Survey-Based Simulation of User Satisfaction for Generative Design in Architecture

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Abstract. This paper describes a novel humanist approach to generative design through the measurement and simulation of user satisfaction in an office environment. This technique involves surveying hundreds of employees for their adjacency preference and work style preference, and then calculating how well different floor plan layouts match these preferences. This approach offers an example of how design goals which are typically considered to be "qualitative"—and beyond measurement—might become part of a "quantitative" generative design workflow for architectural design and space planning. The methodology is demonstrated through an application in the design of a 49,000 square foot office space for 270 people.

Keywords: Modelling and design of data · Generative design · Simulation · User satisfaction · Survey methods

Introduction

Generative design integrates artificial intelligence into the design process by using metaheuristic search algorithms to discover novel and high-performing results within a given design system. Its framework is dependent on three main components: (1) a generative geometry model that defines a 'design space' of possible design solutions; (2) a series of measures or metrics that describe the objectives or goals of the design problem; (3) a metaheuristic search algorithm such as a genetic algorithm which can search through the design space to find a variety of high-performing design options based on the stated objectives. This paper is an extension and in-depth overview of the second component of the generative design workflow. In this work we focus on the development and use of a comprehensive system to automatically evaluate qualitative properties of office space designs based on user survey data.

A Humanist Design Approach

While architectural design is an extremely complex task composed of many competing small-scale requirements, the traditional design process avoids complexity and specificity through generalization. In fact, the standardization of anthropometric needs into idealized canons has a long history: from Da Vinci's *Vitruvian Man* and Le Corbusier's *Modulor* to *Dreyfuss*' Joe and Josephine ergonomic charts. More recently, Nicholas

K. De Rycke et al., *Humanizing Digital Reality*,
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Negroponte discussed the human designer's limitations in accommodating particular occupant-level requirements such as "single individual or family needs" (Negroponte 1969). To address these limitations, he argued for a humanist approach based on a collaboration between human designers and intelligent machines. This approach would allow designers to navigate complex problems by "treating pieces of information individually and in detail" (Negroponte 1969). Building upon this possibility, our work extends the capabilities of generative design to the inclusion of human desires and work pattern requirements with the objective of discovering design solutions that satisfy nuanced user preferences.

Measuring Performance

The application of generative design to engineering applications is well known. In this context, however, performance measures tend to be straight forward, dealing primarily with goals such as maximizing structural performance (by minimizing stress, structural displacement, etc.) while minimizing material use. In architectural design, however, measuring performance can be more difficult. Although many software tools exist for measuring a building's overall performance (such as structural analysis, air circulation and daylighting), these engineering-based measures are rarely the only or even the primary goals of a design project.

Even more important are occupant-level concerns such as how the space will be used, how the space feels, and how the layout of the space matches the needs of the program. Such measures are typically considered "qualitative" rather than "quantitative", and thus can be difficult to measure deterministically from a design model (Fig. 1). Because of this difficulty, there are few existing software tools or guidelines for measuring such occupant-level goals.

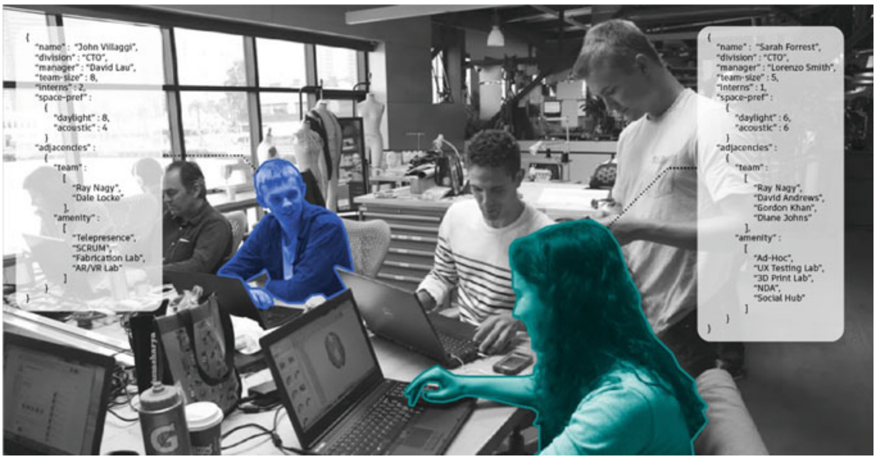

Fig. 1. Measuring occupant-level preference data in an office environment

Office Design and Productivity

The open-plan office has gained popularity among designers and enterprises worldwide (Konnikova 2017; Waber et al. 2014), as it is assumed to inspire collaboration and foster informal interaction within the office. While unplanned exchanges have been proven to boost productivity (Pentland 2012), many employees find the noise and lack of privacy caused by open layouts to negatively impact their personal performance (Kim and de Dear 2013). In fact, several studies have shown that open workspaces actually decrease overall user satisfaction and do not lead directly to productivity gains (Gensler: US Workplace Survey 2016; Brennan et al. 2002).

