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A multi-objective optimization framework for designing climate-resilient building forms in urban areas

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Abstract. With the increasing global awareness about the impacts of climate change on the built environments, the need for improving the climate resilience of buildings is being more acknowledged. Despite the high number of relevant studies, there is a lack of frameworks to assess the resiliency of buildings and urban areas. This study presents a multi-objective framework to optimize the form of buildings against its energy performance and thermal comfort considering its resiliency to the uncertainties of climate change during three thirty-years periods (2010-2099) of a warm region. Three performance sections related to building's form are identified and categorized for the impact assessment including (1) urban form, (2) orientation, and (3) transparency with ten influencing parameters. The analysis of non-dominated solutions out of the optimization process showed that the annual energy performance (cooling and heating demand) of the urban areas can improve about 34% in both typical and extreme weather conditions whilst maintaining thermal comfort by optimizing the overall form of the buildings with similar built density and heights. Moreover, Buildings with 15 to 30-degree rotations and 33% glazing ratio showed the highest energy performance. Finally, the top 20 resilient building forms with the highest energy performance and climate resiliency were selected out of the database of results to derive design suggestions.

1. Introduction

Urban areas are responsible for over 70% of world final energy consumption [1], and with the current rapid urbanization rate, this number is expected to increase due to the demand from the building sector [2]. According to several studies, the energy demand from the building sector will increase with a higher rate in non-residential buildings in the next two decades [3]. Globally, about 23% of this category are office buildings, which are accounted for over 48% of supplied energy for heating and cooling to achieve indoor thermal comfort during working hours [4]. There have been several attempts to reduce this share and demands from office buildings in the two recent decades with a focus on designers. The most recent approach is attempting to develop and use new computational power and associated tools to design the energy performance of buildings. In this approach, a common and well-acknowledged technique in the building design process is adopting an optimization algorithm in line with numerical simulation methods [5]. Considering several influencing parameters and constraints in the building design process, multi-

objective optimization to solve complex design problems. Thus, dozens of optimization algorithms have been developed for multi-objective problems based on evolutionary algorithms [6]. These optimization algorithms have been adopted for the building design process in the early stages. In addition to regular programming platforms and tools such as *Matlab* [7]. The most common tools adopted and used by /for designers with more design-based interfaces are Grasshopper in *Rhinoceros* and Dynamo in Autodesk Revit with several practical plugins based on different simulation engines such as EnergyPlus, TRANSYS, and DOE-2. Adopting these tools, different features, and components of building such as building facade [8] or materials characteristics [9], glazing and shading [10] have been studied. Several other studies have focused on developing optimization frameworks to optimize the energy performance of buildings [11,12]. However, a comprehensive optimization framework with a back and forth process to finding optimal forms is still missing in the available literature.

On the other hand, the majority of the studies in the literature are only developed for the current climate conditions by adopting widely-available climatic data such as Epw weather files in regular Energy Performance Simulation (EPS) studies. These weather files are usually based on locally recorded weather data for typical years, such as different versions of Typical Meteorological Year (TMY) to represent long-term average climate conditions of a location [13]. These weather datasets mostly fail to consider different weather conditions such as typical and extreme which can introduce large peak loads and cause higher total energy demand on average [16]. Moreover, these weather datasets cannot represent the uncertainties and the impacts of climate change. The climate change impact can introduce a huge impact on the local climate and consequently energy performance of buildings and urban areas by higher average air temperature and more frequent and stronger extreme conditions [14]. For example, the average air temperature in Europe has increased by about 1.7°C compared to the pre-industrial level and expected to increase 1 to 2°C by 2050 [15]. Another example of the climate change impacts on the built environments is several blackouts, power outages, and grid failures due to massive heat waves in recent decades [16].

