AN OPTIMIZATION FRAMEWORK AND TOOL FOR CONTEXT-SENSITIVE SOLAR-DRIVEN DESIGN USING CELLULAR AUTOMATA (SDCA)

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ABSTRACT

This article develops a framework and computational tool that integrates cellular automata (CA) as a generative design (GD) system into the solar radiation incident (SRI) simulation. It automates generating and optimizing urban building form considering the surrounding morphological context. The proposed framework is tested for designing the building form located at dense urban districts at multiple locations where abundant shadows are cast on the target building from neighboring structures. Findings indicate that this framework can automatically produce forms with increased solar energy gain by buildings in urban environments for suggestive use in the early-stage design. Comparison studies upon the equal-volume control forms indicate that the proposed framework can maximize SRI on building surfaces for renewable energy generation applications through form generations by up to 24%. The proposed framework and toolkit aid architects in building form-finding with increased solar-energy harvesting through optimizing context-sensitive exploration at early-stage design.

Keywords: Generative Design; Cellular Automata; Solar Radiation; Form Finding; Context-sensitive

1 INTRODUCTION

Artificial intelligence (AI) has recently been applied to early-stage architectural design to facilitate the complex design process by exploring design needs and possible solutions as an approach to optimizing architectural forms (Abbasabadi and Ashayeri 2019; Castro Pena et al. 2021). Particularly, it has been applied significantly in sustainable design practices to address urban challenges, including climate change –as buildings account for over one-third of energy consumption and nearly 40% of CO_2 emissions globally (UN Environment Program 2019) and contribute to exposure to pollutants and increasing human health risks (Ashayeri et al. 2021; Ashayeri and Abbasabadi 2022). Generative design (GD), a computational and evolutionary system reflective of a specific design problem or characteristic determined by the designer (Herr 2002), has long been viewed as a paradigm shift by using rules to dynamically and autonomously generate complex outcomes unconceivable by humans alone (McCormack et al. 2004). By bringing the power of GD into existing design workflows and automating the process, high levels of accuracy, consistency, and efficiency can be achieved to strike a balance between subjective preferences and performance-based criteria. In performance-driven design, environmental factors such as solar (Lobaccaro et al. 2016; Zhang et al. 2016) and daylighting (De Luca 2017; Jalali et al. 2020; Pinto de Araujo 2018) are improved by simulating a building form's massing, orientation, etc. (Sams 2017). The iterative nature of GD makes it an ideal early-stage (ES) design approach by allowing for rapid exploration of countless design alternatives. This provides an opportunity to find higher performing solutions when optimizing for sustainability-related objectives such as increased solar energy potential is demanded (Shaviv 1999).

Design of holist urban architecture should be supported by a suggestive form-finding exploration facilitated by creating, simulating, and analyzing patterns to deep levels of complexity. Cellular automata (CA), a dynamic system consisting of cells with various states for generating highly complex arrangements (Batten 2007) has been applied in GD workflows for generating novel form design through creative volumetric solutions (C. Cruz et al. 2017). First used in architecture by Frazer in 1995 (Frazer 1995), CA has since been used as a morphogenetic "bottom-up" design approach in which predetermined results are avoided, and generated outcomes are complex and unpredictable (Herr and Ford 2016). The main advantage of CA derives from its capacity to reach status from the local dynamics, making it suitable for context-sensitive design exploration. Context is principal in performance-based design of densely populated high-rise buildings areas. Studies for ensuring a more sustainable and low-carbon design commonly utilize solar-driven optimizations toward increasing renewable energy capturing, as cities with many high-rises have excessive levels of untapped solar energy potential. In developing performance-based workflows for increasing solar energy, some studies aimed to maximize solar radiation incident (SRI) at neighborhood block level (Kämpf et al. 2010; Yi and Kim 2015). However, they are not suitable for individual building level design because they disregard the more complex form properties of the building as they derive from context. Some studies have applied other GD algorithms to maximize the amount of SRI (Manni et al. 2020) based on form explorations (Lobaccaro et al. 2016; Zhang et al. 2016) but overlooked spatial exploration of the individual building considering urban context, particularly within high-rise environments. There still exists gaps in utilizing CA for building form generation with maximum SRI for increasing the potential of renewable solar energy usage by considering the urban context in the workflow.