In a recent survey of UK and US workplaces, Gensler urges businesses to invest in environments that match work processes and are attentive to user needs (Gensler: US Workplace Survey 2016). Haynes and Duffy further stress the importance of designing layouts from the occupants' perspective (Haynes 2007a; Duffy 1992). Despite the potential benefits of such an approach, it can be difficult for designers to manage the complexity involved with satisfying many users' needs simultaneously. This is especially true in contemporary workplace settings where not only human desires but also work patterns can vary dramatically across different job roles (Fig. 2).

Quantification of Preference

To incorporate occupant-level measures in the generative design process for office space planning, we developed a new method that simulates future occupancy based on surveys of future occupants. These surveys ask each user about their preferences within the office space, both in terms of *spatial* and *work style* preference.

Spatial preference involves asking each occupant to select and prioritize all the people, teams, equipment, and amenities that they want to be near. Work style preference involves asking each occupant to indicate their preferred ambient conditions (quite/loud space, bright/dark space, etc.) (Fig. 2). Based on the survey results we encode this data in our model through a series of metrics which become objectives or constraints to guide the generative design process. These occupant-level metrics are:

1. *Adjacency*, which directly measures the travel distance from each employee to their preferred neighbors and amenities.
2. *Work style*, which measures the suitability of an office area's ambient environment and distraction levels to the assigned team's surveyed preferences.

To derive the work style metric, we also need calculate four additional measures:

- *Distraction*, which measures the amount and distribution of high-activity zones to determine noise and distraction levels throughout the office.
- *Productivity*, which measures concentration levels at individual desks based on sight lines to other desks and other noise sources.
- *Daylight*, which measures the amount of natural daylight at each work space throughout the year.
- *Views to outside*, which measures each work space's visual access to an exterior window.

