

An Adaptive Workflow to Generate Street Network and Amenity Allocation for Walkable Neighborhood Design

Yang Yang¹, Samitha Samaranayake², Timur Dogan³

¹Cornell University
Ithaca, NY, USA
yy848@cornell.edu

² Cornell University
Ithaca, NY, USA
samitha@cornell.edu

³ Cornell University
Ithaca, NY, USA
tkdogan@cornell.edu

ABSTRACT

This paper proposes a novel generative workflow for walkable neighborhood design. Key components of the workflow include automating the process of parsing the map data, building contextual models with population and amenity data, conducting an integrated mobility simulation, and generating a street network and amenity allocation plan accordingly. The proposed framework is versatile and adaptive by allowing designers to tune simulation parameters and customize the decision-making process. The applicability and effectiveness of the workflow are tested in a pedestrian-oriented neighborhood design case study. Three scenarios that adapt to different design goals and boundary conditions are presented. This research equips designers with capabilities to co-design of mobility solutions and urban form early on in the design process. Further, it can be leveraged by more stakeholders in sectors such as real estate, public services, and public health to make decisions as the urban built environment has a fundamental impact on all these fields.

Author Keywords

generative urban design; walkability; mobility; simulation.

1 INTRODUCTION

Population growth, urbanization and ever-increasing vehicle use in urban areas have a significant impact on the quality of life and the environment. Increasing traffic-related energy consumption, greenhouse gas emissions, air and noise pollution, as well as lifestyle-related health issues such as obesity and diabetes can be promoted by poor urban design [1]. While these are worrisome circumstances, the need for urban renewal and densification [2] also provides a unique opportunity to rethink planning paradigms and design approaches. Emerging design movements aim to remedy the aforementioned mentioned issues. They [3] promote high density, walkable neighborhoods as one solution for these challenges. Studies have shown that walkable neighborhoods can significantly reduce traffic-related pollution and lower the risk for chronic diseases [3,4], support local businesses, promote tourism, attract investors, higher property values [6] and foster an increase in social capital and political participation [7]. Walkable amenities, one of the most important ingredients of a

walkable city, have also been associated with socioeconomic growth [7,8] and quality of life [10]. Understanding the implications of urban design choices on walkability while incorporating this understanding into early stages of urban design process provides a unique opportunity to address these issues. This is particularly important because street grids hardly ever change once the urban design is set [11].

One of the major challenges in designing walkable neighborhoods is the lack of effective metrics and workflows that can provide measurable and actionable feedback to facilitate design decision making. To evaluate the walkability of cities, researchers have proposed to rank neighborhoods based on the distance and density analysis of points of interest (POI) in the city. These walkability ratings, commonly referred to as Walkscore [12], are computed on a scale of 1-100 and include factors such as accessibility to amenities like grocery stores, restaurants, banks, parks, and schools. Generative design workflows for walkable neighborhoods that leverage this metric have been developed [13]. They usually first generate an urban layout by spatial logics and then optimize the Walkscore through an evolutionary process that places additional amenities until a sufficiently high score is reached. However, the main question regarding the use of Walkscore as a sole metric in such workflow is its insensitivity to the interactive relationship between key urban design parameters including street network, amenity allocation, and population distribution in the model. This can result in several questionable design decisions: Firstly, generating a street network without considering amenity placement or population distribution can be problematic because the latter two factors significantly influence street utilization and therefore play important roles in urban morphology. Secondly, placing or adding services and amenities only to drive up Walkscore may not be feasible as those new services may not be sustainable as demand is spread too thinly. Thirdly, the amounts and categories of amenities to which it is essential to have walking access differ by population groups. Thus, designers should be able to evaluate walkability with demographic-specific metrics. As a result, it is imperative to propose a more integrated

generative urban design workflows that can take into consideration all the mentioned factors.

Additionally, common generative design workflows rely on optimization solvers such as the Genetic Algorithm, which searches for optimal solution evolutionarily based on each iteration's performances on certain metrics. Although such a strategy is widely used in many generative urban design studies [13,14], it remains questionable in terms of speed of convergence and stability [15]. Although such a trial & error approach is unavoidable for certain ill-defined design problems, this paper proposes a simplified, efficient and transparent approach using the Urbano toolkit [16]. In this workflow, the first step is to build a mobility model with urban data such as streets, buildings, amenities and population densities. Then the potential pedestrian volumes of streets and amenities are evaluated by a mobility simulation. The simulation outcome can directly inform the generative process of the street network and amenity allocation. Throughout this process, designers can customize the model and control the simulation by tuning key parameters and changing variable constraints so that different design conditions can be accommodated.

Overall, this paper introduces a novel generative urban design workflow that is sensitive to street networks, amenity allocation, and population distribution. The workflow is implemented in a pedestrian-oriented neighborhood design case study, and its adaptivity is tested by accomplishing different design requirements.

2 METHODS

Urbano allows designers to build mobility models, run the network and amenity analyses within the Rhinoceros CAD platform and the visual scripting environment Grasshopper. The automated modeling and simulation process is used to drive the generative processes described in this paper.

2.1 Data-Driven Modeling

There are three layers of data that are necessary for the mobility model: Street network, amenities (points of interest), and buildings with building-level population information. Knowing the location and boundary of the site, Urbano can import streets, points of interest (POIs) and buildings, along with their metadata, from sources such as shapefiles (shp), OpenStreetMap (osm) [17] or Google Places API [18]. Streets, buildings, and amenities are represented by geometric primitives such as curves or points. Metadata such as names, types, and addresses are attached to the geometric data using serializable dictionaries that can be modified and customized alongside the geometric objects parametrically within Grasshopper or

through the CAD user interface in Rhino. If required information, such as building-level population, is not accessible from the sources, Urbano provides functions that can infer data or can help to synthesize this information using other data sources. For example, it can estimate building-level population size using total building floor area, customized area usage breakdown, and generalized occupant densities [16,17].