Therefore, in this research, we aim to develop a solar-driven form-finding framework and tool assisted by CA (SDCA). The framework and tool enable maximizing SRI for energy generation applications in a context sensitive exploration of building form development at the early stage of design. The proposed method provides suggestive forms by addressing contextual forces (i.e., surrounding morphology and their casted shadows). The proposed methodology entails two main steps for execution: 1) parametric form construction based on SRI and 2) form optimization using a generative CA based approach for exploring various architectural scenarios. A tool in the Rhino/Grasshopper environment will be developed based on the proposed framework that efficiently automates the entire process. To demonstrate the effectiveness of the methodology, testing will be done within dense urban contexts with varying types of morphological high-rise contexts as it is identified a more challenging case study in terms of harvesting solar energy. The final output geometries are evaluated for their performance compared to two corresponding control volumes. The findings of this research can aid designers in providing suggestive building forms in the form exploration process to achieve low-carbon and sustainable built environment goals.

2 MATERIALS & METHODS

2.1 Materials

This study develops a computational design framework and tool for optimizing SRI concerning a site's contextual morphology. The study aims to offer a flexible framework that architects can implement into the designing of buildings, specifically high-rises, to maximize capturable solar energy across the building-envelope surfaces. We tested the framework in generating high-rise building forms in multiple dense urban districts in Chicago, IL, Minneapolis, MN, and New York City, NY which are located in cool to cold areas to maximize SRI, increasing the potential for solar energy harvesting. The three sites were chosen to demonstrate the replicability in different locations and provide less biased results in the development of the proposed method. Urban morphology was considered because cities' continual growth in population and density warrants additional attention when designing sustainable high-rises. Additionally, solar energy potential is largely influenced by many morphological fluctuations as in Chicago, New York City, and Minneapolis.

Chicago and New York City both reside in ASHRAE's Cool Zone (Climate Zone 5), while Minnesota resides in the Cold Zone (Climate Zone 6) (U.S. Department of Energy 2015). It is crucial in Cool and Cold Zones to increase solar radiation exposure because most building energy in these areas is spent on heating the buildings during cold months, in addition to harvesting solar energy for electricity generation. The Chicago site is located at 71 South Wacker St. (Site A), one block east of the River and three blocks north of the Willis Tower. The Minneapolis site is located at 122 South 7th St. (Site B) between the three tallest buildings in the city. The New York City site is located at 321 Broadway St. (Site C) and has four high-rises surrounding the east, south, and west portions of the site. The three locations currently have existing buildings on the chosen sites; these were removed from the 3D models so that the hypothetical experimentation could take place.

Figure 1**:** 71 South Wacker St., Chicago, IL (A); 122 South 7th St., Minneapolis, MN (B); and 321 Broadway St., New York City, NY (C). Credit: OpenStreetMap.

2.2 Step 1: Parametric Form Construction

2.2.1 Input

The initial form is created in Step 1 using parametric methods in Grasshopper, along with open-source plug-ins Ladybug (Sadeghipour and Pak 2013) and Anemone (Zwierzycki 2013). The workflow requires two types of inputs by the user: pre-defined inputs and user-defined inputs. Pre-defined inputs are those that are automatically determined when a site is chosen and include A) an EPW file for the specified location, B) the building context geometries, and C) the site plot boundary, each of which are plugged into Ladybug.

EPW files (A) were retrieved from the DOE using Ladybug components. Besides the site location, building context geometries (B) are the primary determinant of how the sun impacts a site. Therefore, it is essential to define surrounding building geometries as accurately as possible so that the simulation can provide more realistic results. 3D models for context geometries in this study were downloaded from Cadmapper, a website that compiles open-source data from OpenStreetMap, NASA, and the United States Geological Survey into CAD files at a global scale. Finally, the plot boundary (C) represents the largest allowable footprint of the proposed building and is input into Ladybug as a surface.