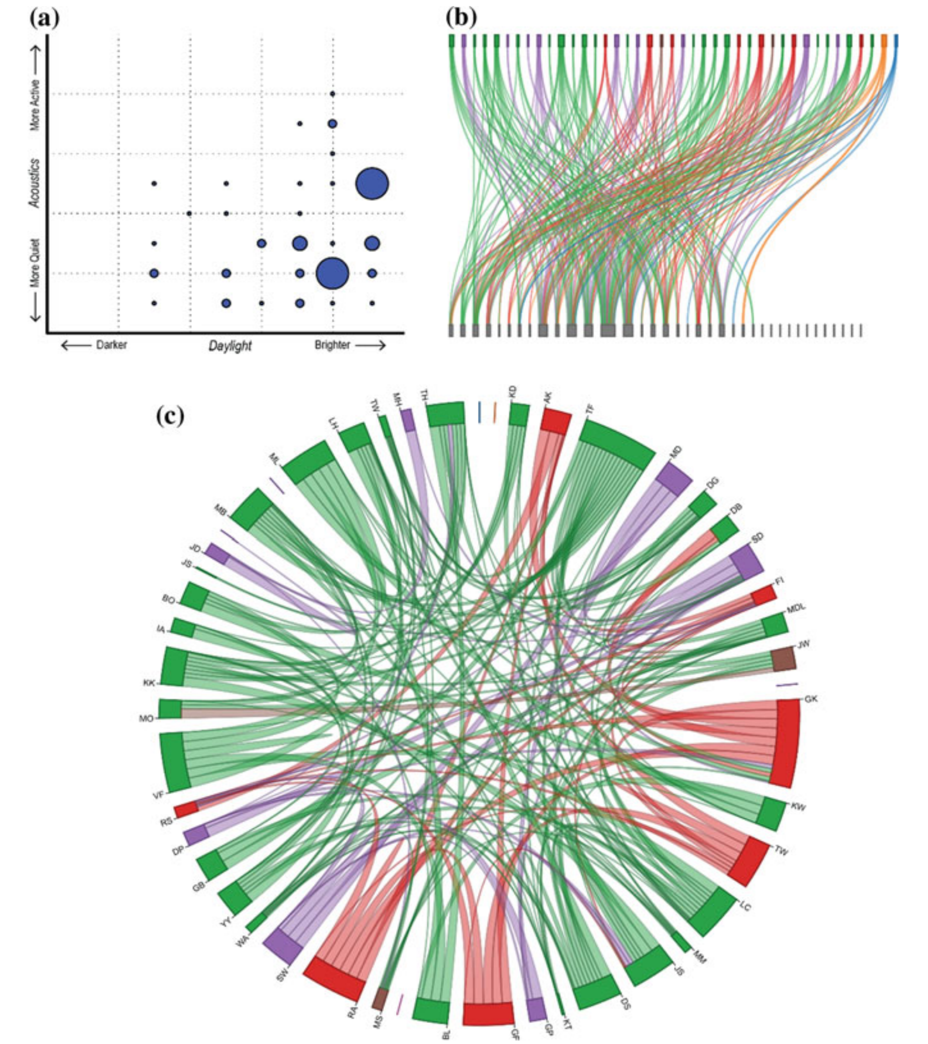

Fig. 2. Visualization of user work style preference based on survey data: **a** ambient preference, **b** team to amenity adjacency, **c** team to team adjacency

By integrating these two human-level metrics into a generative design workflow, we can automate the process of discovering high-performing office layouts that maximize its suitability to the individual preferences of its future occupants.

Related Work

A comprehensive review by Calixto and Celani of 22 years of applications of evolutionary algorithms to problems in space planning reveals a general focus on the efficacy and efficiency of the optimization algorithms in generating satisfactory results with little or no discussion about the metrics by which the designs should be evaluated (Calixto and Celani 2015). Researchers have tended towards known computationally difficult problems such as facility assignment without considering human-level metrics such as preference or feeling which are crucial to the success of a spatial layout.

To broaden the applications of generative design tools to real-world space planning problems, our work extends this method to occupant-level measures that automatically simulate the qualitative needs of the future occupants of the space. To ground the work, this section discusses related research in the quantification of occupant-level measures and their impact on workspace occupants' satisfaction, well-being, and mood.

Adjacency

Adjacency requirements have been widely used as an indispensable evaluation criteria in space allocation problems. Krejcirik (1969) uses adjacency requirements between rooms in a semi-automated space planning method. Muther (1973) defines "relationship charts" composed of weighted proximity relationships between rooms to inform layout designs. Krarup and Pruzan (1978) advance a model for layout adjacency evaluation. In a similar fashion, Liggett discusses the use of graph techniques to generate layouts to meet adjacency requirements (Liggett 2000), while Arvin and House (2002) and more recently Helme et al. (2014) use adjacency as a topological constraint in computerized space planning tools.

Work Style Preference

Recent work in user satisfaction in office spaces reveals that the lack of correspondence between workspace design and worker desires is one of the major causes in drops of employee productivity (Gensler: US Workplace Survey 2016; Haynes 2007a; Duffy 1992; Haynes 2007c; Stallworth and Kleiner 1996; Becker and Steele 1995). Though the importance of such measures for workspace design is well understood, examples of its actual quantification and implementation in design methods have been limited.

To address the need for such methods we propose a novel work style metric which calculates the correspondence between work place environment and stated preferences in terms of daylight, views, and distraction levels. We chose these criteria based on literature about the factors which most often contribute to workplace satisfaction.

Productivity and Distraction. Research about the relationship between workspace layouts and employee satisfaction is primarily focused on the measure of user productivity (Leblebici 2012; Haynes 2008; Uzee 1999; Leaman and Bordass 1993). Haynes, however, explains how productivity remains ill-defined and its quantification lacks standard guidelines (Leblebici 2012; Haynes 2007b). Nevertheless, the literature shows that there is sufficient evidence to claim that certain properties of the office environment do affect user productivity: the room layout and environmental comfort

(Leblebici 2012; Mak and Lui 2012; Mawson 2002; Oldham and Fried 1987), employee proximity (Clements-Croome and Baizhan 2000) and correspondence between work patterns and spatial configuration (Gensler: US Workplace Survey 2016; Haynes 2007a; Stallworth and Kleiner 1996; Mawson 2002). A major cause of productivity loss is distraction (Leblebici 2012; Haynes 2008), defined by Mawson as "anything that takes attention away from the task to be performed (like) noise and visual disturbance" (Mawson 2002).