2.2 Trip-Sending Simulation

The simulation framework is initially driven by the Activity Demand Profile (ADP). The ADP describes pedestrian activities over time and can be adapted to reflect activities of specific demographics. One way to derive location-specific ADP is to interpret the spatiotemporal distribution of human activities in a local area by measuring the activeness in urban amenities in this area [21]. The main data source for this method is Google Places "Popular Times" data. Table 1 shows a sample set of the integrated ADP which presents the hourly percentage of population that engages in particular activities in one day in the case study area (Figure 5). Each column represents a one-hour time slot in a day, which can be further synthesized into time periods such as morning, noon and evening. Figure 1 is a graph for ADP data using a 24-hour timeline, which depicts a more detailed activity distribution. The y-axis refers to the overall amount of activities, which peaks during the day and dips in the early morning. Each color layer represents the demand pattern of an amenity. For example, banks and post offices tend to stop service in the early afternoon, while bars and pubs become dominant activities at midnight. Nevertheless, ADP data can also be customized by the designer to target an assumed demographic group. In the simulation, one or multiple sets of ADP can be utilized to represent different human activity patterns coexisting in the area.

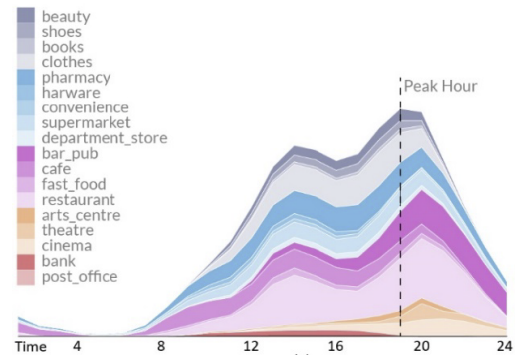


Figure 1. 24-hour timeline representing Activity Demand Profile.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
errands	0	0	0	0	0	0	0	0	0.4	1.1	1.3	1.5	1.6	1.8	1.8	1.8	1.6	1.1	0.3	0.2	0.2	0.2	0	0
restaurant	1.1	0.1	0	0	0	0.4	1.7	5.5	8.3	9.1	9.9	13.3	19.6	22.1	19.5	15.8	14.2	16.8	20.6	21.8	19.4	14	8.2	3.3
grocery	1.8	0.9	0.7	0.5	0.7	0.8	1.6	3.1	5.7	7.6	9.4	11.2	12.9	13.8	14.2	14.1	14.5	14.9	14.3	12.3	9.7	7.3	5	3.2
shopping	0	0	0	0	0	0	0	0	0.8	3.3	7.1	10.7	12.8	14.9	15.1	15	16.1	17.5	16.2	10.7	4.4	1	0.4	0
entertainment	6.2	4	3	1	0	0	0	0	0	0.3	0.4	2.7	5.3	5.7	7.2	7.9	11.6	17.2	24.8	31.6	29.1	25.8	21.8	17

Table 1. Sample of Activity Demand Profile data for the study area. (unit: %)

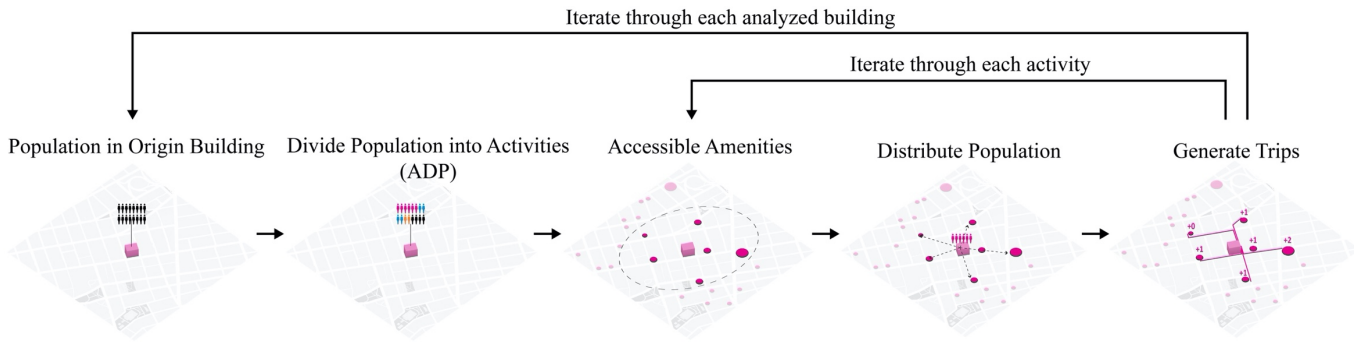


Figure 2. Diagram of the trip-sending simulation algorithm.