This means that buildings as a complex system can be no longer designed or optimized for the current climate conditions [17]. This can lead us to the concept of resiliency in system design which is 'an ability of the system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time'[18]. Different components from smart air conditioning systems in a building [19] or material design [20] to a larger scale such as urban energy system in a district or city level [21] can be redefined in the general concept. However, it is not feasible or even practical to design the overall form of a building with such a responsive manner considering the current limitations and restrictions. The overall form of a building in an urban area should be designed based on the local microscale [22], current, and future weather conditions [23]. This process can be started in the early stages of design and regardless of its associated component in the future.

A climate-resilient form should have an optimized performance in both typical and extreme conditions. Moreover, it should have a relevantly optimized performance during uncertain weather conditions. In other words, a climate-resilient building form should be time-dependent and have a robust performance during its occupancy and function. This paper aims to define this concept by optimizing the building form against typical and extreme weather conditions in current and future scenarios using optimization functions. This concept has been described in detail in the Methods section as well as the adopted optimization approach, influencing parameters, and applied inputs for the whole process. The Pareto front plot of the developed optimization algorithm along with the geometrical characteristics of the top 20 best design options is presented in the Results section. Moreover, the energy performance of the five best solutions, as well as the design-based characteristics of the best solutions, are also presented to assess the impacts of the introduced framework.

2. Methods

A multi-objective framework with a replicable process is developed based on an earlier work of the authors [24] based on consists of four main comprehensive steps including (1) Form-generation, (2)

Form-Simulation, (3) Form-Optimization and (4) Form-Solutions; where each step includes several integrated phases (Figure 1). The genetic algorithm (GA) was adopted in this study due to an efficient, fast, and accurate approach for the whole building simulation using the Pareto-dominance approach. The proposed framework is based on an introduced technique namely "Building Modular Cells" (BMC). In an earlier work of the authors [25], the BMC technique was introduced and validated to generated and evaluate building and urban forms. Here, by defining an optimization algorithm thousands of forms can be generated with a modular shape. The BMC technique is based on an 8×8 m rectangular module; these dimensions are selected according to the typical reinforced concrete structures, in which the height of each floor is 4m. By using this grid resolution with 8008 possible form combinations, almost all the well-known building forms (L, U, CY, C, T, etc.). A series of form generation rules as design parameters constraints were also defined to reduce the number of the not-functional form based on simple architectural logics (Figure 2).
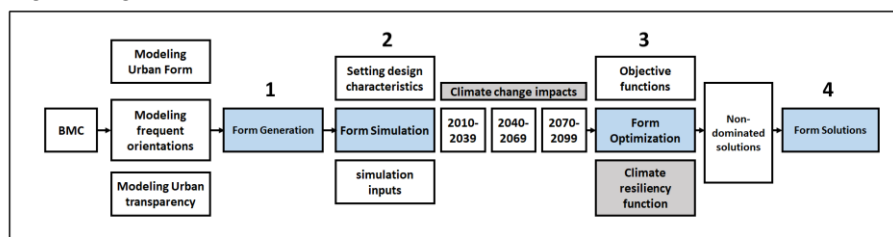

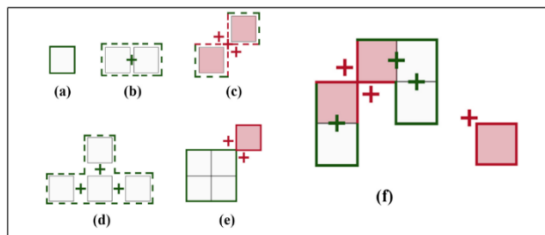Figure 1: The adopted framework in the study

Figure 2: applied form combination rules as design parameter constraints, (a): the 8×8 module cell, (b) and (d): selected cells must be connected from their sides, (c): connection from edges are not acceptable, (e): unacceptable cell connection from edges, (f) detached selected cell and edge connection.