Daylight and Views to Outside. While there is no consensus about the necessary amount of light for user's well-being (Veitch et al. 2004), the relationship between access to natural daylight and user satisfaction and health has been widely studied and the literature shows enough evidence to claim correlations between the two (Clements-Croome and Baizhan 2000; An et al. 2016; Mahbob et al. 2011; Veitch 2006; Wilkins 1993). Similarly, access to windows and views to the outdoors and its positive effects on user well-being has been extensively studied (Mahbob et al. 2011; Kim and Wineman 2005; Menzies and Wherrett 2005; Sims 2002).

Methodology

Our workflow for simulating user-based desires is divided into two primary steps: (1) the collection and structuring of data for use within the design model and for design validation, and (2) the design of a series of quantitative performance measures which can directly measure the performance of each design.

Data Gathering

The data acquisition process is structured to move from broad, human-interpretable data which is used to shape the design problem to specific, machine-readable data that is integrated directly into the generative design workflow. The result is a dataset with enough specificity to capture the complexity of user desires while being general enough to ensure completeness and offer some degree of flexibility in the final architecture.

Our method uses three stages of surveying to arrive at the final dataset: (1) early exploratory sessions to determine broad survey goals & constraints, (2) individual questionnaires of all 270 employees to identify the domain of user preferences, and (3) team-based questionnaires structured for direct operability with the design model and measures. While the initial two stages don't produce an actionable dataset for direct use within the design model, they were critical in ensuring that the final dataset and design model were correctly addressing user needs.

Early Survey: Focus Group. Early sessions were carried out within small focus groups to collect responses to a series of prompts regarding spatial concerns and workspace ambitions. The responses from these sessions were collected and distilled into broad goals that were used to explore initial geometric strategies and measurement methods.

Intermediate Survey: Individual Questionnaires. A follow-up anonymized individual questionnaire identified the domain of user needs, including typical daily usage of spaces, individual workspace needs, and ambient condition preferences along

					OPEN		ENCLOSED		PRIVATE			
Division	Team Manager	Team Size	Answered	% Answered	Hot Desk	Cubicle	Collab. Team Room	Quiet Team Room	Semi-Private Office	Mini-Private Office	Typ. Private Office	Pref. Strength
[illegible]	[illegible]	46	26	56.52%	5.96	3.58	4.62	4.15	3.15	3.35	3.19	
[illegible]	[illegible]	19	13	68.42%	6.15	4.00	3.92	3.85	3.23	3.62	3.23	41.76%
[illegible]	[illegible]	12	7	58.33%	5.86	3.29	5.43	4.57	3.43	2.71	2.71	44.90%
[illegible]	[illegible]	54	18	33.33%	6.72	3.56	4.61	4.00	3.67	2.78	2.67	
[illegible]	[illegible]	3	1	33.33%	7.00	3.00	4.00	1.00	6.00	2.00	5.00	85.71%
[illegible]	[illegible]	8	1	12.50%	7.00	1.00	3.00	4.00	6.00	5.00	2.00	85.71%
[illegible]	[illegible]	4	2	50.00%	6.00	2.50	6.50	5.50	3.50	2.00	2.00	57.14%
[illegible]	[illegible]	3	0	0.00%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
[illegible]	[illegible]	5	2	40.00%	7.00	5.50	4.50	3.50	2.50	4.00	1.00	85.71%
[illegible]	[illegible]	6	0	0.00%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
[illegible]	[illegible]	4	2	50.00%	7.00	3.00	6.00	4.00	3.00	2.00	3.00	71.43%
[illegible]	[illegible]	7	3	42.86%	7.00	5.67	3.00	3.00	4.00	3.00	2.33	66.67%
[illegible]	[illegible]	78	31	39.74%	6.13	3.87	3.23	3.39	3.77	3.61	4.00	
[illegible]	[illegible]	12	4	33.33%	7.00	4.25	2.75	3.25	3.25	3.50	4.00	60.71%
[illegible]	[illegible]	9	5	55.56%	5.80	2.20	3.80	3.60	4.00	4.20	4.40	51.43%
[illegible]	[illegible]	13	5	38.46%	6.00	4.80	3.40	4.40	3.60	3.20	2.60	48.57%
[illegible]	[illegible]	29	11	37.93%	5.73	5.09	3.55	2.91	3.55	3.18	4.00	40.26%
[illegible]	[illegible]	5	0	0.00%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
[illegible]	[illegible]	6	4	66.67%	7.00	2.25	2.50	3.75	3.75	4.50	4.25	67.86%
[illegible]		22	10	45.45%	6.04	2.00	4.24	4.60	3.33	3.36	4.42	
[illegible]	[illegible]	5	2	40.00%	7.00	2.00	4.00	4.00	3.00	3.00	5.00	71.43%
[illegible]	[illegible]	2	0	0.00%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
[illegible]	[illegible]	4	3	75.00%	5.33	2.00	4.33	5.00	3.00	3.67	4.67	47.62%
[illegible]	[illegible]	1	0	0.00%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
[illegible]	[illegible]	1	0	0.00%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	N/A
[illegible]	[illegible]	9	5	55.56%	5.80	2.00	4.40	4.80	4.00	3.40	3.60	54.29%
AVERAGE SCORE:					4.72	2.41	3.17	2.94	2.81	2.28	2.41	
PREFERENCE 1:					0	7	1	2	1	6	3	
					0.00%	35.00%	5.00%	10.00%	5.00%	30.00%	15.00%	
PREFERENCE 2:					0	2	1	2	3	5	6	
					0.00%	10.53%	5.26%	10.53%	15.79%	26.32%	31.58%	
PREFERENCE 3:					0	4	4	2	3	3	3	
					0.00%	21.05%	21.05%	10.53%	15.79%	15.79%	15.79%	
TOTALS:					0	13	6	6	7	14	12	

