Generative Urban Design: Integrating Financial and Energy Goals for Automated Neighborhood Layout

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ABSTRACT
This paper demonstrates an application of Generative Design to an urban scale through the design of a real-world residential neighborhood development project in Alkmaar, Netherlands. Problems in urban design can benefit greatly from the Generative Design framework due to their complexity and the presence of many stakeholders with various and potentially conflicting demands. We demonstrate this potential complexity by optimizing for two important goals: the profitability of the project for the developer and the potential for energy generation of solar panels placed on the roofs of the buildings. This paper points to further research into the application of the Generative Design framework to solve design problems at an urban scale.

Author Keywords
Generative Design, urban design, optimization, genetic algorithm, parametric modelling, solar analysis, profit optimization

ACM Classification Keywords
I.6.5 SIMULATION AND MODELING - Model Development

1 INTRODUCTION
Generative Design allows designers to tap into the power of computation to explore large design spaces and derive design solutions which are both novel and high-performing relative to a chosen set of goals. This process relies on a set of technologies including parametric design software for modeling the space of all possible solutions, simulation software for deriving metrics to evaluate each potential design, and optimization solvers such as the Genetic Algorithm (GA) which can automatically search through the design space to find the most optimal designs. In recent years, this type of workflow has become widely used to solve design problems in a variety of domains such as engineering, industrial design, and architecture.

Urban design problems tend to be very complex, involving a multitude of stakeholders, each with their own complex and competing goals for the project. These complex goals are difficult to resolve through a traditional design process, forcing designers to rely on intuition and prior experience which can limit potentials for novel design solutions. The Generative Design methodology can help urban designers navigate complex design spaces and a multitude of competing goals across different stakeholder domains. Such applications, however, have not been widely explored.

This paper describes a novel application of the Generative Design methodology at an urban scale through the design of a residential neighborhood of 7,000 sqm in Alkmaar, Netherlands. To show the utility of this workflow, we consider two important and competing goals, each representing the desires of different stakeholders in the project. The first is the cost and revenue of the development project, which is important for the developer. The second is the potential energy generation of solar panels attached to the roofs of each building. This is important not only for minimizing the environmental impact of the development but also for the future homeowners who will benefit financially from the energy being generated. Through this example, we demonstrate how the Generative Design process can help reveal the potential tradeoffs between competing design goals and help urban designers discover designs which solve these goals in novel ways.

2 LITERATURE REVIEW
While the application of evolutionary algorithms for optimization of design spaces is well known within the manufacturing industry [1], they are under-explored in the architectural and urban design domains.

Prior work by the authors [2] explored the application of this workflow to the interior layout of an office space. Calixto and Celani [3] also described over 15 years of work exploring applications of evolutionary computing for spatial layouts. However, these studies were mostly theoretical and did not show the feasibility of applying such a process to a real-world design project. Furthermore, none of these studies were applied at an urban scale nor dealt with profitability or energy generation requirements.

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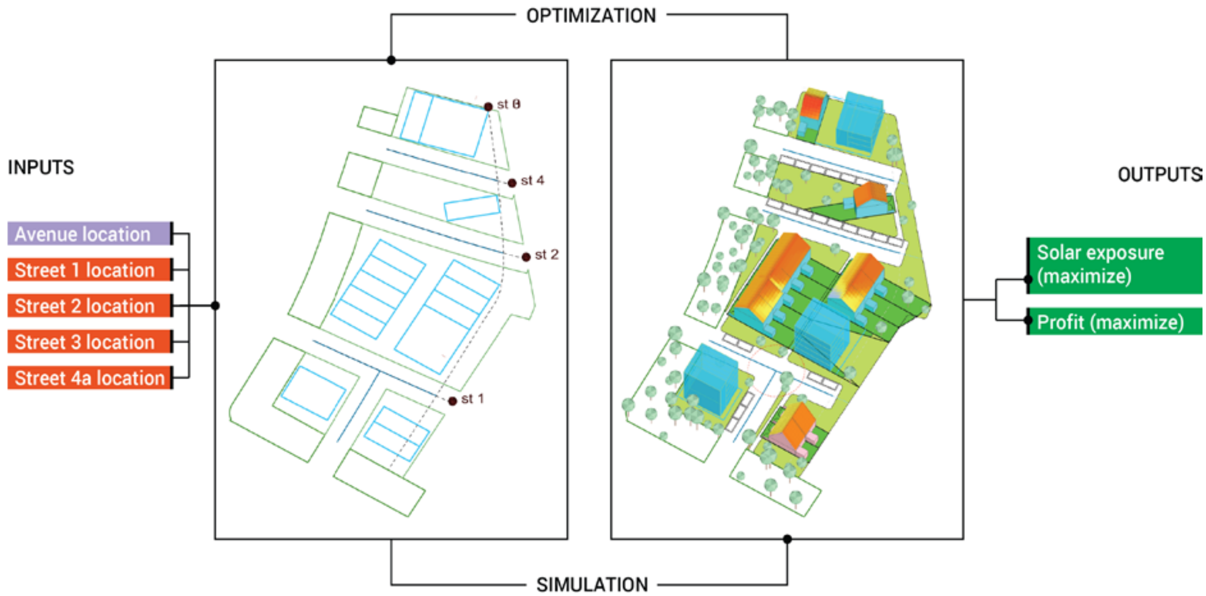

