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Quantifying potential dynamic façade energy savings in early design using constrained optimization

Laura E. Hinkle [a,*,1], Julian Wang [a,b], Nathan C. Brown [a]

[a] Department of Architectural Engineering, Penn State University, University Park, PA, 16802, USA
[b] Department of Architecture, Penn State University, University Park, PA, 16802, USA

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ABSTRACT

Parametric design and optimization studies have demonstrated high energy savings for dynamic building envelope materials compared to static high-performance envelopes. However, most parametric studies about dynamic buildings were conducted on prototypical buildings with a focus on either optimal geometric settings or idealized material property characteristics, neglecting the potential collective effects of geometric and material design decisions on energy performance. This study investigates the implications of an automated sequential optimization process while designing with dynamic envelope materials. Two case studies were used to quantify energy savings across different optimization-based design procedures and identify the relative importance of various decision categories. When considering realistic design constraints and intrinsic material limitations, geometric optimization alone yielded only 2% energy savings, while dynamic material optimization savings reached up to 19%. Significantly, a sequential design process in which the geometry is configured first before the façade is optimized and vice versa can lead to around 5% missed energy savings. These findings encourage changes to traditional design guidelines and simulation-based building design approaches when working with dynamic façades.

1. Introduction

Buildings consume around 40% of primary energy around the world [1], which creates both a challenge and a set of opportunities for designers. With the introduction of parametric design and rapid simulation, computational tools are increasingly leveraged during early design to iteratively explore features or configurations that can mitigate or offset building energy loads. Researchers have experimented with design approaches ranging from optioneering to automated optimization to produce low-energy buildings. While optimization can be implemented with varying degrees of user input [2–4], it can quickly direct designers towards high-performance solutions within a design space. Within the emerging research field surrounding dynamic building envelope materials, including thermochromic- and electrochromic-based glazing [5–8] and PCMs [9–11], optimization has been used to maximize energy savings. Dynamic building façade characteristics open the possibility of variation at high-resolution time intervals for external stimuli such as solar radiation, wind availability, and heatwaves, as well as long-term changes such as an evolving climate or new buildings constructed nearby that can occur years or decades into the lifetime of a building. Existing studies show the performance of dynamic façade materials is highly sensitive to orientation, self-shading, and radiant heat exchange in relation to building shape. However, the dynamic material properties are often determined after the early-stage architectural design is established.

Due to limitations in simulation tools and the novelty of many dynamic technologies, the interplay of geometric and material design decisions and their joint effects on energy performance have not been extensively explored using computational tools. Additionally, the steps of the traditional building design are often sequential, which can limit opportunity for early integration [12–14]. The traditional building design process for commercial buildings first establishes a building form, and then develops the floorplan and façade construction, which can separate decisions about geometry and materials [15]. Yet the façade plays a key role in regulating the indoor thermal environment, and materials selection heavily influences energy performance. It is unlikely

* Corresponding author.
E-mail address: luh183@psu.edu (L.E. Hinkle).
[1] Present/Permanent Address: Department of Architectural Engineering, The Pennsylvania State University, 104 Engineering Unit A, University Park, PA 16802, USA.

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that sequentially optimizing a building's massing and glazing placement, and then its floorplan for that set geometry, and finally the façade construction will lead to the best overall result, since geometry, program, and materials all affect one another.

Overall, these divergences necessitate a platform to explore complex building geometries and emerging dynamic building envelope materials taking both optical and thermal properties into account. In response, this paper first quantifies simulated energy saving across different optimization-based building design procedures for dynamic glazing materials via two office building case studies in separate climates. A comparison between approaches can evaluate the current sequential design process as it applies to dynamic materials and reveal the importance of design decisions related to dynamic materials on energy savings. Only glazing was modeled as dynamic rather than other opaque façade elements, due to the proliferation of highly glazed contemporary office buildings and the current outlook of advanced glazing technologies. Following these analyses, this paper proposes a new building design process to determine the optimal material-geometric configuration.