Fig. 3. Statistical analysis of surveyed data was used to understand general trends and ranges in user preference

with basic demographic data (Fig. 3). With a 70% response rate, this survey allowed us to identify areas of high variability across employees (in terms of amenity usage, ambient preferences and inter-team collaboration), as well as areas of high agreement (Fig. 2). These finding were used to refine the design model by constraining areas of low-variability and calibrating its combinatorial capabilities to capture the breadth of user needs.

Final Survey: Team-Based Data. For the final survey, an aggregation at the team level was deemed sufficient to reflect the diversity of user preferences while providing flexibility for future growth and restructuring. A questionnaire was supplied to each team leader and non-team-based individual to collect: (1) identification data, (2) environmental preferences for ambient light and activity levels, (3) amenity adjacency preferences, and (4) team adjacency preferences ((2), (3) and (4) were complemented by user weighting) (see Fig. 4). By taking this approach and reaching out directly to team leaders we were also able to obtain 100% participation in the survey. Data collected from the final survey was translated into an object-oriented structure, using standard JSON conventions, to allow for linkage to data specific geometric elements in the design model (see Fig. 1).

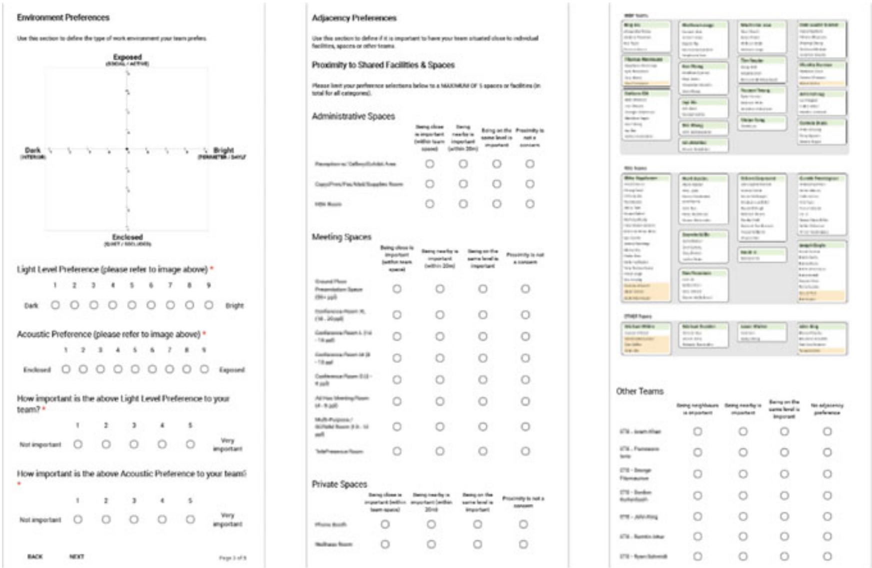

Fig. 4. Web-based questionnaire issued to users with descriptions and diagrams of answer ranges

Designing Measures

Based on the results of the survey, we can calculate two human-level metrics that evaluate the performance of a given office layout according to future occupant preferences (see Figs. 5 and 6).