Several design-based tools which are familiar for designers such as Rhinoceros/Grasshopper plugins (Diva-for-Rhino-Archsim, Ladybug tools, and Octopus) and EnergyPlus are adopted in this study. In the first phase, the BMC technique was defined, modeled, and prepared for simulations by the aid of an innovative GH algorithm. The geometry of eligible combinations out of the defined constraints are converted and exported into EnergyPlus using Archsim in the GH algorithm for energy simulations. For metrological weather data, nine annual data with hourly resolution were generated based on a method introduced by Nik [43] to synthesize typical and extreme weather files based on the outdoor temperature based on thirteen climate scenarios for Athens, Greece with a warm climate, to be used in energy simulations (figure 3). In this method, the representative and extreme months using Finkelstein–Schafer statistics are selected and verified for hygrothermal simulations [44]. Thus, these typical and extreme weather conditions are divided into three sets of typical, high, and low wind speeds are synthesized for the three 30-year periods of 2010-2099, considering six weather scenarios simulated by the RCA4 regional climate model (RCM) with the spatial resolution of 12.5 km. For the purpose of this study and to represent climate uncertainties, one extreme year has been selected from each typical and extreme year; one year with the highest average temperature out of thirty-year weather data– to be called the 'Extreme Warm Year' or EWY –, one year with the lowest average temperature– to be called the 'Extreme Cold Year' or LWS out of thirty-year weather data–, and one year with the typical average temperature out of thirty-year weather data– to be called 'Typical Downscaling Year' or TDY. The generated weather data were converted to EPW format to be read by the EnergyPlus engine in the Form Simulation step.
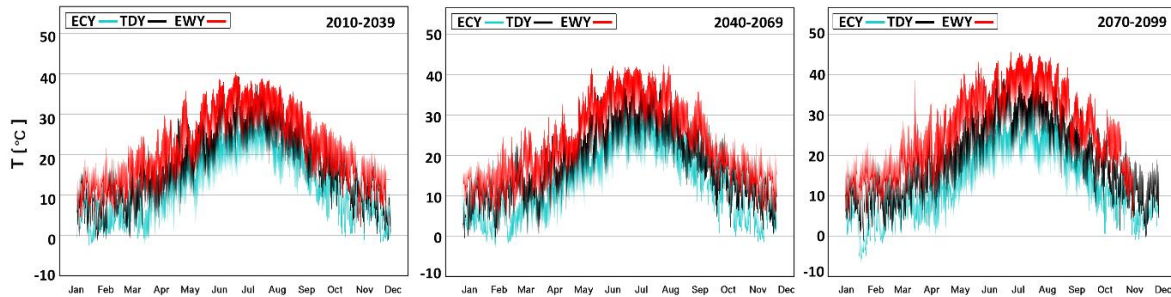
Figure 3, Synthesized typical and extreme temperature for Athens, Greece from 2010 to 2099.

A regular urban area is hypothetically selected in Athens to consider the impact of urban form into the calculations. The surrounding area including buildings (built density and heights) and the characteristics of the urban pattern such as the geometry of the streets and canopies were also modelled in detail. Figure 4 shows the plan, selected areas for the BMC technique, and three-dimensional view of both. Table 1 presented the defined performance sections related to building form and their associated parameters in this study.

Table 1: The defined performance sections related to building form and their associated parameters

Sections	Parameter	Description
	Site coverage	The area of the ground floor divided by the total site area of the site
	Building layout	L, U, CY, C, T layouts
	Built density	The area of the ground floor of the building divided by the total area
Urban form based on BMC	Building function	The function of designed thermal zones
	Building height	The total number of floors based on BMC
	Relative compactness R_C	The volume of each building divided by the total area of the external surface
	H/W ratio	The final height of the form divided by the width of the surrounding area
	Material	The material used in the building in walls, ceiling, floor, window frames
Orientation	Building orientation	The orientation of generated forms with 15° tolerance
Transparency	Glazing ratio	The total area of windows divided by the area of facades
* Each performance section is connected to the multi-objective optimization algorithm as genome		