The second type of inputs is user-defined inputs. These are adjustable based on the user's preferences to allow for flexibility in the design process. Instead of inputting an initial starting form, the user defines A) 3D grid size/voxel granularity, B) time to optimize for, C) proposed building height, and D) percentage of site volume to use. The grid size and analysis period are input into Ladybug. The proposed building height is used as a value to terminate the simulation, and the target volume percentage is used to construct the polyhedra.

The grid size value (A) is used to divide the Ladybug analysis plane into uniform measurements, which then determines the size of the 3D voxel cubes. By using a smaller grid size, the final volume will have a finer resolution which could provide more insight into the design process at the cost of increased computational times. Various previous voxel-based approaches utilized a $3m^3$ ($9.8ft^3$) 3D voxel grid (De Luca 2017; Pinto de Araujo 2018), so a similar sized voxel grid of $10ft^3$ is defined in this study. This grid size strikes a balance between high model resolution and low computational expenditure. An analysis period (B) is required for the SRA to know which hours of the year to simulate. This allows the user to optimize the building form at any temporal granularity (i.e., annual, monthly, weekly, etc.) In this study, forms were constructed based on seasonal and annual simulations.

The proposed building height (C) is a value that represents the maximum number of voxel layers to allow for along the z-axis (vertically). In building design, this value could be representative of number of floors in the building. In this study, the proposed building height matched the height of the tallest contextual building, similar to the procedure implemented by (Jyoti 2015). The target volume percentage (D) is a value from 1 to 99 input by the user, representing the percentage of grid spaces per floor to receive voxels. For this research, optimizations were carried out for 50 and 75% of the site volume, but this value remains highly flexible.

2.2.2 Output

Once inputs are set, the parametric form construction can begin. SRA is performed for the base level n on the site, and values for the amount of solar radiation received by each grid square (the grid size is determined by user-input) in kWh per square foot (kWh/m^2) for that level are recorded. These solar radiation values are sorted in descending order, with the highest values at the top. Then, based on the user-input target volume percentage (x), voxels are deployed for the top x percent for that level n. From there, the system checks to see if the proposed building height has been reached. If not, the SRA level is raised one level ($n+1$), and the process is repeated using the Anemone plug-in for Grasshopper. This process continues until the proposed building height has been reached, and the loop is terminated, outputting a 3D polyhedron.

2.3 Step 2: Form Improvement via CA

2.3.1 Input

The stacked layering method used to create the initial polyhedron in Step 1 yields forms with many imperfections and noise that would make it difficult to use in the architectural form-finding process. Because the majority of solar radiation is not distributed uniformly across a site, the output voxel geometries from the parametric form construction consistently possessed noise such as floating voxels and internal pockets of missing voxels. Such anomalies could get in the way of the form serving its purpose as a suggestive early process building form. To solve this, a cellular automata approach was integrated to eliminate most of the noise from the polyhedra without deviating from the initial volume shape. Inputs for Step 2 include the proposed building height, grid size, plot boundary, output polyhedron from the first step, and rules for the CA. All inputs for Step 2 are the same as inputs for Step 1 with the exception of A) the output polyhedron from Step 1 and B) the rules for defining the CA. Because the purpose of Step 2 is to improve upon the form created in Step 1, the output from Step 1 becomes the input for Step 2. Secondly, rules are needed for the CA to determine which voxels to add or remove. The set of rules used in this study is further explained below.

2.3.2 Output

This research utilizes Rabbit (MORPHOCODE 2010), a cellular automata plug-in for Grasshopper. The plug-in requires a set of CA rules and the number of generations (number of cycles through the CA improvement process). In terms of CA, rules define the state (occupied or empty) of each cell, or 3D grid space. For a given cell, the rules pertain to the amount of occupied neighboring cells it possess. A Moore Neighborhood (Moore 1962) is used for the CA system, meaning each square cell has 8 total neighbors, 4 on each side and 4 on each corner. Based on the state of these neighboring cells, a voxel is placed (turned on) or removed (turned off). In this study, the CA rules system is fully described by two rules: 1) an empty cell turns on when it has 4, 5, 6, 7, or 8 occupied neighboring cells, and 2) an occupied cell turns off when it has only 0, 1, or 2 occupied neighboring cells (Figure 2). This set of rules occupies cells that neighbor 4 or more voxels, filling most internal cavities in forms output from Step 1. These rules also remove voxels with 2 or fewer neighboring voxels, eliminating most of the noise from Step 1's output forms.