Adjacency. The adjacency metric is directly calculated from the geometry of the plan by measuring the travel distance from each employee to their preferred neighbors and amenities. For each design iteration, a mesh-based traversal graph—represented as nodes and edges—is generated to describe all possible movement pathways within the

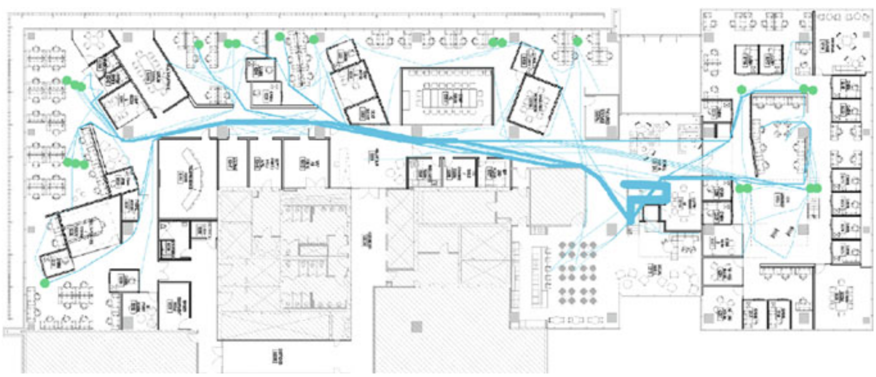

Fig. 5. Visualization of *adjacency metric* in a sample office design

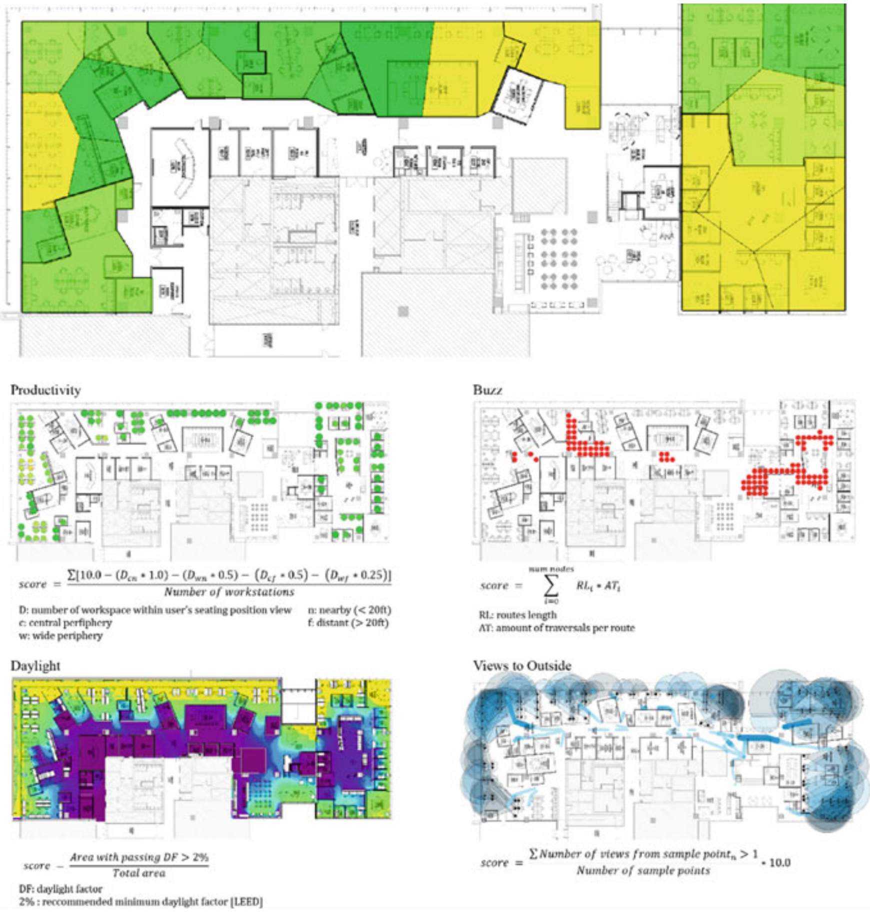

Fig. 6. Visualizations of *work style metric* and related sub-metrics

plan. Team desk and amenity positions are then assigned to nodes within the graph. The system iterates through each assigned team desk, calculates the shortest path to nodes associated with preferences, and sums a total distance weighted by designated importance. The objective of the optimization is to minimize this total travel distance.

$$\text{Adjacency score} = \frac{\sum [SPL * (1 + \Delta Floors * VM)]}{NSP} * 10.0 \quad (1)$$

SPL shortest path length
VM vertical multiplier
NSP number of shortest paths

Work Style. The work style metric calculates the suitability of daylight, view, and distraction measurements at each desk to the assigned team's surveyed preferences.