Two functions were defined based on the concept of resiliency, where the energy performance of the building form in the typical and extreme conditions should have the minimum variations during three-thirty years of datasets (2010-2099). The developed method by Nik [14] used in the context of two functions. The total energy demand as the sum of annual cooling and heating demand was defined as the sum of the latent and sensible cooling and heating energy. Each generated form combination is consisting of eight floors and each floor has two zones: private office rooms and shared spaces. Based on Athens weather, summer and winter were defined from April 1st to September 30th and from January 1th to March 31th and October 1th to December 31st respectively. Equation (1) and (2) are defined to calculate the heating and cooling demand for each generated form in the first step of the framework:

$$CL = \sum_{i=1}^{n} q_{Ci} \qquad (1)$$
$$CL = \sum_{i=1}^{n} q_{Ci} \qquad (2)$$
$$Q_w = CL + HL \qquad (3)$$

Here Q_w is the total energy demand of the generated form, where q_{Ci} and q_{Hi} are cooling demand and heating demand of each floor respectively calculated by EnergyPlus. The index '*w*' represents the type of weather data used to calculate the energy demand based on the generated weather data files. Thus, for each generated form '*w*' is TDY$_{2010-2039}$, ECY$_{2010-2039}$, EWY$_{2010-2039}$, TDY$_{2040-2069}$, ECY$_{2040-2069}$,

EWY[2040-2069], TDY[2070-2099], ECY[2070-2099], EWY[2070-2099]. Two main constraints were imposed on the performance of the scheduled ventilation system during working hours to control the operative temperature. The maximum load limit of 100 w/m^2 with the temperature setpoint boundary of 18 in winter and 27 in summer were considered in the calculations. Using a Python script in the defined algorithm, the average value of each dataset is calculated and results in three final energy demand equations including: Q_{TDY}, Q_{ECY} and Q_{EWY}. To achieve resiliency in the energy performance of each form, the variations between Q_{ECY} and Q_{EWY} should be squeezed towards Q_{TDY}. For this purpose, the first objective function is defined as equation (4):

$$f_x = \frac{1}{2p}\sum_{i=1}^{p}\left[\left(Q_{ECY_{(u_1).i}} - Q_{TDY_{(u_1).i}}\right)^2 + \left(Q_{EWY_{(u_1).i}} - Q_{TDY_{(u_1).i}}\right)^2\right] \qquad (4)$$

To minimize the energy performance of the building during typical weather conditions, objective function two is defined (equation (5)):

$$f_y = \Sigma_i^p Q_{TDY_{(u_i).i}} \qquad (5)$$

Using two functions, first, the generated forms will have an optimized performance during the typical conditions. Second, their energy performances in extreme conditions will remain as much as possible close to their performance in the optimized typical conditions. Such a form will have a similar thermal behavior during all weather conditions based on a time-dependent process (adopted future weather data). Finally, the optimization problem in the study can be defined using equation (6):

$$min\{f_x.f_y\}; x\epsilon R^n \qquad (6)$$

To solve this optimization, function the following settings were used: population: 200, Max generation: 50, crossover rate: 0.8, mutation rate: 0.5. The average runtime for each iteration was about 180s which can be considered as fast considering the high amount of calculation defined for each generated form.