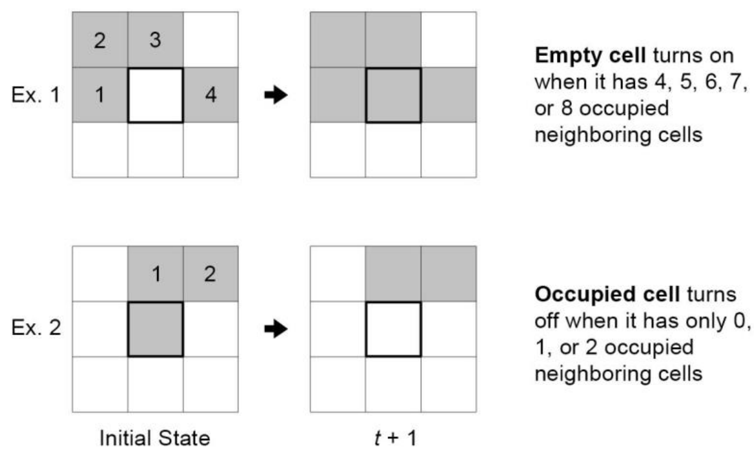

Figure 2: Cellular Automata Rules.

Because CA is a generative process, generations are used to describe each iteration. In this study, the initial voxel configuration from Step 1 is called generation *t*. Similar to the form construction in Step 1, the CA starts at the base level *n* and repeats for each level, ascending by one until the proposed building height has been reached. After the proposed building height has been reached, one generation, named t+1, is completed. With the previously described set of rules, the polyhedra were significantly improved after one generation, with most standalone/floating voxels removed and much of the internal voids in the form filled. After a second generation ($t+2$), the polyhedra were further improved slightly without deviating too much from the original optimized form. It became unnecessary to proceed beyond two generations of CA because it would cause too much deviation from the initial maximized form produced in Step 1. Therefore, the output polyhedron from Step 2 after generation $t+2$ is the final output of the workflow and can be used by architects in the early form exploration process when designing for maximum SRI in dense urban environments. Figure 3 illustrates the entire 2-step methodology.