Figure 1. Description of design space showing five input parameters, definition of a single design's geometry, evaluation of design through simulation, and two output metrics.

Several authors have explored applications of optimization for urban-scale layouts. Elezjurtaj and Franck [4] showed an application of genetic algorithms for town planning, but limited their fitness function to formal and topological features. Koma et al. [5] used an interactive genetic algorithm approach to optimize urban landscape features, but applied their study to an abstract fictitious city block. Luo and He [6] used a rule-based model for generating city layouts, but their approach was only generative and lacked a system for evaluating the resulting designs according to specific performance criteria.

Building energy modeling has also been widely applied at the building level [7], but its application to an urban scale is still under-explored. Reinhart and Davila [8] presented the opportunities and advantages of UBEM (Urban Building Energy Modeling) while also discussing the challenges and obstacles that limit its implementation at an urban scale. Our study relies on a computationally lightweight solar energy calculation which is scalable to urban neighborhoods and compatible with an automated Generative Design workflow. To address the complexity of typical urban design problems, we also integrate cost and profit as goals within our model. Such financial objectives are typically modelled in the real-estate development industry but are rarely combined with other objectives in a unified model such as the one described in this paper.

3 METHODOLOGY

3.1 Design space model

The first step of the Generative Design process is to create a design space model which can generate various design solutions subject to the constraints of the problem. In this case the design problem consisted of laying out a residential neighborhood on an existing 7,000 sqm lot in the town of Alkmaar, Netherlands. A series of workshop sessions held together with our client (the developer of the lot) aimed at understanding the high-level goals of the project and gathering the specific constraints and requirements that the final layout would need to satisfy. In addition to profitability, one of the developer's main goals was to create a neighborhood which was both sustainable and functional for the end-user. Several constraints and requirements were gathered and have been grouped into two main categories: site constraints and program requirements. Site constraints define those restrictions that are derived from local building code and existing topographical features, while program requirements synthesize the developer's programmatic goals for the project.

The site constraints included:

- A predefined site boundary that delineates the Generative Design zone
- Fixed unit orientations orthogonal to the existing streets adjacent to the site
- A maximum building height of 5 floors in the south and 3 floors in the north
- A minimum of one access road to the West and to the South side of the lot
- Parking lots need to be at least 5m away from road intersections
- Only same house unit types can be adjacent to each other and can aggregate only laterally

