# An Algorithmic Optimization Model for High-Density Urban Settings

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**Keywords:** Urban form; multi-objective optimization; Pareto efficiency; generative design.

## 1. Introduction

The research presented in this paper discusses the use of algorithmic design in the generation and evaluation of urban form. With the use of Multi-objective optimization evolutionary algorithms (MOEA), several functional constraints and objectives are outlined for a simulation model. Based on this, designing an urban generation model seeks to explore self-organizing geometries through objective evaluation. Considering the degree of design intricacy that an urban development model implies, our study makes use of multi-objective optimization methodologies to interpret the intrinsic complexity of conflicting objectives present in a living urban system. For this, an evolutionary computing solver and Pareto front evaluation methodology are used in order to evaluate and rank a myriad of optimized solutions.

## 2. Background

While considering cities as complex organisms it is essential for urban designers to think of design practices that can allow for evolutive growth and adaptability of the urban scenery. During the 1980s, Christopher Alexander(1) proposed an urban design methodology that is characterized by an organic, bottom-up design concept that offers means to better adapt and adapt to living spaces for the designers and users of the urban space alike. To achieve this design concept with the use of algorithmic design, it is necessary to establish a logical conceptual framework that can define a model capable of formulating, generating and evaluating the urban form(2).

Subsequently, this kind of framework for urban generative design models, such as urban shape grammars(3), when coupled with a comprehensive, site-specific formulation model and a dynamic evaluation methodology such through evolutionary algorithms can offer a relative diversification and optimization in results while also keeping a cohesive logic to the urban space. Following this, we can notice a paradigm shift in the design process where the subject of the design shifts from the actual architectural or urban space to the formulation of the system and process of it.

## 3. Multi-objective optimization evolutionary algorithms

The use of evolutionary algorithms or genetic algorithms goes back to the early 1960s. It refers to algorithms that use a number of variables, referred to as “genes” that are changed in order to find the best combinations of input variables that satisfy an objective function and find the highest value in what is known as the “fitness landscape”.

### 3.1. EVOLUTIONARY SOLVERS

Evolutionary solvers in algorithmic design software, such as Galapagos or WallaceiX plugins in Grasshopper (GH), are programs that apply evolutionary principles to problem-solving in the design process. This means that the chosen input parameters, or “genes” will be selected as variables to be modified by the solver in order to achieve the best possible range of solutions for the prescribed problem. The optimization data and geometry are referred to as “phenotypes”, it is logged into GH and specific solutions can be reinstated as 3D geometry in Rhinoceros 3D. While Galapagos is a single-objective optimization solver, WallaceiX is a multi-objective solver, meaning that it can optimize a model with a more complex design problem requiring differing objectives, and consequently more calculation time.

### 3.2. PARETO FRONT OPTIMIZATION

In architecture and urbanism, a design problem is every so often complex and require to be represented through multiple objectives. These design objectives can often be conflicting in nature and require evaluation criteria to be well designed. In such complex problems, the Pareto front methodology refers to the selection of solutions with the optimum distribution of resources when there is no alternative to finding a better ranking position for all the criteria. This means that there is no single dominating solution for all the criteria, but rather multiple solutions variably optimized for all criteria. For a solution in the Pareto frontline, making one criterion better will necessarily result in the decline of the others.

日本建築学会情報システム技術委員会
第42回情報･システム･利用･技術シンポジウム論文集，24-27，2019年12月，東京
Proceedings of the 42nd Symposium on Computer Technology of Information，
Systems and Applications，AIJ，24-27，Dec.，2019，Tokyo

**4. Previous work**

Previously[(4)], our research was centered on urban settlements in Morocco, it studied the distinctiveness of urban form in urban settings known for their self-growth and organization. The subject of our precedent study was one of the last remaining slums in the urban perimeter of Rabat city in Morocco[(5)]. Its characteristics were used for setting up the model's site constraints and discussed the use of an MOEA in order to incorporate characteristics of old Islamic urban form as a base for the optimization of spatial solutions. Two conflicting objectives were used in order to test the model, the first one is physical accessibility whereas the second one was environmental sun exposure. With this, a set of algorithmic rules and functional objectives were used for an abstractive urban form-defining model.

Based on these features, the development of a parametric model sought to grasp certain characteristics of spontaneous urban tissues in old Islamic cities and incorporate them into an experimental social housing proposal. Using genetic algorithms, the model offers better adaptability and more diversification while keeping a degree of preservation to the distinctive aspects that define those settlements. The use of a genetic solver showed itself to be a method that can simulate and offer a wide range of objective-based spatial that are considerably adaptive to urban contexts.

**5. The experiment**

5.1. THE METHODOLOGY

As presented in our previous research[(4)], the model initiated its conceptual framework on the observation of self-organizing urban tissues in the city of Fes, Morocco and how an algorithmic design methodology can be correlated to the same organic urban generation and growth process.