The objective of the optimization is to minimize the average difference between the measurement and the stated preference.

$$\text{Work style score} = \frac{Err_{daylight} * W_{daylight} + Err_{activity} * W_{activity} + Err_{views} * W_{views}}{W_{daylight} + W_{activity} + W_{views}} * 10.0 \quad (2)$$

Daylight is measured using Radiance, an open-source lighting engine provided by the US Department of Energy, following the Daylight Factor method at grid-based sampling points (Reinhart 2011). While daylight can be calculated using existing analysis tools, the other three components of the work style calculation were custom-designed and built directly into the generative design model.

Views to outside are measured by finding non-occluded lines-of-sight from each desk to any exterior window. *Buzz* measures the amount and distribution of high-activity zones by taking the routes calculated for the adjacency metric and aggregating them by nodes. This node activity is used to calculate the likely noise and distraction at each desk.

Productivity measures the concentration levels at individual desks based on sight lines to other desks and proximity to noise sources. Each desk is scored with a cumulative penalty of visual and auditory distractions. Nearby desks with unobstructed lines-of-sight are tabulated with graduated penalties based on position in the visual cone (central vs. periphery) and distance. Nearby high-traffic nodes from the Buzz measure are tabulated with graduated penalties based on distance.

Validation

To validate our metrics, we had to compare the results of our quantitative measures with the perception of actual occupants in a real office space. To do this we modelled the users' existing office space and scored it according to our six measures. For comparison, several volunteers from the user group were given high-level descriptions of the measures and asked to score the existing office based on their experience and judgment.

In the first analysis, five of the six measures had high similarity between the computed and perceived scores. However, we noticed a substantial discrepancy in the distraction measure. After further analysis we determined that the discrepancy resulted from the fact that our computed distraction measure was not accounting for the way that visible circulation zones and areas of congestion contribute to distraction. After revising our distraction measure to include these congestion areas, all six measures were found to match the intuitions of the users in their current office space.

Results

To use these metrics in the final office design, we first developed a generative space planning model which could create a large variety of valid floor plan layouts for the office. We then used a variant of the NSGA-II genetic algorithm (Deb et al. 2002) to