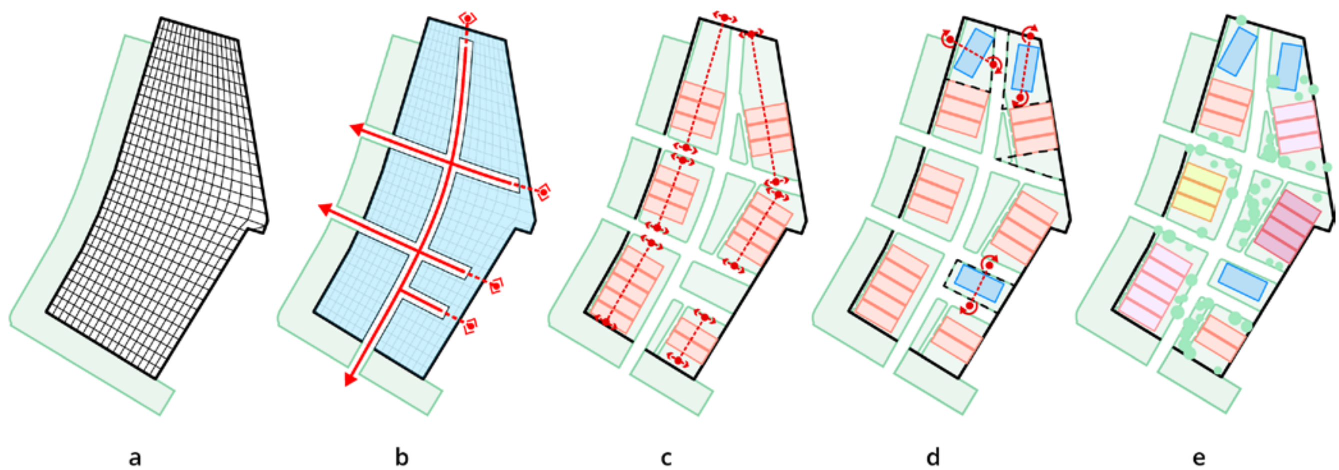

Figure 2. Description of parametric model for generating each design option

The program requirements included:

- The layout should have at least 3 single houses TYPE A
- The layout should have at least 4 single houses TYPE B
- The layout should have at least 2 single houses TYPE C
- The layout should have a minimum of 3100 sqm of apartment units

Based on the constraints and requirements described by the client, a parametric model was created which can generate a wide variety of valid design options based on a small set of input parameters (fig. 2). While the site constraints were directly integrated into the model (each design solution satisfies all given constraints) the program requirements were represented as an objective for optimization. This allows the discovery of design solutions that, although not fully meeting certain targets, might offer unexpected layout strategies that prioritize other objectives.

The model is based on an initial subdivision grid which adapts to the edges of a given lot boundary (2a). The edges of the grid are used to identify streets that run in both directions across the site (2b). The streets divide the lot into zones, which are tested against internal model constraints such as minimum region aspect ratios and surface areas. Those that do not meet such requirements are either split (generating new streets) or joined together (removing the separating street). Each resulting zone is populated with green public areas, house units, apartment buildings and pedestrian paths (2c-e). Each road is also populated with parking spaces running along one of its edges.

The model is parameterized by 5 continuous floats with domain [0.0, 1.0]. Considering the initial subdivision grid as a matrix of streets organized in columns and rows, the first input parameter controls the selection of one avenue that runs North-South, while the remaining ones control the selection of 4 streets that run East-West.

3.2 Design goals

To evaluate the performance of each design option relative to the goals of the project, the design space model needs to include one or more metrics which can be used as objective targets during optimization. Through discussions with the client, we developed seven individual goals which were used for the final optimization. For the purposes of this paper, however, we focus on two of the goals which were found to be most important: the profitability of the project for the developer, and the potential solar energy that can be captured by the roofs of the residential buildings (fig. 3). These goals represent the competing desires of two major stakeholders in the project - the developer who wants to maximize profits, and the future homeowners who will benefit from the solar energy collected by the buildings. Although both goals are critical to the success of the project, they are potentially conflicting, for example if certain building configurations which maximize profit are not in the ideal solar orientation. By combining them within a single design space model and optimizing for both objectives at once, we can better understand the tradeoff between these competing goals and find the optimal designs which solve this tradeoff in the best way possible.

To calculate the profitability of the project (fig. 3a) we used financial data provided by the developer that lists all construction cost and selling value for each type of residential unit and neighborhood infrastructure. Profit is the difference between the total selling price of the units and the total cost of the project which are calculated according to the following equations:

$$Profit = total\ selling\ price - total\ project\ cost$$

$$Total\ selling\ price = total\ house\ price + total\ apartment\ price$$

$$Total\ project\ cost = land\ cost + construction\ cost + development\ cost + selling\ and\ rent\ cost + profit\ and\ risk\ factors$$