In summary, this study presents three unique contributions:

1) it establishes a new optimization-driven framework with parametric modeling and simulation methods at the early design stage for taking both geometry and dynamic material (thermal and optical) properties into account.
2) it increases understanding of the relationship between these two categories (geometry and material) of design variables towards building energy performance, especially in the context of intrinsic dynamic material limitations, while establishing the potential benefits of joint exploration; and
3) it quantitively illustrates the architectural and performance implications of using such an approach in early design. It does this for a suburban commercial case study in a heating-dominated climate and an urban commercial case study in a cooling-dominated climate, providing new information for two building types most likely to be designed using computational tools.

2. Literature review

2.1. Simulation in early design

Computational tools are currently a vital part of building design, helping to visualize or automate many intricate tasks. They are utilized in all phases of design, from design ideation to construction documentation. In the AEC industry, one important computational area for early design is parametric design, which allows for the generation of numerous design iterations without significant manual effort [16–18]. Parametric design is often implemented through visual coding platforms such as Grasshopper [19] or Dynamo [20] in which users develop dynamic design variables to explore combinations of these variables and ultimately investigate interrelated design goals. During early design, designers also make assumptions about building systems and occupant behavior to simulate and predict how a constructed building will perform.

Creating combinations of the variables forms a "design space", and mapping these designs to metrics that describe their performance, whether related to structure, energy, or daylighting, generates an "objective space" [21]. The goal is often to explore the design space with reference to the objective space in an effective and systematic manner. It has been shown that utilizing design space exploration methods allows designers to develop and select high performance design concepts for gradual refinement throughout later stages [18,22,23]. Since simulation engines across multiple domains are now accessible within a shared environment, research towards dynamic façade systems in buildings has taken advantage of these software environments used by designers today. However, there is limited existing literature that applies parametric design for both geometrically and materially flexible design decisions to understand the energy implications of designing with dynamic building materials.

2.2. Quantifying potential dynamic façade energy savings

Many researchers claim dynamic façades are necessary to achieve nearly net zero buildings (nNEB) [24]. Dynamic façades alter their form or function repeatedly and reversibly over time in response to environmental conditions or human controls [25]. Dynamic façade technologies refer to both micro-scale properties of façade materials, including thermochromic glazing [26], memory shape polymers [27], and phase-change materials [10,11,28,29], and physical-scale elements such as kinetic shading devices [30,31]. While a variety of technologies are possible, this paper focuses on the micro-scale, specifically adaptive glazing technologies. Existing studies have demonstrated whole building energy savings of using dynamic façade technologies range from 8 to 46% [32–34], even compared with static high-performance envelopes. While electrochromic glazing is perhaps the most mature and widely implemented example, material scientists are working in coordination with architectural engineers to improve the thermal and optical capabilities of dynamic glazing [32]. Existing electrochromic glazing operates from state-to-state, where there is a strict tradeoff between visible transmittance (VT) and solar heat gain coefficient (SHGC). Adaptive U-value may be achieved through switchable insulation elements [35], thermochromic technologies that change emissivity [36], or other future technologies. However, several researchers have explored the optimization of adaptive glazing properties to justify further development of the technology.

Several previous studies have investigated dynamic glazing technologies across multiple climates, on different resolutions (e.g., monthly, daily, hourly), and with various control strategies. Wang et al. [34] used EnergyPlus EMS to alternate both opaque assemblies and window construction and achieved an average of 46% energy savings across multiple climate zones. Favoino [26] investigated an inverse performance-oriented approach to optimize visible transmittance (VT), g-value, and U-value to minimize primary building energy. Using an office reference room with 40% window-to-wall ratio (WWR) and four cardinal orientations tested in multiple climates, the study showed high energy savings are achievable by adapting the transparent part of the building envelope alone, the largest factor being cooling energy demand. Since dynamic façade systems respond to outdoor climatic conditions, results varied per orientation and location, with the highest achievable savings 55% for an east-facing zone in Rome, Italy. Similarly, Tavares [37] recommended electrochromic glazing for cooling-dominated climates and found the largest savings on the east and west façades, rather than the south. As mentioned previously, these findings suggest dynamic façade materials are highly sensitive to their immediate environment, which is dictated by the geometry of the building. This notion introduces the possibility of early design intervention, which is explored throughout this study.