The following simulation is based on a trip-sending process, and the concept of each trip is made up of multiple information: the origin building, the destination amenity, the route taken and the corresponding population. The executed trip-sending algorithm is as follows (Figure 2):

1. **Input** model consisting of streets, amenities, and buildings; one or multiple ADPs with same time metrics
2. **For each** time step of ADPs
 3. **Initialize** empty list of trips
 4. **For each** building in the model
 5. Set the building as origin and get its population size
 6. Divide the population into activities according to the percentage data in its ADP
 7. **For each** activity
 8. Search for corresponding amenities as destinations within walking distance (user-defined) using a shortest-path algorithm influenced by *biased routing factors*
 9. Distribute the activity population to destinations according to *biased destination factors*
 10. Generate trips with the distributed population and add the trips to the list
11. **Output** a data tree of trips grouped by time steps

The *biased factors* are inputs allowing for more control by designers. There are currently two types of them in the presented algorithm. The first one is the *biased destination factor*, defined as the weight of a destination which determines the proportion of the population sent to them. The higher the weight, the more proportion of the total accessible population the amenity can receive. This factor can be set according to the quantifiable quality parameters of amenities such as the capacity, popularity or rating. The other one is the *biased routing factor*, defined as the coefficient of calculated street length. This coefficient allows certain street segments to be “shortened” in the simulation so that they can be more utilized in the shortest-path routing process, or “lengthened” in the opposite way. By modifying this coefficient, the simulation can count into

more factors influencing the route choice other than distance, such as shade, landscape, facades, urban environment, etc.

Output: Each time step has a distinct set of resulting trips. Trips data can be post-processed into three complementary metrics: Street Hits and Amenity Hits. Street Hits counts how many people use a certain street segment on all trips. Amenity Hits tallies up the total number of people that are sent to a specific amenity on all trips. Moreover, a building-level Walkscore can also be computed according to its original method [12] using data of all trips that originate from a single building. All these metrics will inform the generative design process.

2.3 Generative Process

The primary setup for the generative method is to replace the original design site with a dense grid mimicking a virtual environment that lets people cross freely. This step parallelly establishes a perpendicular coordinate grid representing all potential locations for amenities (Figure 3). Street Hits results from the simulation on this dense grid can reveal people’s potential movement trails across the site. Street segments with high Hits can be transformed into new roads in the designed network. Amenity Hits results on the coordinate grid can identify the most profitable locations for amenities that grant most walking access to the population in the model, which can inform the placement of new amenities.

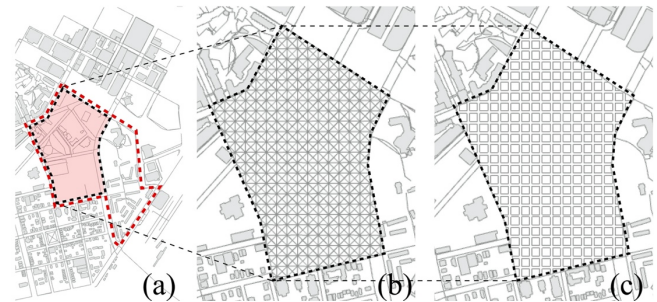


Figure 3. Using part of the case study’s site as an example (a), the primary setup is to replace the original site with a dense grid (b) mimicking a virtual environment that lets people cross freely. It parallelly establishes a coordinate grid (c) representing all potential locations for amenities

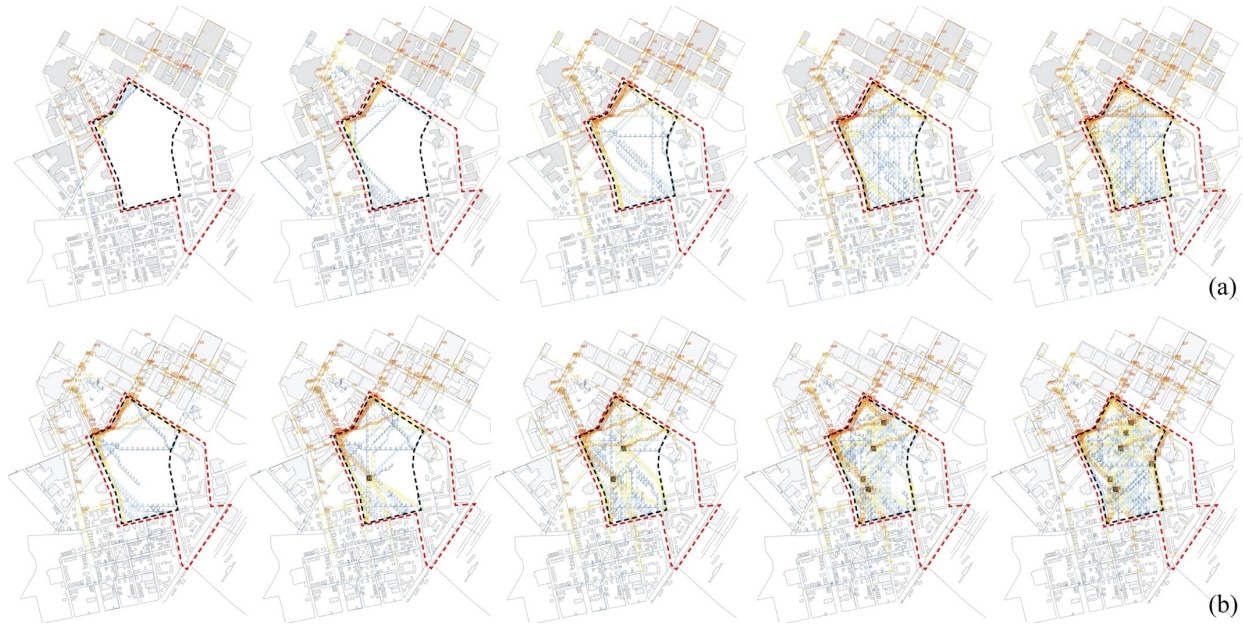


Figure 4. Two series of visualizations of Street Hits output. The first row (a) shows evolving results when increasing the user-defined walking distance. The second row (b) presents changing results when placing new amenities on the design site.