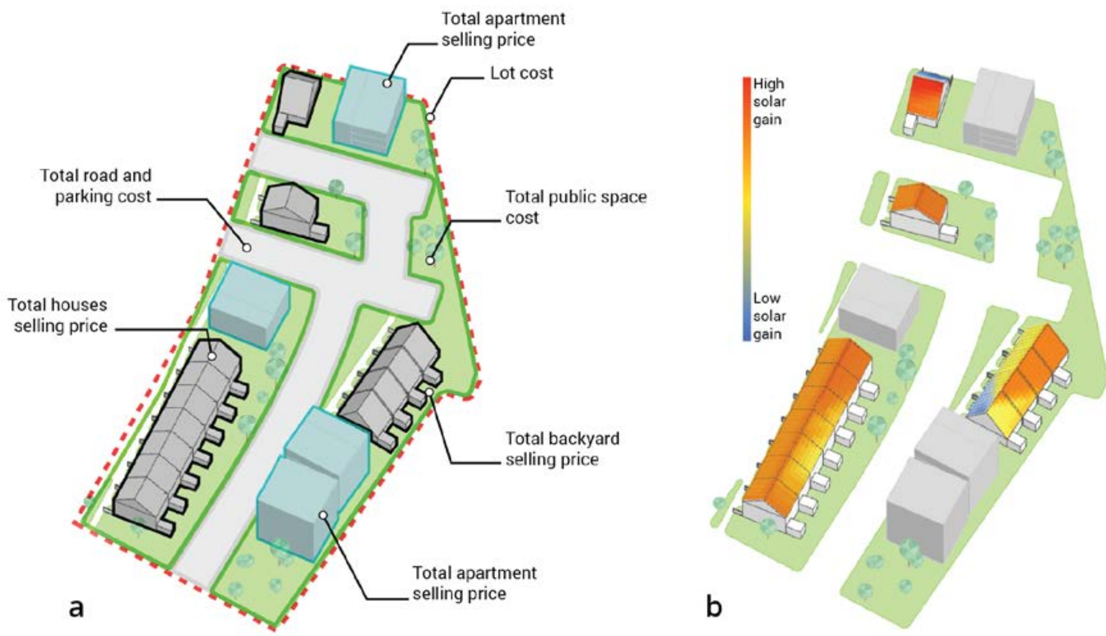

Figure 3. Description of two metrics, development profitability (a) and potential for solar gain (b).

The resulting score is an estimate of the profitability of each design solution and is maximized during optimization.

To calculate the potential for solar energy collection (fig. 3b) each roof surface is tested for occlusions against 48 sun ray vectors (based on 15 minute increments on equinox and solstice dates). The calculation of solar energy is based on the equation below:

$$solar\ energy\ = \frac{potential\ solar\ collection}{solar\ energy\ availabilty}$$

Potential solar collection: number of unoccluded sun rays

Solar energy availability: number of available sampled sun rays

The resulting solar energy score is the average utilization of the potential solar energy by the roofs of all buildings on site and is maximized during optimization.

By looking at several possible designs, we can begin to see the relationship between the two goals and the potential tradeoff between them (fig. 4). The design in the lower right optimizes for solar energy by placing the single housing unit in an east-west orientation. However, it does not maximize profit because the site is under-utilized. The design in the upper left optimizes profit by placing a large number of units on site but perform poorly on solar energy because much of the sunlight of the long row of housing is blocked by the large apartment building next to it. The design on the lower left performs poorly in both goals because it only has two small buildings, with the solar exposure of the single house almost completely blocked by the apartment building south of it. The design on the upper right does well in both goals. It has a good amount and mix of housing types while orienting the houses to take maximum advantage of the solar angles. This high-level analysis reveals potential conflicts between the two goals, as well as opportunities for finding high-performing designs which optimize the tradeoff between them.

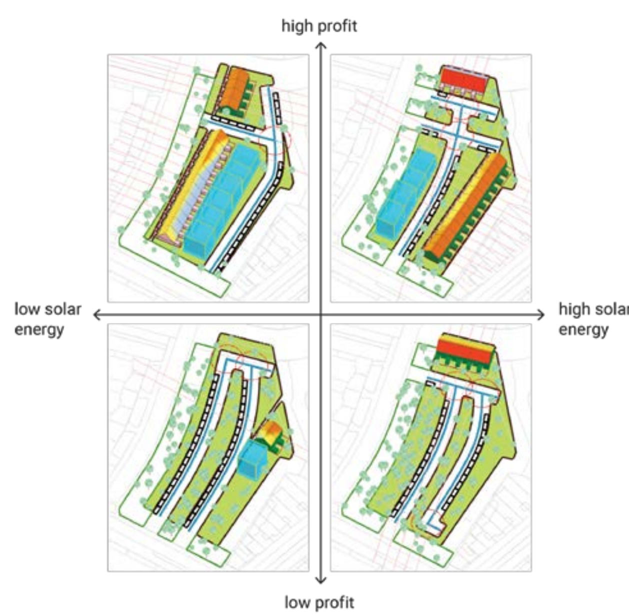

Figure 4. Comparison of designs at performance extremes.