While many researchers have focused on simulating existing or theoretical dynamic envelope materials, others have focused on the control algorithms themselves, which have a large influence over performance [38]. Hoon Lee [6] investigated various control parameters, including outdoor air temperature, room air temperature, solar radiation incident on windows, and global horizontal irradiance to develop an algorithm for optimal electrochromic performance. Using ASHRAE 90.1 prototype for a medium office building as a reference, the size of the cooling equipment was reduced by up to 20%. It was acknowledged additional savings could be achieved by integrating controls with air handling units, lighting controls, and shading systems; most importantly, the study concluded that future studies should utilize real building data. In additional efforts to develop a control strategy, Wang et al. [39] performed a multiple regression analysis of window factors based on a large database of existing windows and incorporated the model into an EnergyPlus simulation-based optimization study. Though this model was developed to optimize on an annual basis (static), it could be used to investigate optimization on a daily or monthly resolution, and it is indeed incorporated into the methodology of this paper. As in previous studies, the ASHRAE prototype model was assumed and used as a reference in comparing energy savings. Although this model acts as the standard, it does not capture the potentially complex geometries of contemporary office building architecture.

2.3. Building geometry optimization

In early design stages, there are opportunities to conduct optimization on building form and fenestration configuration [40]. For most climates, the ratio between the external surface of a building and its volume most strongly correlates to energy demand, meaning that simplified models can be adequate [41]. However, some researchers have demonstrated exceptions. For example, Granaderio et al. [42] used a case study in Lisbon, Portugal to show that the surface area to volume building shape coefficient was not strongly correlated to energy demand. Similarly, while Depecker et al. [43] found a strong correlation between shape coefficient and energy consumption for a case study in Paris, France, there was no clear correlation for the case study in Carpentras, France. Further, building geometry optimization results differ depending on the formulation of the design space. Fang [44] performed multi-objective optimization on nine geometric variables for a small single-story building, reducing Energy Use Index (EUI) by up to 20% while increasing Useful Daylight Index (UDI) by 39%. Jin and Jeong [45] used a genetic algorithm to optimize a free-form building shape, including geometric parameters such as top polygon type, top length, and tilt angle, and were able to reduce annual heat gain/loss by up 60.4% in certain climates. While these case studies exist in specific climates and design spaces, they demonstrate that geometric considerations can affect building energy consumption, often in complex ways.

Other researchers have approached this problem by determining the most influential geometric characteristics for predicting energy. Samuelson et al. [46] conducted a sensitivity analysis on various early design building characteristics, including WWR, glass type (static), building rotation, shading, and shape, and determined that, across three major cities, WWR was the most sensitive variable, followed by glass type and rotation. There have been several additional studies exploring the relationship between building geometry and building energy consumption, but the few that have [41] included dynamic characteristics investigated prototypical building types, not potentially self-shading or otherwise complex geometry. Thus, it is difficult to estimate the effects of dynamic façades, both in terms of energy savings and effects on the building design process.

Upon reviewing the sensitivity analysis literature above, there is a further opportunity to implement optimization techniques instead of exhaustive search methods, since optimization can more quickly find the best possible designs within a space and present those for consideration to the designer. However, to fully address the relationship between geometric changes under the direction of an architect and potential dynamic façade properties, realistic case studies must be developed, along with constraints that avoid architecturally infeasible solutions. If incorporating dynamic variables and using non-reference building geometry, an optimization procedure can begin to quantify the potential savings limits of modifying different variable types.

3. Methodology

The methodology investigates optimization-driven, rapid parametric modeling approaches for early building design in practice. As such, it required the creation of parametric models with realistic design variables, constraints, and model resolution that would be considered at this stage of design. Two case studies with different contexts and climates were modeled and analyzed to compare the effects of modifying building geometry and dynamic façade materials on building energy consumption, in sequences and combinations allowed by current simulation-integrated design tools. The procedure for testing the case studies included developing a parametric design space in Grasshopper, establishing an analytical daylighting constraint, simulating energy performance using EnergyPlus [47] through ClimateStudio [48], using a local derivative-free constrained optimization algorithm to find the best performing designs for different sequences, and analyzing the data against multiple baselines (Fig. 1). This section first describes the optimization sequences before detailing the case studies themselves.