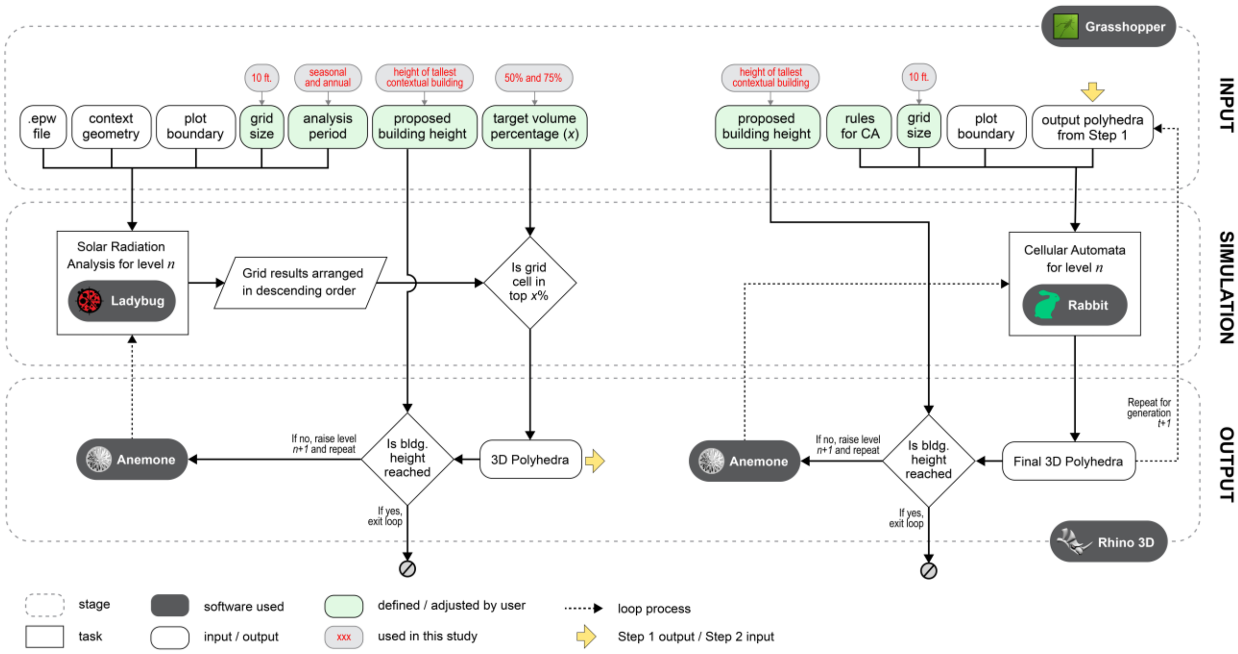

Figure 3: Flow chart for complete methodology.

2.4 Validation

We validated the results for evaluating the effectiveness of the of the proposed SDCA tool to quantify the performance in the production of each resulting form. In doing so, the resulting forms were compared to two different corresponding control volumes. The control volumes were constructed as rudimentary boxes in a similar fashion as the standard contextual high-rises seen in this study. To allow for a potentially equal amount of SRI, the control forms maintained a volume equal to that of its compared form. The first control forms were constructed based on having an equal volume and an equal site area. This resulted in forms that were significantly shorter than their comparative resulting forms. Therefore, the second control forms were constructed based on having an equal volume and an equal height and were placed directly in the middle of the site (Figure 4). The resulting optimized forms for both 50% and 75% of the target site volume, along with their associated control forms underwent final SRI analysis to quantify the success rate of the framework. Only forms that were optimized for annual analysis period were included in the validation process because the annual analysis period was the most holistic representation of the simulation outcomes.

3 RESULTS

The proposed framework allowed for many voxelated geometries to be generated (Figure 5). The SDCA tool produced suggestive polyhedra forms for each of the specified analysis periods (seasonal and annual). Similarly, it produced forms that were architecturally applicable for both 50% and 75% of the target site volume. Furthermore, the two-step framework of parametric form construction and generative CA improvement produced outputs with relatively low computational times. The resulting output voxelated polyhedra each consists of a conglomerate of equisized cubes distributed amongst the three-dimensional site lattices according to amount of solar radiation. In Step 1, forms were constructed parametrically by deploying voxels to areas with the highest amount of solar radiation using a stacked layering method that rarely exceeded 3 minutes in computation. The forms output from Step 1 consistently possessed large amounts of noise due to irregularities in the distribution of solar radiation. The forms output from Step 1 had many clusters of floating voxels, and, conversely, many internal pockets that lacked voxels. The irregularities ranged in size from 1 voxel to large clusters of more than 10 voxels.

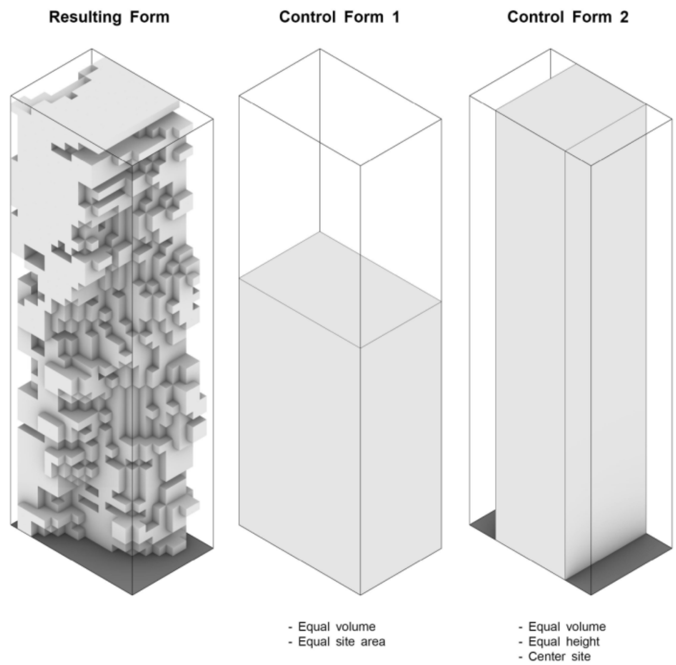

Figure 4: Diagram of resulting form construction (left); and control forms' construction with equal volume and equal site area (middle); and equal volume and equal height centered on the site (right).