The concept behind this algorithmic model is to generate a cityscape that is optimized for sun exposure and accessibility while also being diversified enough in its spatial configuration. Basic modules or units are combined randomly by the program to generate a clustered geometry that forms a housing complex that is evaluated by objective functions. The algorithm is designed in a way as to aim for a range of population density and for a range of hours of exposure to sunlight per day for each housing unit. The results resemble heterogeneous porous units that allow sun rays to get through, consequently allowing an aesthetical diversity as well. Although the algorithm is programmed to only obey the sun exposure condition, it can also be modified to include multiple agents that reflect other evaluation factors if necessary.

In order to attain objectives relative to the above points, a complex generative system must show enough adaptability to be resilient against physical constraints and dynamic change in context. Also, it should be capable of diversifying of solutions, which indicates variation in possible spatial configurations, thus enabling enough interactions between elements of the generative systems on lower levels.

5.2. RESEARCH AIM

The main outcome of the research is to propose a self-organizing urban simulation model through algorithmic design that can propose an optimized abstractive urban form while also offering a degree of resiliency and adaptiveness to change. Using a generative solver as a self-organizing system is expected to offer the advantage of adaptability while exploring a diversity of possibilities in the urban form that break from the redundancy and lack of flexibility of modern planning.

5.3. PRESENTATION OF THE URBAN FORM SIMULATION

5.2.2. Algorithm workflow

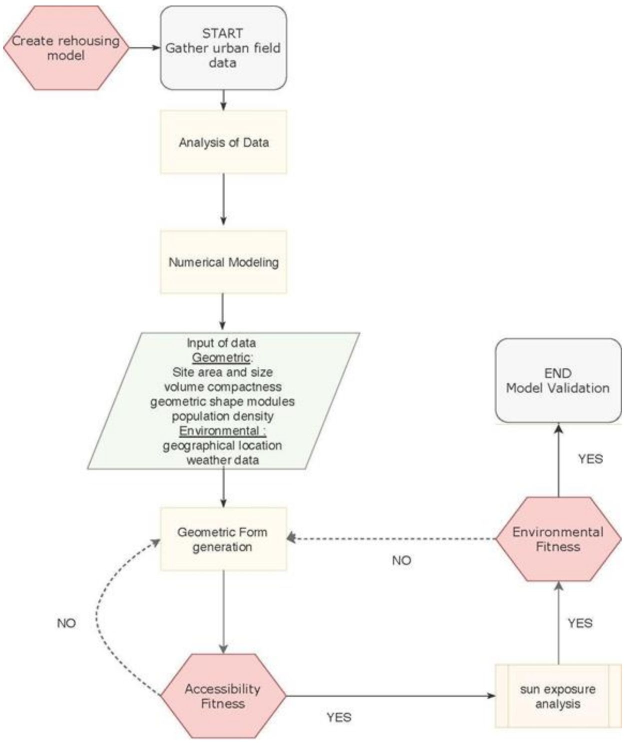


Figure 1. Urban generative design algorithm workflow.

The GH parametric model is made to follow a logical data flow that loops in order to optimize form-finding (Figure 1). First, it subdivides the site's surface into smaller plots and then generates a 3D geometry based on a grid system that represents the dimensions of precast modules. These modules are duplicated following a 3D grid and then randomly reduced to fit the target density. Weather data in the form of sun vectors are also inputted into the algorithmic model, sun exposure has been set to a specific period. The resulting geometry is then meshed and run through a color gradient visualization algorithm that reflects the number of sun vectors that can reach each surface of the geometry.

After that, the resulting geometry is meshed and run through a color gradient visualization algorithm that reflects the number of sun vectors that can reach each surface of the geometry. Finally, the algorithm is run through the evolutionary solver in order to generate, evaluate and rank the solutions dynamically.

Based on two objective fitness functions that seek to maximize sun exposure and accessibility, the Octopus solver evaluates each output of 3D geometry in order to generate a better fitting form. For this simulation, the solver is set to a maximum of 50 generations with a population of 50.

Because the design logic starts from the basis of modules, sun exposure optimization should be made by optimizing units and not the global evaluation which is the average of all units. The problem is that we could end up with a huge disparity in the optimization curve, with some units having no sunlight at all while others having maximum sunlight. The idea is to have a large median base rather than two large extremes. We could answer this problem by setting a minimum percentage and maximum percentage in order to limit the domain better.

The accessibility objective function calculates the distance between each module and the nearest street, thus evaluating the accessibility of each module from the exterior. As for the sun exposure objective function, it is set to reward the algorithm if the optimization result is between the range of 30% to 60% (3 to 6 hours of sun exposure). Thus, it seeks to homogenize the results in order to come up with a larger median base rather than two curves that cluster in the maximum and minimum edges.

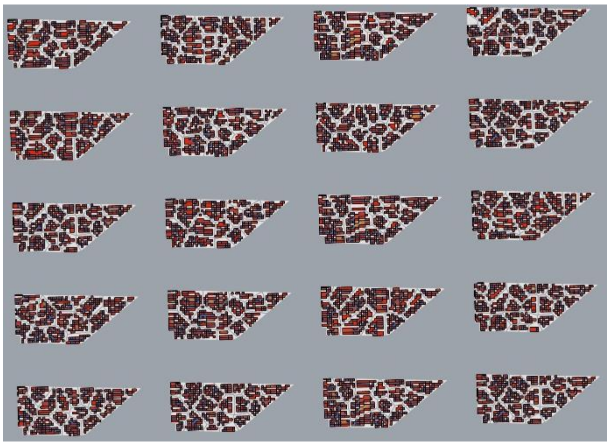

Figure 2. Phenotypes of the Pareto front distributed on a grid.