Rather than a design space exploration or "catalog" approach, which generates options and presents them for consideration, this paper uses optimization to drive towards the best energy performing designs. Obtaining optimization results establishes limits for how much energy could potentially be saved using parametric methods, even if designers might use data generated during optimization only to inform decisions rather than fully automate them. The data in this paper were generated through eight constrained optimization runs and subsequent combinations of variable settings, described in Table 1. For each case study, this includes an optimization of geometric variables (Geo) and dependent dynamic glazing variables based on typical behavior (DG-E). The dynamic existing runs (DG-E) relied on a regression relationship between material properties U-value, SHGC, and VT based on current material databases [39], representing a realistic configuration possible with current technologies.

The optimal settings for each optimization (geometric and glazing) are then combined, replicating a sequential process in which the designer first optimizes one category and then optimizes the other category (Geo → DG-E and DG-E → Geo). Finally, to estimate the importance of each variable type for energy savings directly and compare with the overall optimization procedures, a random forest regression model was built to calculate feature importance. Fig. 2 summarizes relationships between the different optimization runs and combinations, listing run numbers for case study 1; the same sequence is repeated for case study 2.

It was hypothesized that such a sequential process may not reach the full savings potential, and that simultaneous optimization of both variable types is the most effective strategy. However, limitations in current design and simulation tools contain barriers to simultaneous optimization of dynamic properties at high resolution—platforms that enable fully flexible modeling of geometry and platforms that enable fully flexible modeling of dynamic properties (as opposed to existing technologies) are not fully integrated. While future possibilities for simultaneous optimization with full flexibility are discussed in Section 5, this paper makes contributions by first considering both geometry and dynamic properties using available design methods and corresponding sequences and timescales.

3.1. Case study selection

This study focuses on commercial buildings, which are frequently designed with computational approaches. Two case study sites were selected to represent common office building typologies (Fig. 3). Commonalities between archetype characterization methods in building energy modeling include climate, population classification (urban, suburban, rural), fenestration specifications, and building height [49]. Given the density of large office buildings, this paper considers urban and suburban cases. Case study 1 was inspired by Lake Trust Credit Union Headquarters in central Michigan [50], which is a mid-rise suburban office building with ribbon windows. This building features a curved north façade, providing ample opportunity for geometric exploration including glazing placement as well as overall orientation and shape in plan. Case study 2 was inspired by 1603 Broadway in San Antonio, Texas [51]. This building is a high-rise with a curtain wall construction and a more compact footprint for an urban setting, which limits some potential geometric interventions. Dimensions, layouts, and

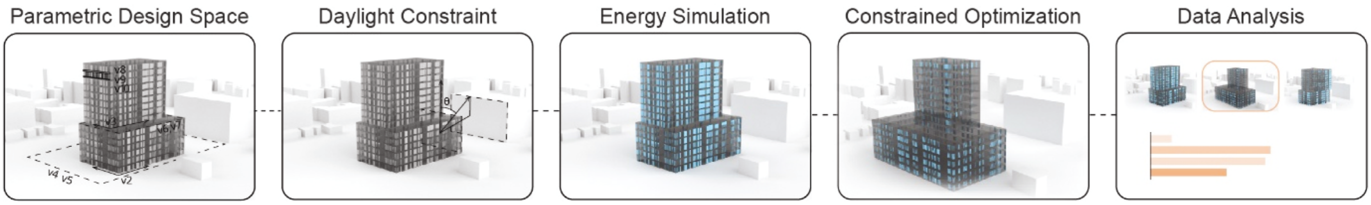

Fig. 1. General framework for optimization procedures.

Table 1
Optimization run specifications.