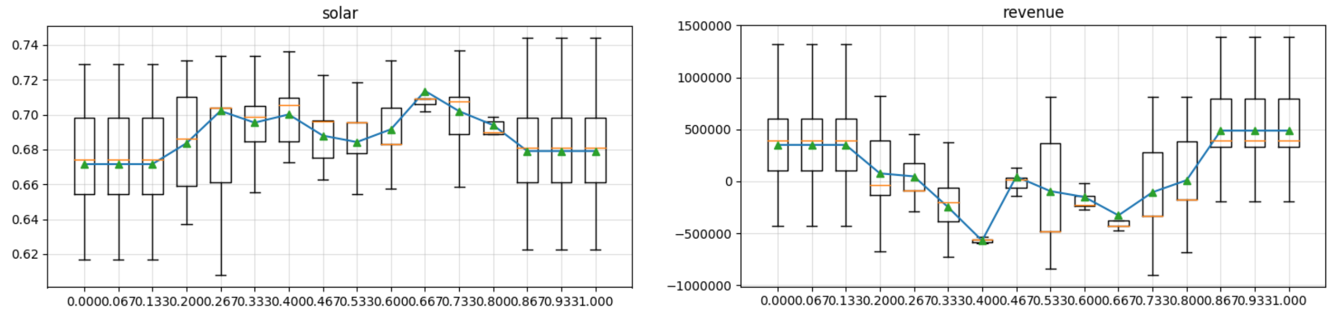

Figure 5. Box plots showing response of each output goal to variations of the input parameters

3.3 Design space analysis

Just because a design space model is well defined does not mean that it will result in a good optimization. In a previous paper [9] we described a set of metrics for evaluating a design space according to two tradeoffs: bias vs. variance and complexity vs. continuity. For analyzing these properties within a given design space we proposed a visualization method which we have also implemented for this project (fig. 6). As described in the previous paper, this analysis should be done before optimization to ensure that the optimization process will be productive and will yield good results.

To produce this visualization, we sample the design space evenly along the most critical parameters of the model. In this case we analyze the single avenue parameter and two of the street parameters. Then, we create pair plots which visualize the value of the two output metrics (developer profit and captured solar energy) for different parameter settings as colors or height fields. These plots allow us to study the response or sensitivity of each parameter to each metric, helping us understand the range of the design space as well as its internal structure.

This analysis shows that the design space is not overly biased because it can generate a variety of design solutions with a range of housing types and street topologies. At the same time, it is not too variant because each design represents a viable solution which respects the constraints of the design problem. At a local level, the plots show a structure and continuity in the relationship between input parameters and output goals, suggesting the model is continuous enough to be efficiently explored by an optimization algorithm. At the same time, there is enough variation and complexity in the response surface to ensure that the optimization process will be productive and discover novel designs beyond those that could be found by intuition alone.

To get a better look at the tradeoff between the two output metrics we can plot both of them relative to a single input parameter (the location of the avenue) and aggregate the effects of varying the other parameters using box plots (fig. 5). Looking at these box plots we can see that for certain settings of the avenue parameter there is more potential for variation in the outputs than for others (shorter whiskers vs. longer whiskers). If we look at the average values, however, we can see that values of the input parameter which tend to result in higher levels of solar radiation (for example 0.40 and 0.67) also tend to result in lower levels of profitability. This shows that there is a potential tradeoff between the two goals. However, due to the variability caused by the other inputs parameters and the complexity of the design space, the relationship between the goals is more complex than what can be visualized and understood through such a simple plot. This suggests the value of optimization for further exploring the design space and discovering designs that achieve the best compromise between the two goals.

3.4 Design optimization

To generate the final design solution, we used a Genetic Algorithm based on the NSGA-II algorithm [10] to find designs within the design space which maximize the values of the two objectives. The optimization trial consisted of 200 generations with 200 designs in each generation. The initial population of designs was seeded with the 200 top performing designs from those generated for the design space analysis described in the previous section.