In Step 2, volumetric irregularities from Step 1 were removed, allowing for the process to suggest plausible building forms. Here, improvements of the polyhedra using CA consistently lasted approximately 1 minute. The output polyhedra after one iteration of CA ($t+1$) showed significantly fewer irregularities than that of the initial generation (t). Most of the unattached voxels were eliminated, while most of the internal voids were filled. But because some irregularities remained, a second round of CA was conducted to improve the forms even further by eliminating additional noise. The output polyhedra after the second iteration of CA ($t+2$) still held a strong resemblance to the initial forms, implying that the initial optimal forms were not greatly deviated from by the end of Step 2. Figure 6 depicts a single form for each of the three sites at all three stages of the process (generations t, $t+1$, and $t+2$), highlighting the value of Step 2's CA system in removing most of the initial forms' irregularities.

Regarding the input variable of the target volume percentage, two values were used in this study (50% and 75%) to achieve two sets of results. Heat maps of the SRI for the final forms and each of their Control Forms can be seen in Figures 5. The results of internal validation of forms using 50% of the site volume illustrates that at Site A, the amount of solar radiation received annually by the building form was calculated to be 17,314,918 kWh/m^2, 94.7% more than Control Form 1 (equal volume, equal site) and 13.6% more than Control Form 2 (equal volume, equal height, center site). At Site B, the generated form for 50% of the site volume exhibited 29,900,157 kWh/m^2 annually upon the building envelope, 73.2% more than Control Form 1 and 23.8% more than Control From 2. At Site C, the resulting output form received 10,035,700 kWh/m^2 of annual solar radiation, 59.8% more than Control Form 1 and 6.6% more than Control Form 2.

The results of the validation of final output forms using 75% of the site volume indicate that at Site A, 19,142,688 kWh/m^2 of solar radiation are received annually by the optimal generated form, 32.8% more than Control Form 1 and 5.1% more than Control Form 2. At Site B, the 75% site volume form received 31,650,324 kWh/m^2 of annual radiation, 18.0% more than Control Form 1 and 3.9% more than Control Form 2. Finally, the resulting polyhedra at Site C received 11,636,023 kWh/m^2 of annual solar radiation , 23.5% more than Control Form1 and 2.8% more than Control Form 2. To reiterate, the forms generated from the proposed framework consistently exceed the control forms in terms of the target of maximizing SRI for all analyzed scenarios (Table 1)

