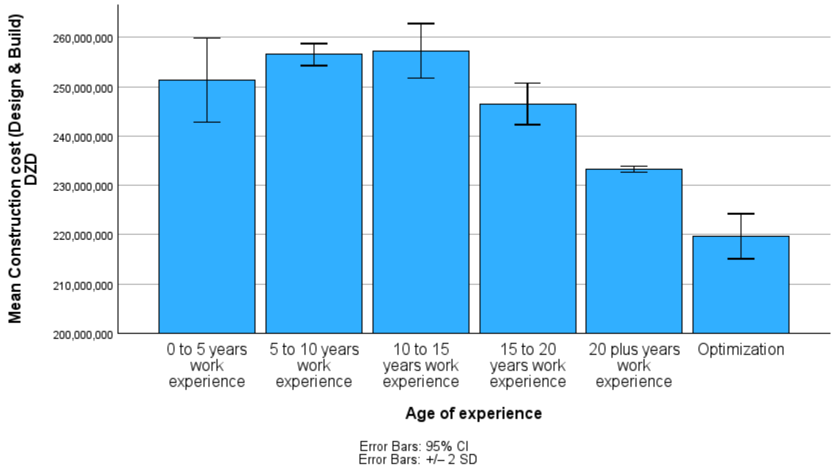

Figure 10. Mean construction cost of designs produced by architects with various years of experience.

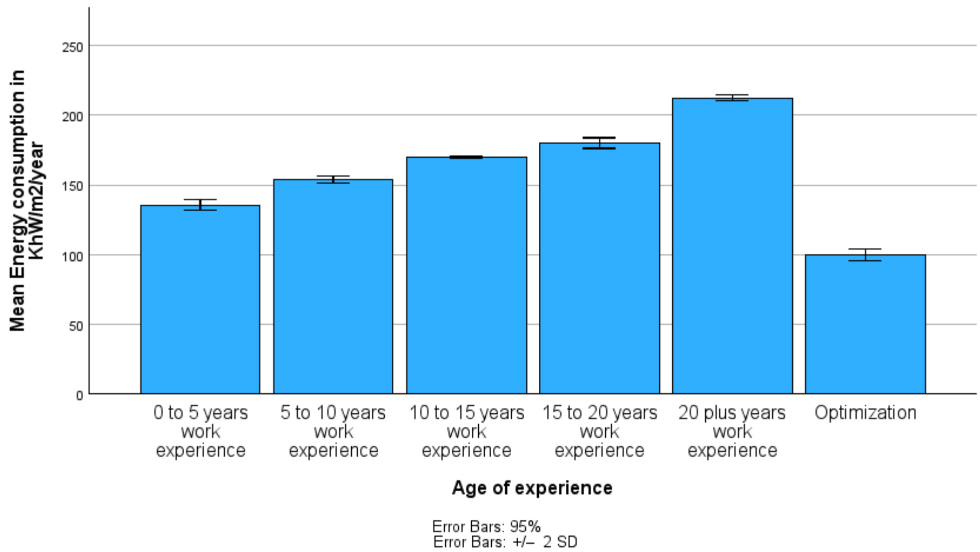

Figure 11. Mean energy consumption of design produced by architects with various years of experience.

Architects with between 0 and 5 years of experience generated the most energy efficient designs, while those having over 20 years of experience generated the least energy efficient designs. The failure in achieving a competitive trade-off between design objectives worsens as experience increases. The mean energy consumption and mean construction cost was calculated for the 13 solutions in the Pareto front and taken to represent the performance of the computer optimisation. Figure 11 indicates this mean energy consumption for the optimization Pareto set so that it can be compared to that for architects in various ranges of experience. The computer optimisation decisively outperforms even the best-performing group of architects, those with the least experience.