4 RESULTS

Figure 7 shows the results of the optimization, with each generated design represented as a single dot in the scatter plot according to the two objectives. Designs closer to the upper right corner are the best performing, with all the designs along the pareto boundary representing the best tradeoffs between the two objectives. Looking at the best performing designs, we can see that most used linear arrangements of single houses and apartment buildings with very few long roads cutting across the site. Intuitively, this allows for a maximum packing of units while minimizing the cost of road infrastructure.

From the full set of designs, three were chosen which represent three different strategies for laying out the lot. After review with the client the most preferred strategy was selected and further refined to create the final design

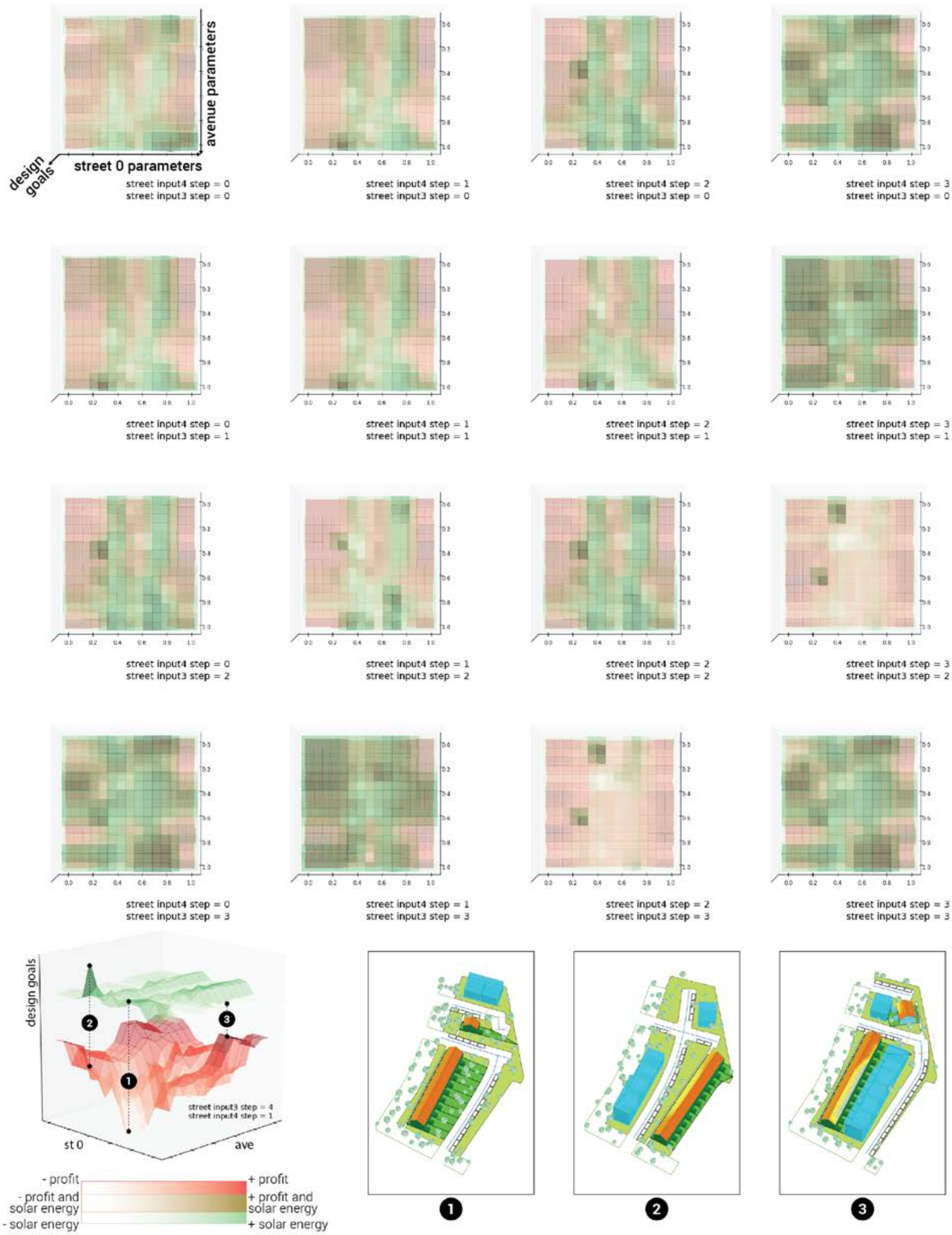

Figure 6. Design space visualization with plot x and y axes representing input parameters and z-axis and color representing averaged values of output metrics.