Due to the nature of the trip-sending algorithm, the outcome spontaneously concerns the interactivity between streets, amenities and population distribution in the model. It is also responsive to changes. Figure 4 shows the example of two series of visualizations of Street Hits output from the same simulation (Figure 3) but only with a specific parameter modified. The first row shows when increasing the user-defined walking distance, more trips are generated because more amenities become accessible to all buildings within that distance. The second row presents changing results when placing new amenities on the design site. Besides these, other parameters such as the biased routing and destination factors, or ADPs can all impact the generative process. A highly customizable framework like this enables designers to tune the generative process for specific conditions or goals in design practice as in the case study.

3 CASE STUDY

The site in Figure 5 is located in New Haven, Connecticut. It has residential neighborhoods to the South, a high-density commercial district to the North, institutions to the West, and an industrial area to the East. A highway and a railway adjacent to the East and the North form obstacles isolating the site. The current street network does not connect urban amenities well as Street Hits analysis on the original site reveals that most activities do not take routes across the site (Figure 6). The site is predominantly used as parking lots and is considered as an empty area as the initial condition in this study. However, the site has great potential as it can connect the railway station to the city and fill the gap in pedestrian mobility between different urban areas surrounding it.

The initial site model consists of existing streets, amenities, and buildings. Building types are categorized into

residential and non-residential so that population data can be synthesized accordingly. The overall design objective is to develop a new mixed-use and pedestrian-oriented neighborhood that can alleviate some of the described connectivity issues. All the existing streets and buildings on the site are supposed to be overridden.

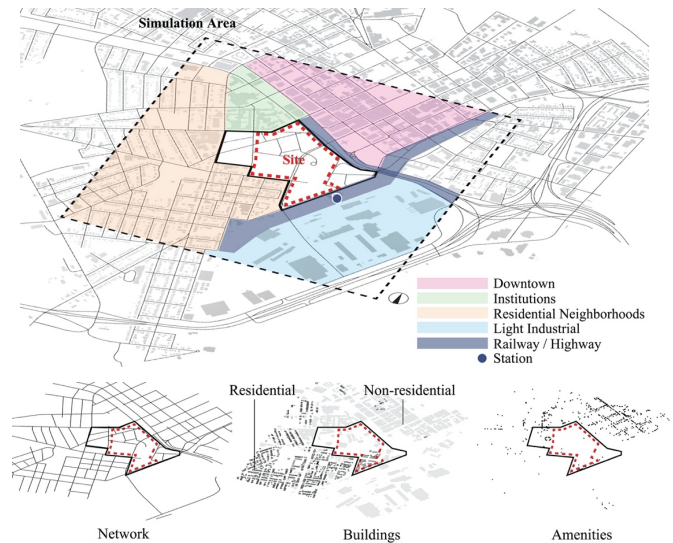


Figure 5. The site and the main components in the initial site model.



Figure 6. Street Hits analysis of the original site shows that most activities do not take routes across the site.

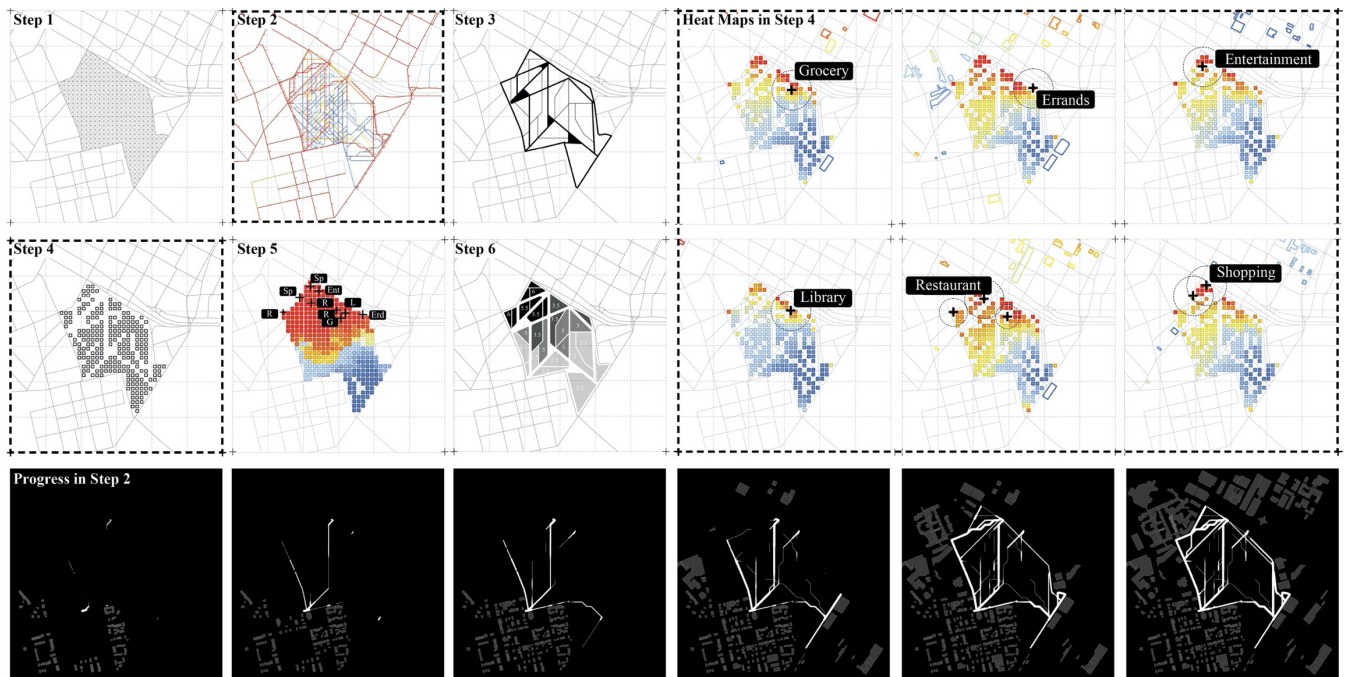


Figure 7. Diagram of the generative workflow of Scenario One.