The findings of this study suggest that professional design experience only improves construction cost prediction but not design for low energy consumption. From Figure 9, it appears that only a subgroup of architects was able to compete with the optimisation in terms of construction cost (the horizontal strip of points at about the DZD 230 million level, equivalent to GBP 1,336,518). The construction cost performance of the architects' designs improves (i.e., cost decreases) as the architects become more experienced and appears to converge towards the optimisation prediction, as seen in Figure 10. (The least two categories of experience on the left-hand side of Figure 10 are a minor exception, but these might not be significant.) On the other hand, the energy performance of the architects' designs deteriorates (i.e., predicted energy consumption rises) as the architects become more experienced, as can be seen in Figure 11.

It is striking in the results that the human architects (despite being instructed explicitly to balance the two objectives of construction cost and energy efficiency), were more concerned with construction cost. The decline in energy performance as the architects become more experienced is also striking. Construction cost estimation is known to be highly affected by the architects' reasoning that is nurtured through learning by doing and professional expertise [32]. Elfaki and Alatawi [33] argue that early construction cost estimation relies on human judgement, and there often are differences between estimates even in the same project. This resonates with the data from the design experiment. Despite receiving the same data, base case model, and instructions, there was a large variance in the cost performance of the human architects (as evidenced by the large error bars in Figure 10). It appears, however, that the more experienced architects can compete with the Pareto front in terms of construction cost estimation.

In his book on Building Performance Analysis, De Wilde [6], on page 457, contrasts the research into performance-based design with the practice of performance-based design decision-making. He observes that, whereas the research (often by academics) assumes a normative model of decision-making, design practice is actually based on tacit knowledge, where decisions are made "on the go". Performance criteria are usually incorporated into designs through the application of tacit knowledge and expertise. This aligns with the research of Woo et al. [34], who similarly highlights the importance of *tacit* (over explicit) knowledge in the design and construction of buildings. From the research reported here, the central issue seems to be the balance accorded to the two competing objectives of construction cost and energy performance. The knowledge acquired during education is effective in achieving better energy-efficient designs, but experiential knowledge seems to tip the balance more in favour of reducing construction cost.

5. Conclusions

In general, the contribution of this research highlights that computer optimisation outperforms human architects decisively in terms of the energy performance of the designs but less conclusively in terms of the cost performance of the designs. Rather than improve design performance in general, the architects' reasoning that is nurtured through experience seems to tip the balance from energy performance to cost performance. That is to say, while computer optimisation shows promise in cost-effective design, the results are less conclusive when compared to human architects. This nuanced outcome can be explained by that the fact that experienced architects bring invaluable insights into local building practices, material availability, and labour costs. Furthermore, in terms of qualitative factors, humans excel at considering subjective elements like aesthetics and user experience, which can impact overall project value.

The findings in this study challenge the assumption that experienced architects possess extensive and effective reasoning in making design decisions. The reliance on the designers' reasoning in this context is only useful when making construction cost predictions. Considering the objective of energy-efficient design in isolation, the performance of novice architects is good (perhaps an indication of the Algeria system of architecture training) but still sub-optimal compared to the computer optimisation. Practical experience causes it to deteriorate further. In Algeria, during the first two years after graduation, architects undertake training within a qualified architecture practice before being accredited to practise independently. During this period, there is a knowledge transfer from expert architects to novices, as novices collaborate on projects with experienced architects. This allows experienced architects to share their knowledge with novices through "Communities of Practice". This shared knowledge is fundamental to the practice of architecture [34]. Moreover, this can also explain that, particularly among the younger population, there is a growing ecological awareness driving a shift towards sustainability. This demographic is increasingly passionate about addressing climate change through more environmentally responsible design decisions. However, further research is needed to understand why mid-career professional practice of architecture seems to erode the importance of energy efficiency which is imparted during architecture training.

There is scope for future research in understanding the inner workings of the human designers' reasoning during design decision-making, perhaps using think-aloud verbal protocols. The research reported here was limited in its use of a single design problem, a single geographic location, and a single computer optimisation platform. A larger sample size would have provided more statistical power. Ultimately, the framing of human versus computer might be unhelpful. Architects can deploy computer optimisation in a meaningful way appropriate to the respective strengths of humans and computers. Computer optimisation can augment human reasoning, rather than compete with it or replace it. This is particularly true in creative design or design teamwork [35].

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