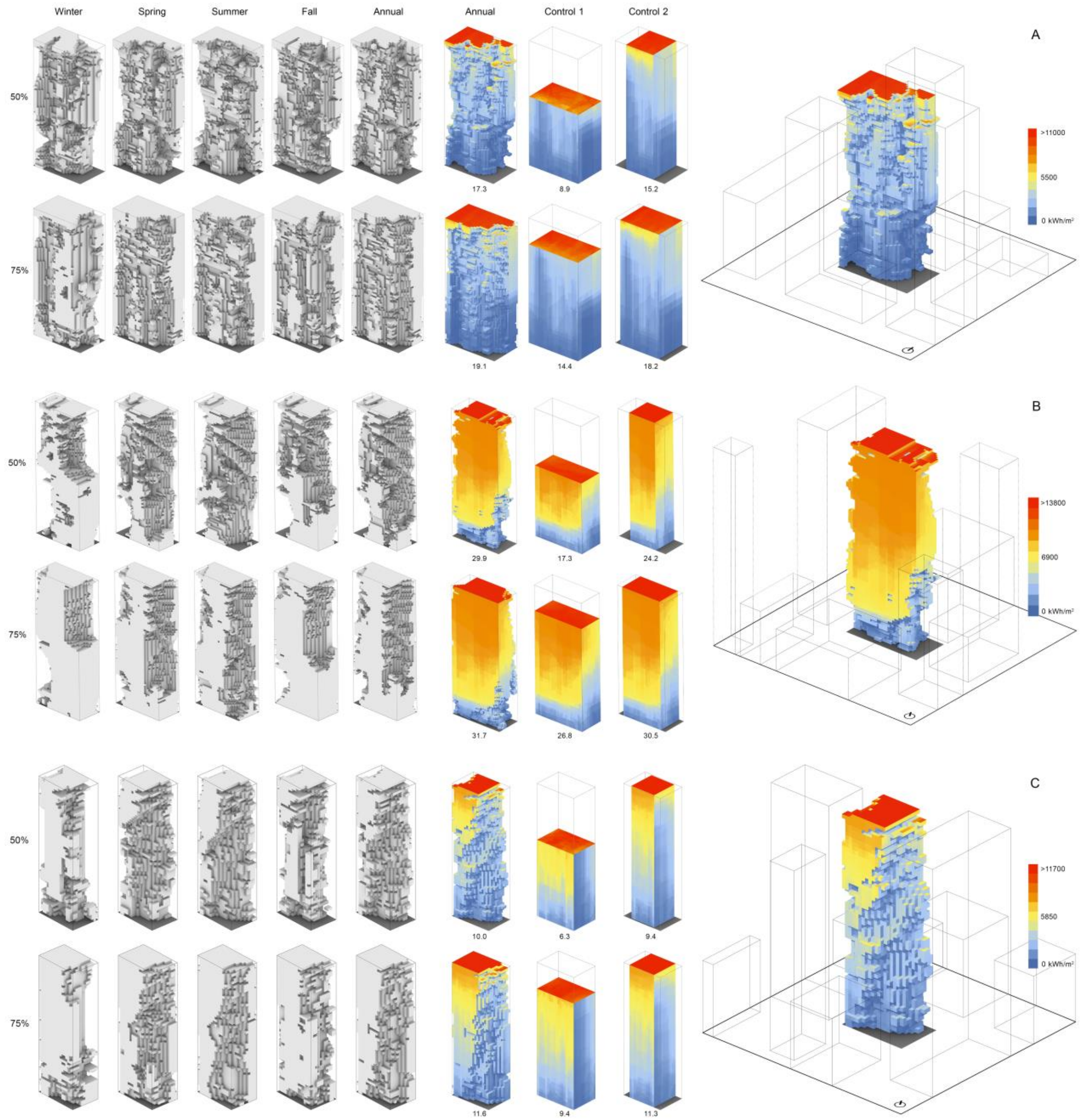

Figure 5: Final output forms for the three sites located in Chicago (A); Minneapolis (B), and New York City (C) including variations of SRI upon annual and control forms.

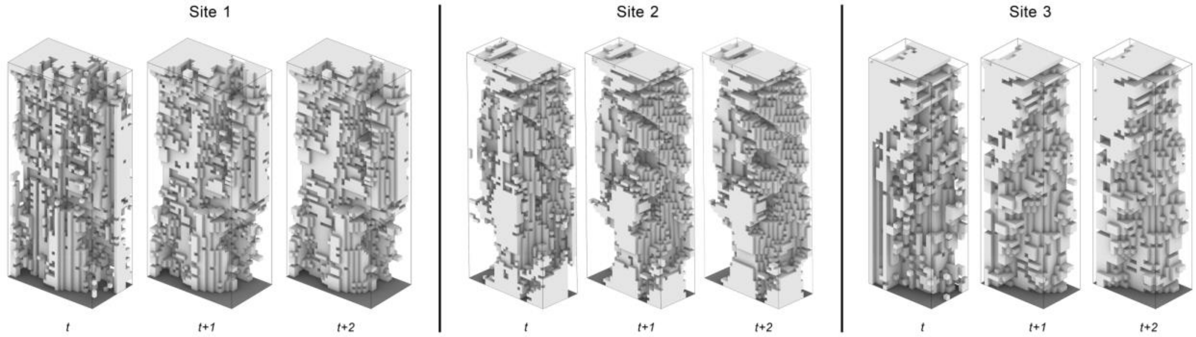

Figure 6: Forms from each generation for annual analysis period and 50% site volume.

Table 1: Calculated annual SRI (kWh/m^2) values of generated forms vs. control forms in two volumetric scales and the three sites/cities.