To test the proposed workflow, three scenarios are generated under distinct design intentions and assumptions. They follow the same primary generative methods but differ in modeling and decision-making process.

3.1 Scenario One

This scenario aims to create a better linking zone. The new network should contribute more efficient passing routes so that increasing pedestrians can go across the site and support new businesses and amenities.

In Figure 7, Step 1 is the primary setup. Step 2 presents the Street Hits result using one normalized ADP data of Table 1. The progress in Step 2 is expanded below to show how the main routes with high Street Hits gradually become visualized during the simulation iteration of all buildings. Using this result, Step 3 generates a new street network by straightening the busiest streets, merging the minor links, and converting the largest intersections into potential plazas. This step is drawn manually at the current stage. Based on this network, Step 4 analyzes Amenity Hits distribution by setting all cells on the 20m*20m coordinate grid as one amenity type. The results are visualized in heat maps highlighting the recommended locations for each amenity type (grocery, errands, library, entertainment, restaurant, shopping). Since the population density is much higher in the northern downtown, all new amenity locations tend to concentrate at the north edge for maximized potential patronage. However, heat maps still vary in color uniformity due to the influences of existing nearby amenities. For amenity allocation, designers can place amenities on the best performing locations, conduct a new simulation for the scenario and evaluate the Amenity Hits of the newly placed amenities. Comparing the resulting Hits

with the Hits of other same-type amenities existing in the model can help designers measure the balance between supplies and demands of new amenities, and then make decisions about their amounts and locations.

One thing to mention is this paper does not focus on the parcellation in the lots or generation of building footprints. However, to present that the previous results can be further developed into actionable design scenarios, the workflow integrates the last two steps. Step 5 computes the final Walkscore based on the coordinate grid, which is used in Step 6 to inform the distribution of development density (FAR) on the generated lots. Since better walkability indicates improved property values, the lots with a greater Walkscore get a higher density. Figure 8 presents an example of how the final masterplan could look.

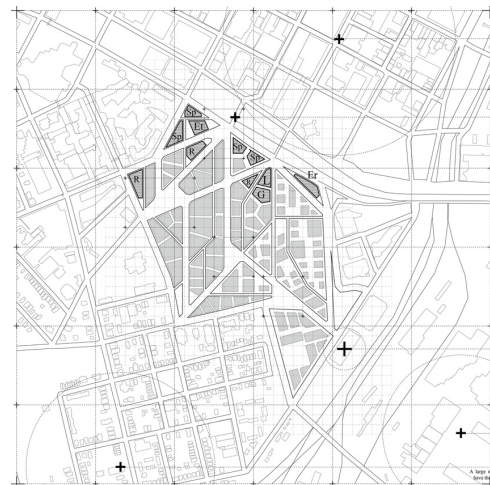


Figure 8. Sample masterplan developed for Scenario One.

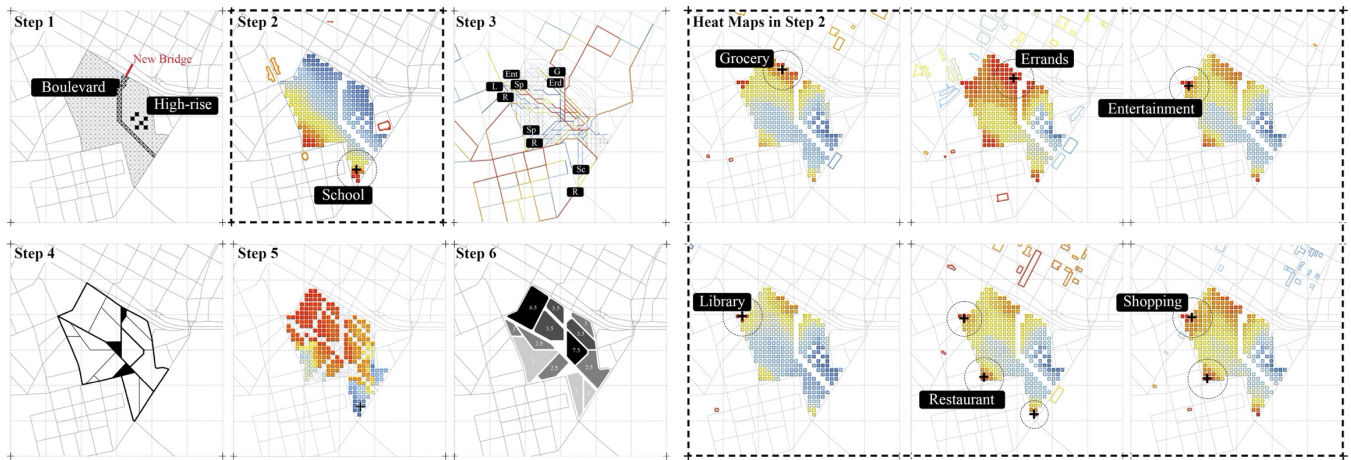


Figure 9. Diagram of the generative workflow of Scenario Two.