Run	Description	Case study 1	Case study 2	Dynamic glazing optimization	Geometry optimization
1	Geo	x			x
2	DG-E	x		x	
3	Geo → DG-E	x		x	
4	DG-E → Geo	x			x
5	Geo		x		x
6	DG-E		x	x	
7	Geo → DG-E		x	x	
8	DG-E → Geo		x		x

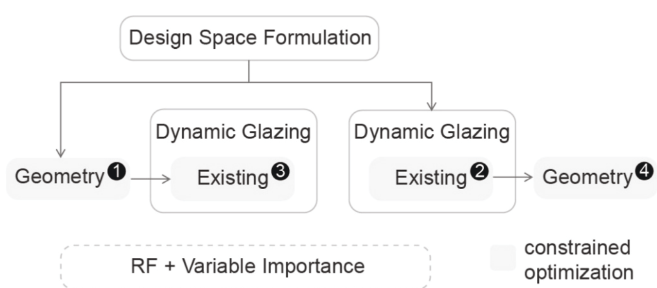

Fig. 2. Flowchart explaining the constrained optimization runs where the run numbers correspond to Table 1.

model settings were approximated using Grasshopper plug-in Elk [52]. Additional information about each case study is provided in Table 2.

3.2. Design space formulation

In contrast to previous studies using static benchmark geometry, a design space was established containing flexible form, orientation, and fenestration to accurately represent early design, in which alternatives are considered but some affinity to an original design concept is maintained. This was done to quantify the energy savings potential of architect-designed office buildings and understand the gaps in the traditional design process that may prevent widespread implementation of dynamic façade materials. Parametric variables are described in Tables 3 and 4 and visualized in Fig. 4. In each design, three fenestration variables were extrapolated: sill height, head height, and the percentage of opaque panels. The façades were panelized into linear sections, and the percentage of opaque panels dictated how many panels were assigned opaque construction versus glazing. Case study 1 also included three control points along the curved façade, building rotation, and a variable that transitions between a linear and L-shaped form (v_8). Case study 2 allows for variation of floor area distribution between the tower and podium building volumes, adjustments in length-width aspect ratios, and tower location. Additionally, because Case study 2 is located in an urban setting with surrounding obstructions, the entire building can move around on the site (v_4, v_5). By incorporating the unique aspects of each building geometry, such as the curvature and the tower/podium relationship, this study attempts to capture the design implications of optimizing contemporary office building architecture.

Additional variables were established for the dynamic properties of

Table 2
General case study assumptions.

	Case study 1	Case study 2
Inspiration building	Lake Trust Credit Union Headquarters	1603 Broadway
Location	Brighton, Michigan	San Antonio, Texas
Gross building area (m^2)	9290	58530
ASHRAE climate zone	5	2
Population classification	suburban	urban
Window-to-wall ratio	0.4	0.4
Number of floors	3	15
Floor-to-floor height (m)	4.6	4.6

Fig. 3. Case study 1 (left) and 2 (right) location and site.

Table 3
Case study 1 geometric variables.

	Variable	Minimum	Maximum	Range	Original Design
v_1	Curve control point 1[a] (m)	0.50	0.75	0.25	0.65
v_2	Curve control point 2[a] (m)	0.50	1.75	1.25	1.15
v_3	Curve control point 3[a] (m)	0.01	0.49	0.48	0.25
v_4	Site rotation (deg)	0.00	360.00	360.00	0.00
v_5	Window fraction	0.01	0.98	0.97	0.15
v_6	Window head height (m)	2.00	4.37	2.37	3.00
v_7	Windowsill height (m)	0.20	1.00	0.80	0.65
v_8	L-shape (deg)	0.00	25.00	25.00	0.00

[a] Moves control point with respect to the start of the defined façade curve.

Table 4
Case study 2 geometric variables.

	Variable	Minimum	Maximum	Range	Original Design
v_1	Tower: base building volume fraction	0.20	0.60	0.40	0.40
v_2	Base length-width aspect ratio	0.50	2.00	1.50	0.85
v_3	Tower length-width aspect ratio	0.50	2.00	1.50	0.75
v_4	Site location x	0.00	1.00	1.00	0.50
v_5	Site location y	0.00	1.00	1.00	0.50
v_6	Tower location x	0.25	0.75	0.50	0.50
v_7	Tower location y	0.25	0.75	0.50	0.35
v_8	Windowsill height (m)	0.20	1.00	0.80	0.60
v_9	Window fraction	0.01	0.98	0.97	0.3
v_{10}	Window head height (m)	2.00	4.37	2.37	3.5

both façades. Glazing properties were accessed through ClimateStudio's window component in Grasshopper. This component wraps the simple window component from EnergyPlus, which allows users to create custom glazing by specifying VT, SHGC, and U-value. The bounds of the glazing variables were established by surveying existing window products in the LBNL glazing database within Climate Studio's glazing component. The bounds for each glazing variable are provided in Table 5.