5.2.2. Solver and genes

In order to set up the solver, the genes that are input include:

- Random reduction seeds.
- Random 2D population for plot subdivision.
- Number of plot subdivisions

As for the fixed inputs in the algorithm, those include:

- Random reduction seeds.
- Maximum building heights
- Weather data
- Population density
- A few fixed 2D population for plot subdivisions

5.4. MOEA EVALUATION STRATEGY

WallaceiX, an MOEA solver is used to optimize, evaluate and visualize the generative algorithm results. The simulation is set to a maximum generation count of 50 by size of 50, making for a population of 2500. The input genes include plot counts and variation seeds, density definition and variation seeds with a total of 9 sliding values. The phenotypes (Figure 2) in this case include the meshes and geometry of the building cells and plot surfaces.

There are three conflicting fitness objectives, including optimizing density count (FO1), optimizing and equalizing the number of hours of sun exposure (FO2) and optimizing physical accessibility (FO3). The first two objectives are set to be maximized whereas the third one is to be minimized (i.e. proximity of blocks to streets).

**6. Findings**

6.1. RESULTS

The solutions calculated through the MOEA solver have been run through data analysis and have shown a global trend for evolving optimization through the flow of the simulation generations.

While analyzing the solution's data (Figure 3), there is a clear trend for further optimizing the mean value of the evaluation scores for all three objectives. Moreover, narrowing the standard deviation graphs through the generations, especially for FO1 and FO2, proves the system's ability for diversification of results.

Beyond the study of general optimization trends, it is also crucial in this methodology to select the optimum outputs for the design problem. This is achieved with the exploration of the Pareto front results.

6.2 SELECTION

After a generation count of 50, the number of solutions represented on the Pareto line is 20. The dynamic change and diversification of results have also shown that the solutions represented on the Pareto front have changed throughout the generations. Visualizing the Pareto front results (Figure 2) is key to select the appropriate solutions and comparing any physical discrepancies between the results and the visual forms. Some first iterations of the model have indeed show inconsistencies between data and generated form, this was caused by a poorly defined evaluation factor.

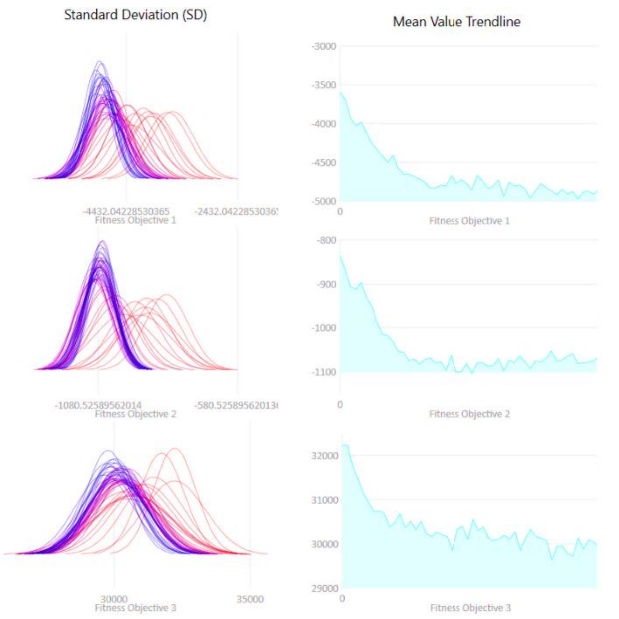


Figure 3. Standard deviation through the generations and Mean value trendline for the fitness objectives scores.

**7. Conclusion and prospects**

Through the study of this experimental tool for self-organizing urban form, the results have shown potential for optimizing morphology to design constraints. It also showed that there is also still ample room to optimize and better develop the algorithmic model itself to address various issues such as calculation times, and poorly defined objective functions, However, to further proof-check this algorithmic model also requires an external evaluation factor for the solutions outside the application of MOEA solvers.

While the model might have partially answered to the morphological and organizational factors discussed in the paper, there is still a need to better define evaluation factors that can optimize social aspects. Comparing and cross-checking, the optimized model with factors external to the multi-objective optimization algorithm can be methods to evaluate its reliability and adaptiveness. Thus, it would be relevant to check the solutions with a participative methodology that can take the input of the target users to better define the urban program.

To conclude, in order to verify the reliability of this computational design model, it is also necessary to experiment with multi-objective optimization algorithms other than evolutionary solvers such as the use of machine learning. These various methodologies should be separately developed and compared to decide of the most suitable design strategy for this self-organizing urban model.


**Acknowledgements**

This research was only possible with the valuable input and contribution the help of Kensuke Hotta, project assistant professor of Keio University.


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