Site/City	**Site Volume %**	**SRI (kWh/m^2)**				
		Generated Form	**Control Form 1[a]**	**%Difference [c]**	**Control Form 2[b]**	**%Difference [c]**
Chicago	50%	**17,314,918**	8,894,684	94.7%	15,243,298	13.6%
	75%	**19,142,688**	14,419,319	32.8%	18,210,506	5.1%
Minneapolis	50%	**29,900,157**	17,259,712	73.2%	24,150,916	23.8%
	75%	**31,650,324**	26,822,539	18.0%	30,457,574	3.9%
New York City	50%	**10,035,700**	6,280,159	59.8%	9,411,406	6.6%
	75%	**11,636,023**	9,421,816	23.5%	11,313,940	2.8%

a: equal building volume, equal site area

b: equal building volume, equal height, center site

c: percentage of SRI changes relative to the generated form via proposed tool

4 DISCUSSION

The main objective of this study was to develop a framework and tool for effectively optimizing SRI upon a building's surface using generative and parametric approaches. The resulting building forms using 75% of the 3D site volume had higher levels of annual solar radiation than the 50% site volume forms. This was expected because larger volumes meant additional surface area exposed to the sun. Across the three sites, Site B received the highest levels of radiation, while Site C received the lowest amount. This was also expected because Site B had the largest 3D site lattice, and consequentially larger volumes, while Site C had the smallest 3D site lattice. When compared to Control Forms 1 and 2, the optimized forms consistently performed better with higher levels of solar radiation per year. The resulting output forms performed 18.0% to 94.7% better than the first control forms. This may be attributed primarily to the lack of height of the control forms. To accommodate for this, Control Form 2 would maintain equal height, as well as equal volume. The second control forms performed significantly better than the first control forms but were still outperformed by the optimized volumes by 2.8% to 23.8%. These percentages describe the effectiveness of the proposed SDCA tool in creating forms with maximized SRI.

The results of study suggest that the proposed SDCA tool can effectively optimize building form for SRI iteratively with more applicable building geometry for construction, compared with existing methods based on both free-form (e.g., lofted spline curves (Zhang et al. 2016)) and voxelated form optimizations (Jyoti 2015) using evolutionary-based systems (e.g., genetic algorithm (GA)). This can be because of spatial capacities that CA algorithm holds for form explorations relative to all other types of GD systems (Singh and Gu 2012) on proposing a more real-world building shape. The results can further confirm SDCA's flexibility in handling various scenarios for land-use related limitations–in terms of percentage of site and building volume) as part of the process in the workflow in exploring building form that maximizes SRI.
In addition to the higher applicability of the discovered form, the SDCA tool is successful in term of a non-deterministic form generation without introducing initial starting forms to be improved upon during the early design process. The current tool can create the first generation of the form by learning from the neighboring conditions along with given geometrical boundaries then create next generations based upon optimizing for SRI. This helps to explore numerous forms without user intervention; a set of scenarios that a designer may even not have a rough silhouette of them at the very early stage of the design process. By only defining boundaries of form expansion toward three spatial dimensions, the proposed tool can provide

such modeling capacity for exploring building forms. Therefore, the proposed framework and tool is successful and can be applied by architects for real-world architectural projects as current limitations involved in existing projects, including a context-free form generation and initialization of a pre-deterministic building shape as a starting form, can be resolved through this tool. The developed code can be accessed through (Luitjohan et al. 2021).

5 CONCLUSION

This study successfully developed a framework and tool for context sensitive solar-driven design using cellular automata (SDCA) in performance-based form exploration process in order to maximize solar radiation incident (SRI) upon building external surfaces in dense urban environments. Many building forms were generated in a context-sensitive manner in three different sites. The results obtained in the validation of this study by comparison of control forms demonstrated that the proposed tool with an integrative approach could generate many suggestive building forms for maximizing SRI considering urban context, building size, and time period. The findings can allow for future high-rise building forms to possess high levels of SRI across building envelopes, increasing the potential for renewable solar energy harvesting. This performance-based optimization tool is valuable to architects aiming to address the 2030 Challenge goal of designing all new buildings to be 100% carbon-neutral, ensuring a more energy-efficient architecture for future sustainable cities worldwide.

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