Window products that are commercially available abide by physical restrictions between VT and SHGC. In general, to decrease SHGC, VT must also decrease, which creates a tradeoff between building energy and daylight. Wang et al. [39] built multiple regression models to relate four main glazing properties: solar heat gain coefficient (SHGC), visible transmittance (VT), U-value (U), and emissivity (E). Using a database of existing window products, Equation (1) was identified as the most accurate model. As current glazing technologies largely follow this relationship, the dynamic glazing optimization included only U-value and VT as variables, and SHGC was calculated using Equation (1). Emissivity was held constant at E = 0.84 per typical window construction [39].

$$SHGC = 0.023 + 0.44*VT + 1.88*E + 0.002*U - 2.38*E^2 + 0.28*VT*E$$

Equation 1

3.3. Performance evaluation

Energy model simulations were performed in Grasshopper using the energy components of ClimateStudio. ClimateStudio links geometry in Rhinoceros to the EnergyPlus simulation engine. The formal optimization objective was to minimize the site energy consumption due to heating, cooling, and lighting requirements, which represent the aspects of operational energy which are affected by geometry and the façade (Equation (2)). The objective function was subject to the daylighting constraint, which depended on whether the run included geometric optimization (left) or dynamic glazing optimization (right) (Equation (2)). The daylighting constraint is described in Section 3.4. The envelope assumptions were determined based on ASHRAE 90.1 2019 in the respective climate zones. Consistent with the DOE prototype for large office buildings, the case study models were mechanically zoned to have four perimeter zones with 4.57 m zone depth and a core zone on each level. All other model settings were also based on ASHRAE 2019 standards and are provided in Table 6.

$$\min f(x) = \frac{\sum_{i=1}^{n}(COP \times Q_{cooling,i}) + (PF_1 \times Q_{heating,i}) + (PF_2 \times Q_{lighting,i})}{GSF}$$

$$s.t.\ g(x) = \frac{\left(\frac{0.88 \bullet DF}{VT} \bullet \frac{90^\circ}{\theta}\right) - WWR}{\left(\frac{0.88 \bullet DF}{VT} \bullet \frac{90^\circ}{\theta}\right)} < 0 \ or \ \frac{\left(\frac{0.88 \bullet DF}{WWR} \bullet \frac{90^\circ}{\theta}\right) - VT_{avg}}{\left(\frac{0.88 \bullet DF}{WWR} \bullet \frac{90^\circ}{\theta}\right)} < 0$$

Equation 2

where i is the load condition at a particular hour and n is the number of hours

Table 5
Glazing variable bounds.

	Variable	Minimum	Maximum	Range	Original Design
v_9/v_{11}	U-value (W/m^2-K)	0.67	5.82	5.15	*See Table 6*
v_{10}/v_{12}	VT	0.05	0.91	0.86	*See Table 6*

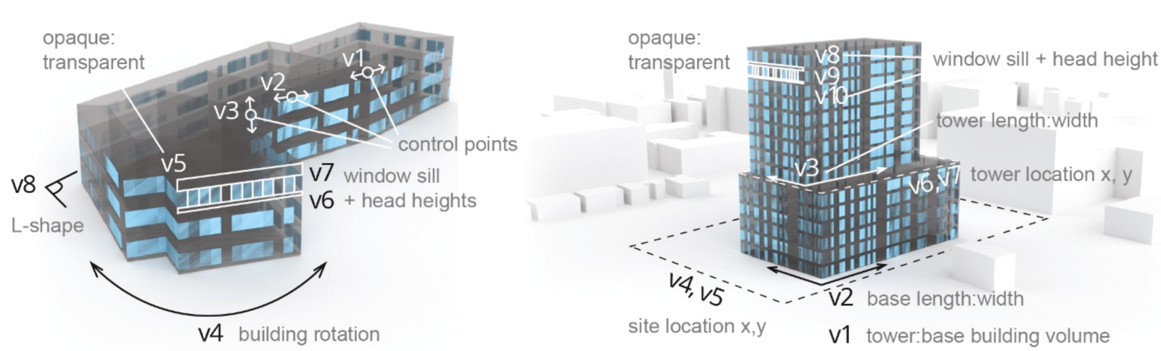

Fig. 4. Variables used to generate the design space, case study 1 (left) and 2 (right).