3. Results

Figure 5 shows the Pareto from for the defined optimization study as well as a simplified guide to show how it is interpreted. The plot shows the trade-offs between two defined objective functions. The non-dominated points represent the best design solutions with minimum f_x and f_y. Figure 6 shows the top twenty generated forms placed in the defined urban area in Athens. The shading effect of the modeled urban area has a huge impact on the final results. A more detailed study on this matter can find an earlier study of the authors [26].
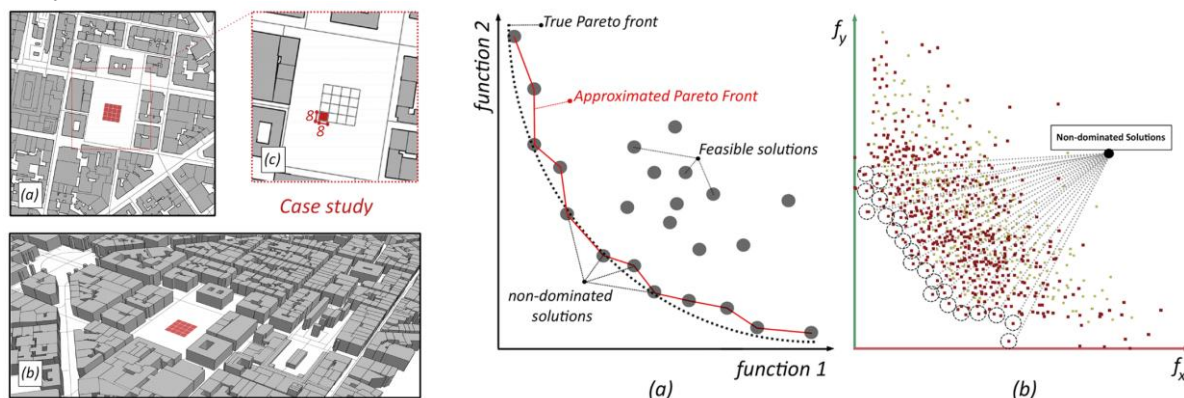

Figure 4, 2D, and 3D view of the selected urban area in Athens, (c) the selected case study and hypothetical site based on BMC.

Figure 5, (a) a guide to show how the Pareto front is interpreted, (b) the Pareto front of the defined optimization study in this research work

According to all non-dominated solutions, over 70% of the climate-resilient solutions urban area have 15-degree clockwise form rotation, enabling a larger part of the target building to face northern elevation. Moreover, 55% of climate-resilient solutions have at least one empty cell in a part of a uniform layout (semi-courtyard form); however, in terms of optimal heating demand design solutions, more than 80% of best solutions have courtyard or semi-courtyard forms. Moreover, 91% of solutions have at least two or more empty cells in the western and northern sides. It is important to notice that about 84% of the best solutions in terms of heating demand have set-backs to the northern side of the site. Results also showed that about 33% lower energy demand between non-dominated forms and feasible options.
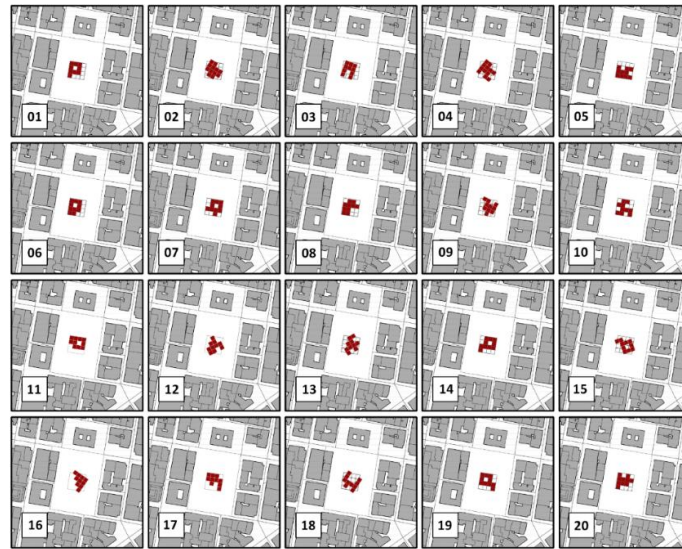

Figure 6, top 20 climate-resilient form solutions with different shapes and orientations