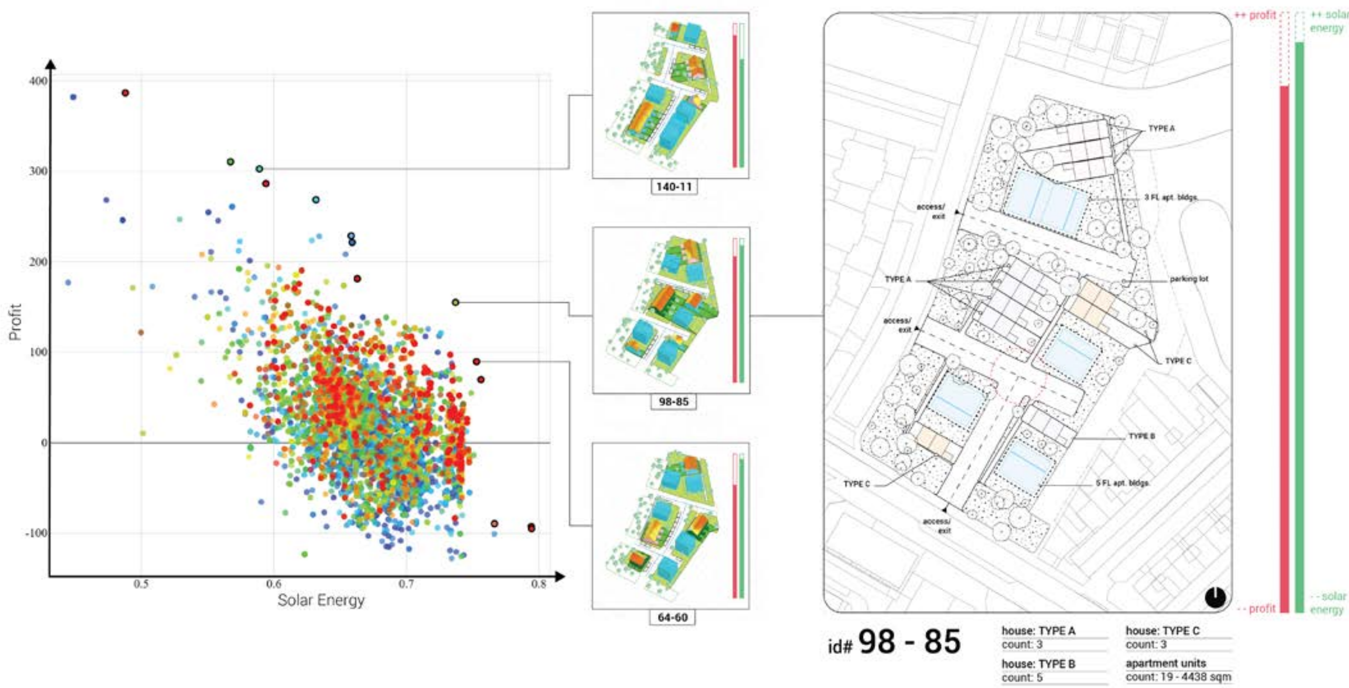

Figure 7. Plot showing tradeoff between the two objectives (color indicates generation with earlier designs in blue and later designs in red). Three chosen high performing designs are shown in the middle and final design after refinement on the right.

solution. This design represents the best of both human intuition and computer-driven design exploration, and results in a neighborhood design which is both novel and high performing.

5 CONCLUSION

This paper described the implementation of a Generative Design workflow at an urban scale through the design of a residential neighborhood in Alkmaar, Netherlands. To measure the success of each design we chose two important and potentially conflicting goals: the maximization of the developer's profit and the maximization of solar energy collected by the building's roofs. This project shows how the Generative Design process can generate good design strategies while also revealing higher-level insights about the potential conflicts and tradeoffs between the goals of the project. Ultimately, these higher-level findings can be used to further refine the generated strategies, leading to a better and more informed final design.

Although the results of this project have been encouraging, the application of Generative Design to the urban scale requires further research and testing. Future opportunities include the integration of additional design metrics that are critical for planning at an urban scale such as user comfort, safety, and traffic. These metrics can expose even more of the complexity of urban design to the Generative Design process, leading to design solutions which are both highly functional and go beyond the intuition of human designers alone.

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