3.2 Scenario Two

This scenario intends to include several design conditions: (1) a proposed pedestrian boulevard linking the railway station and the downtown area through the new bridge; (2) a predefined and specifically located high-rise cluster which will hold a high density of population on design site; (3) a prospective new school mostly serving the southern residential neighborhood. The generative workflow is adjusted to address these particular design issues (Figure 9).

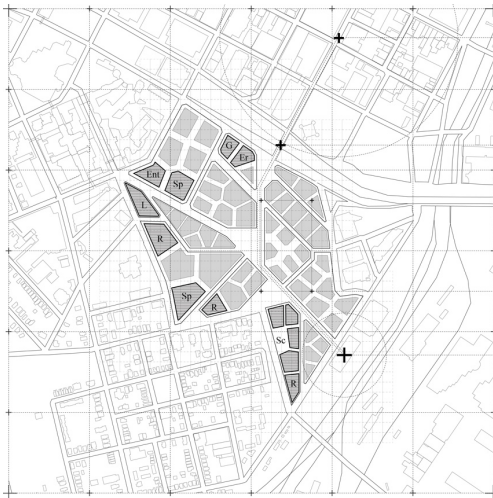


Figure 10. Sample masterplan developed for Scenario Two.

Step 1 models the boulevard and high-rise cluster based on the primary setup. The boulevard is modeled by setting the segments on the grid along the route with a biased routing factor of 0.5. The high-rise cluster is modeled by setting 500 population to each of five high-rise locations on the coordinate grid. Step 2 visualizes heat maps of Amenity Hits. These heat maps differ from Scenario One because the “shortened” boulevard in the simulation attracts more trips crossing the site through this route, and the high-rises also bring more population as consumers. Among all amenities, the analysis of Hits for school differs from the others because it only considers pedestrians coming from the southern residential area. The school’s heat map result also

reveals this adjustment as it is best located on the corners that are closest to the neighborhood side. With all amenity allocation decided, Step 3 visualizes Street Hits on the grid, and Step 4 generates the new street network accordingly. The final two steps of Walkscore analysis and lot-level FAR distribution remain the same as Scenario One. Figure 10 presents an example of how the final masterplan looks.

3.3 Scenario Three

Instead of using one normalized ADP data in the first two scenarios, this scenario considers the temporal difference in street and amenity utilization. It aims to create a 24-hour active neighborhood by overlapping the generative results of time steps. However, this scenario only generates street network while the amenity allocation is an input.

In Figure 12, Step 1 specifies an input of the amenity allocation scenario. Step 2 visualizes the Street Hits for three time-periods: morning, noon and evening. Step 3 generates the network by filtering the most vibrant streets at these times and overlapping them together. Step 4 and Step 5 remain the same for Walkscore analysis and lot-level FAR distribution. An additional Step 6 demonstrates people’s dynamic movement on the network over time.

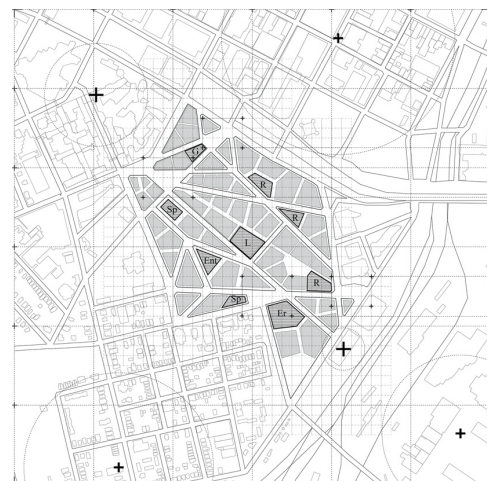


Figure 11. Sample masterplan developed for Scenario Three.