Figure 7 shows the boxplot of the cooling and heating demand of four of the best climate-resilient forms including Cases 2, 14,16, and 18 with four different and distinct layouts. For example, building form with CY form (Case 14) shows 63.99 kWh heating demand in ECY 2010-2039 on average while these numbers are 30.36 and 51.95 kWh in TDY and EWY conditions. Case 16 with L form has a similar heating demand in ECY conditions while in TDY and EWY the average heating demand is 25.5 and 43.7 kWh respectively. This is while in terms of cooling demand Case 16 showed the best performance with 33 kWh in EWY conditions showed the lowest cooling demand between the best solutions. The results show the role of layout geometry of buildings. Thus, it is important to consider all building's design techniques such as mass and void in layout and form, set-backs, height variations, and orientations according to the values of the investigated objectives.
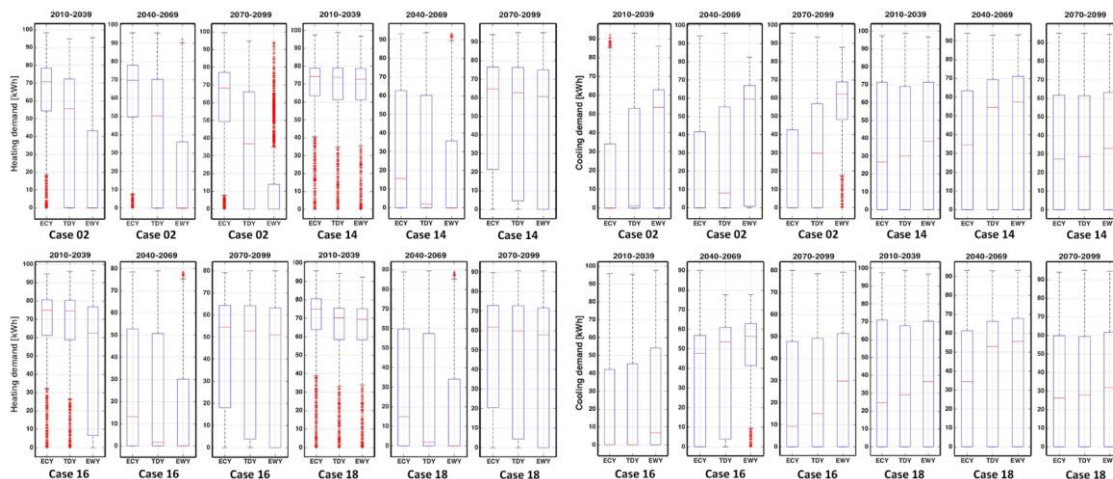

Figure 7, heating and cooling demand of the five best climate-resilient building forms

4. Conclusions

This study presented a multi-objective optimization framework to generate climate-resilient building forms in urban areas. Nine weather data based on typical and extreme weather conditions were generated for the case study, Athens. These weather datasets are Typical Downscaling Year (TDY), Extreme Cold Year (ECY) and Extreme Warm Year (EWY) generated for three thirsty-year statistical data, one year for each from 2010 to 2099. Two objective functions were defined to solve an optimization problem to find climate-resilient forms. The first function aimed to reduce the difference between the form's performance in typical and extreme conditions while the second function attempted to find optimal forms in typical conditions. The trade-offs between these two functions resulted in 67 non-dominated building forms with the most resilient performance. The main findings of this study can be summarized as:

- Forms with up to 15-degree clock-wise on the northern-southern axis (placing the form on NW/SE axis) showed the nest energy performance during studied weather conditions.
- While the best design solution in this study was L-form building, forms with semi-CY and semi-L layout with Rc between 0.85 to 0.98 (forms close to cuboid shape-Rc of a cube is 1) have the best resiliency in the studied urban area.
- Forms with set-backs toward the northern boundaries of the site by gaining more solar radiation through openings showed the best energy performance.
- Forms with step-like shapes by Split the western side of the building's form and consider mass pull and push in the layout showed a better energy performance by reducing surfaces with openings facing west.
- Forms with small open spaces in the southern and eastern boundaries of the site showed higher energy demand on average.
- Forms with high angles of rotation did not show a positive performance in terms of energy demand.

This paper provided further evidence on the importance of considering future weather conditions in the design process of the building forms. Moreover, by taking low-cost decisions in the early design stages by designers, the energy performance of the buildings can be dramatically reduced. The developed framework and resiliency functions in this work can enhance the quality of the form-finding process in the early design stages. It can also allow designers to take more well-informed decisions to address sustainable cities and communities (sustainable development goals, SDG 11). Finally, the database of results is applicable for developing new building codes and regulations in Athens or any other dense city with similar climate conditions.

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