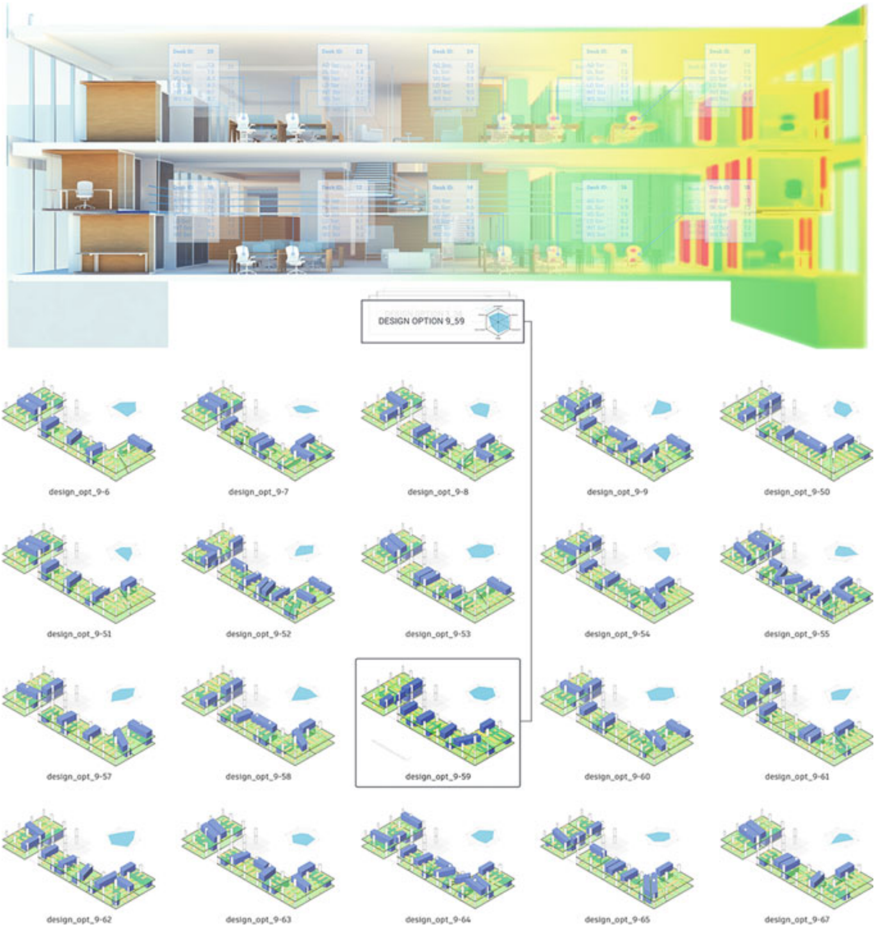

Fig. 7. Selection of high performing designs based on user-defined preference metrics and overlaying of preference data on 3D model

optimize the model and find a set of optimal designs according to the goals of the project.

Although a full description of the optimization process is beyond the scope of this paper, its result was a collection of high-performing schematic design solutions which could be further analyzed and used as a basis for the final design of the office space. To accommodate all the goals of the project the optimization also included several higher-level design goals beyond the occupant-level satisfaction metrics described here. However, by including these metrics we discovered some interesting design solutions which met the varying needs of the future inhabitants in some non-intuitive ways (see Fig. 7). For example, some of the designs featured "back-alley" connections between group work zones that increased adjacency between them. Many of the designs also used non-typical wall and room alignments to obscure sources of distraction and create more daylight for groups which preferred a more open space and more isolation for groups that preferred more privacy (Fig. 8).

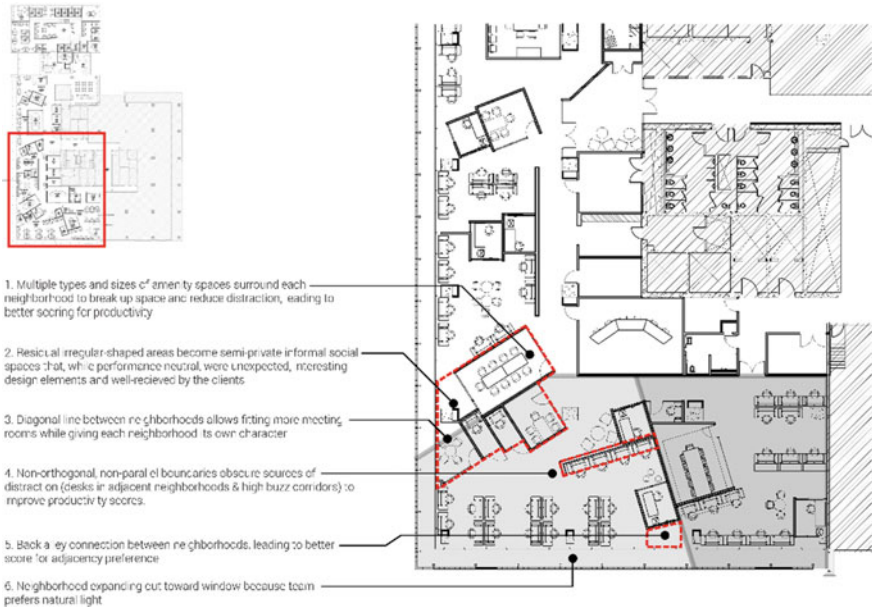

Fig. 8. Non-intuitive physical features of the selected design reflect high performing metrics and high correspondence between local spatial configurations and individual needs

Conclusions

This paper demonstrates an extension of the capabilities of generative design to a more humanist design approach that can satisfy occupant desires in terms of spatial quality and organization. The paper focuses on the evaluative component of generative design for architectural space planning, and describes a series of novel metrics for automatically evaluating user satisfaction within workspaces. The paper also demonstrates an application of this method to the design of a real office space.

To further validate the measures described in this paper we plan to conduct post-occupancy evaluations of the office space once it is built. Through integrated sensors and ongoing digital surveys, data about user satisfaction will be continuously collected and used to further calibrate our measures. We also plan to re-apply the generative design system at later stages throughout the life of the office space to produce new solutions that accommodate changes in both user satisfaction and cor-porate organizational structure.

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