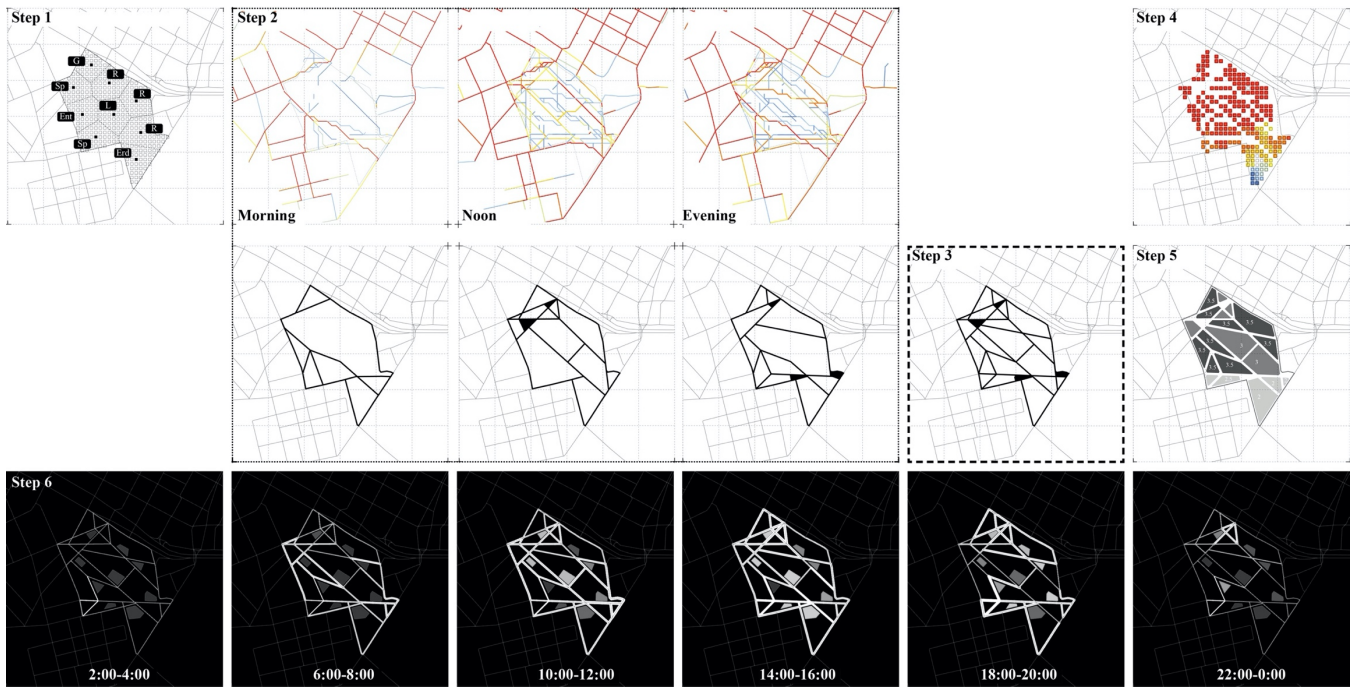


Figure 12. Diagram of the generative workflow of Scenario Three.

3.4 Comparison

To be adaptive to different design goals and conditions, the proposed workflow varies in three scenarios. Firstly, the sequences of decision-making are different. Scenario One generates streets first because it aims to create better links between the surrounding built environment. Scenario Two has more specific requirements for program allocation. Thus, the street network is generated later in the workflow so as to address the new design conditions. Secondly, the generative parameters change. The same one normalized ADP is used in the first two scenarios while the third one uses the ADP of multiple time periods. Also, the biased routing factors and the population distribution are modeled differently in Scenario Two. More parameters such as biased destination factors or walking distance limits have not yet been modified among three scenarios. They are able to allow more precise controls by designers.

4 LIMITATION AND PROSPECT

The limitation of modeling is data quality. For example, high-quality GIS data is only provided in major metropolitan areas. Also, some open data source such as OpenStreetMap has significantly fewer POI entries compared with other sources such as Google data. Consequently, a model that uses data where only a few POIs have been recorded, will yield misleading results. The workflow proposed in this paper will be able to benefit from the ongoing efforts to improve urban data systems.

As for the simulation, there are difficulties in thorough validation, because there is no openly available reference data with which to compare the results. The current ADP data is derived using user-generated data such as Google Places “Popular Times” data, which mostly relies on GPS.

To provide a basic check of the simulation results, five randomly selected samples of cafes and restaurants in the simulation model are used for comparative study. Figure 13 plots their Amenity Hits and their real profiles in Google “Popular Times” data (both normalized and scaled to 1.0) together. There is a certain level of consistency, but exceptions also exist. In the future, more detailed data such as opening hours can be leveraged to improve consistency further. Though “Popular Times” data is indeed an input of deriving ADP, such comparison can still verify the interpretation process of the framework along with other synthesized parameters such as population distribution.

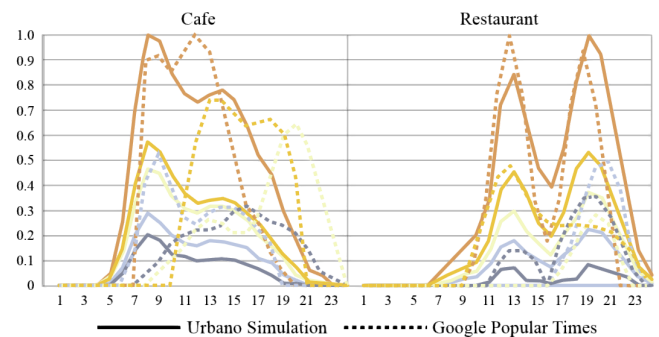


Figure 13. Comparison of five random samples' Amenity Hits results and their real profiles in Google Popular Times data.

In the generative workflow, caution is needed when taking advantage of its adaptivity. Some customized parameters, such as biased routing and destination factors, provide designers with the power to control the generative process, but they also open to the risk of being arbitrary or biased. More sophisticated metrics defining these factors are in demand.

5 CONCLUSION

Design decisions such as zoning, density, program allocation, and the layout of public spaces and streets can have a fundamental impact on the performance of mobility systems. Employing urban planning to mitigate traffic-related problems is widely recognized as an effective strategy. It is expected that this research can equip designers with capabilities that enable the co-design of mobility solutions and urban form, thus motivating the early discovery of cost-effective solutions.

This paper proposes a novel workflow of automating the process of parsing the map data, building contextual models with population and amenity data, conducting integrated mobility simulation, and generating street network and amenity allocation for urban design. The effectiveness and adaptivity of the workflow are tested in a pedestrian-oriented neighborhood design case study by generating three scenarios for different design goals and conditions. This versatile framework can contribute to the design profession and education in terms of increasing awareness and responsiveness to mobility-related urban factors. Moreover, as mobility metrics also have economic and environmental implications, the proposed framework can become more valuable by including other stakeholders in urban development. Practitioners in sectors such as real estate, public services, and public health can leverage the analysis result to make decisions, and designers can benefit from involving a broader range of data and metrics from these fields into the design solution-seeking process.

ACKNOWLEDGMENTS

The authors would like to thank Cornell CTECH for funding this research and Nikhil Saraf for assisting with software development of Urbano.

REFERENCES

- [1] A. Loukaitou-Sideris, "Addressing the Challenges of Urban Landscapes: Normative Goals for Urban Design," *Journal of Urban Design*, vol. 17, no. 4, pp. 467–484, Nov. 2012, doi: 10.1080/13574809.2012.706601.
- [2] UNEP, "Sustainable Buildings and Climate Initiative," 2015. Accessed: Aug. 05, 2015. [Online]. Available: <http://www.unep.org/sbci/AboutSBCI/Background.asp>.
- [3] T. Haas, Ed., *Sustainable urbanism and beyond: rethinking cities for the future*. New York: Rizzoli, 2012.
- [4] L. D. Frank, J. F. Sallis, T. L. Conway, J. E. Chapman, B. E. Saelens, and W. Bachman, "Many Pathways from Land Use to Health: Associations between Neighborhood Walkability and Active Transportation, Body Mass Index, and Air Quality," *Journal of the American Planning Association*, vol. 72, no. 1, pp. 75–87, Mar. 2006, doi: 10.1080/01944360608976725.
- [5] I.-M. Lee and D. M. Buchner, "The Importance of Walking to Public Health," *Medicine & Science in Sports & Exercise*, vol. 40, no. Supplement, pp. S512–S518, Jul. 2008, doi: 10.1249/MSS.0b013e31817c65d0.
- [6] S. Claris and C. Luebke, "Cities Alive: Towards a walking world," ARUP Publications, 2016. [Online]. Available: https://www.arup.com/-/media/arup/files/publications/c/cities-alive_towards-a-walking-world_lowres.pdf.
- [7] K. M. Leyden, "Social Capital and the Built Environment: The Importance of Walkable Neighborhoods," *Am J Public Health*, vol. 93, no. 9, pp. 1546–1551, Sep. 2003, doi: 10.2105/AJPH.93.9.1546.
- [8] T. N. Clark, R. Lloyd, K. K. Wong, and P. Jain, "Amenities Drive Urban Growth," *Journal of Urban Affairs*, vol. 24, no. 5, pp. 493–515, Dec. 2002, doi: 10.1111/1467-9906.00134.
- [9] A. Zandiatashbar and S. Hamidi, "Impacts of transit and walking amenities on robust local knowledge economy," *Cities*, vol. 81, pp. 161–171, Nov. 2018, doi: 10.1016/j.cities.2018.04.005.
- [10] G. F. Mulligan and J. I. Carruthers, "Amenities, Quality of Life, and Regional Development," in *Investigating Quality of Urban Life*, vol. 45, R. W. Marans and R. J. Stimson, Eds. Dordrecht: Springer Netherlands, 2011, pp. 107–133.
- [11] T. Dogan, S. Samaranayake, and N. Saraf, "Urbano: A new tool to promote mobility-aware urban design, active transportation modeling and access analysis for amenities and public transport," in *SimAUD 2018*, 2018.
- [12] M. Brewster, D. Hurtado, S. Olson, and J. Yen, "Walkscore.com: A New Methodology to Explore Associations Between Neighborhood Resources, Race, and Health," presented at the 137th APHA Annual Meeting and Exposition 2009, 2009, [Online]. Available: https://apha.confex.com/recording/apha/137am/pdf/free/4db77adf5df9ff0d3caf5cafe28f496/paper205082_1.pdf.
- [13] T. Rakha and C. F. Reinhart, "Generative Urban Modeling: A Design Workflow for Walkability-Optimized Cities," 2012.
- [14] D. Nagy, L. Villaggi, and D. Benjamin, "Generative urban design: integrating financial and energy goals for automated neighborhood layout," in *Proceedings of the Symposium on Simulation for Architecture and Urban Design*, Accessed: Jan. 09, 2020. [Online]. Available: <https://dl.acm.org/doi/abs/10.5555/3289750.3289775>.
- [15] T. Wortmann, C. Waibel, G. Nannicini, R. Evins, T. Schroepfer, and J. Carmeliet, "Are Genetic Algorithms Really the Best Choice in Building Energy Optimization?," in *SimAUD 2017*, Accessed: Jan. 10, 2020. [Online]. Available: https://www.researchgate.net/publication/317277483_Are_Genetic_Algorithms_Really_the_Best_Choice_in_Building_Energy_Optimization.
- [16] T. Dogan, Y. Yang, and S. Samaranayake, "Urbano: A tool to promote active mobility modeling and amenity analysis in urban design," *TAD Translation*, 2020.
- [17] "OpenStreetMap." <https://www.openstreetmap.org/#map=17/52.90112/-1.22824> (accessed Apr. 01, 2020).
- [18] "Places | Google Maps Platform," *Google Cloud*. <https://cloud.google.com/maps-platform/places> (accessed Apr. 01, 2020).
- [19] ASHRAE, "ASHRAE Handbook—Fundamentals (SI)," ASHRAE, Atlanta, 2013.
- [20] SIA, 2024: *Standard-Nutzungsbedingungen Für Die Energie-Und Gebäudetechnik*. Zürich: Swiss Society of Engineers and Architects, 2006.
- [21] Y. Yang, S. Samaranayake, and T. Dogan, "Using Open Data to Derive Local Amenity Demand Patterns for Walkability Simulations and Amenity Utilization Analysis," in *Proceedings of ECAADe 37 / SIGRaDi 23*, Porto, Portugal, 2019.