Table 6
EnergyPlus settings accessed via Climate Studio.

	Case study 1	Case study 2	Units
Roof R-value[a]	5.28	4.40	K-m^2/W
Exterior Wall R-value[a]	2.01	1.00	K-m^2/W
Floor R-value[a]	2.57	1.11	K-m^2/W
Window SHGC[a]	0.38	0.25	
Window U-value[a]	2.04	2.55	W/K-m^2
Window VT[c]	0.60	0.60	
Schedule[a]	Typical office occupancy, equipment, and lighting		
Occupancy[a]	0.05		p/m^2
Equipment[a]	8.07		W/m^2
Lighting power density[a]	6.89		W/m^2
Daylighting[a]	Continuous dimming, 500		lux
Heating set point[a]	21 (constant setpoint – all on)		°C
Cooling set point[a]	24 (constant setpoint – all on)		°C
Mechanical ventilation[b]	2.5		L/s/person
	0.3		L/s/zone area m^2
Heat recovery[c]	Sensible, 60% recovery effectiveness		
Infiltration[b]	0.5		ACH
Peak flow[d]	0.12		L/h/person
Supply temperature[c]	60		°C
Mains temperature[c]	10		°C

[a] ASHRAE 90.1.
[b] ASHRAE 62.1.
[c] Industry standard.
[d] LEED spreadsheet.

The ClimateStudio components output the idealized heating, cooling, and lighting energy in Joules (J). The idealized loads were converted to site energy requirements assuming the system efficiencies listed in Table 7. To make direct comparisons as building geometry changed, building energy consumption was normalized by the gross building area (GSF).

3.4. Optimization method

To find the best possible results for each case study and sequence, local derivative-free constrained optimization was performed on the building geometry and glazing properties. Specifically, COBYLA (Constrained Optimization BY Linear Approximations) was implemented through the Grasshopper component Radical, available with the Design Space Exploration (DSE) plug-in [21]. This algorithm models the objective and constraint functions by linear interpolation [54]. A local derivative-free optimization approach led to shorter run times compared to evolutionary algorithms, since it constructs successive linear approximations of the objective function and constraints via a simplex of $n+1$ points (in n dimensions) and optimizes these approximations in a trust region at each step, leading to fewer evaluations [55]. For a starting point, all variables were set to the middle point. The convergence criterion was a 0.01 change in objective function.

While building geometry was optimized on an annual basis as a static characteristic, glazing properties were optimized on a monthly resolution. Previous electrochromic glazing studies identified monthly simulations as a sufficient starting point to estimate energy savings [26].

Table 7
Secondary energy conversion assumptions. Values from [53].

	Load	Assumption
PF$_1$	Heating	85% site efficient
COP	Cooling	COP = 3
PF$_2$	Lighting	100% site efficient

Once the optimal properties for each month were determined, the monthly building energy values were summed to represent annual building energy. Because the beginning of each monthly simulation begins a new environment in EnergyPlus, there is a small discrepancy between summing monthly values and the result of a single annual simulation. The authors determined this error was less than 1% for the case study models.

Reviewing previous related optimization studies revealed a tendency to reduce the glazing area and lower visible transmittance well below industry-accepted values. As the main arguments of this paper are based on the typical building design process at the conceptual design phase, it seemed inappropriate to deem the optimal solution as one with small windows with low visible transmittance. However, accurate daylighting simulations are computationally expensive. To counter the algorithm's tendency to minimize glazing area, a daylighting proxy constraint was implemented on window-to-wall ratio (WWR) and VT. The minimum WWR required to meet daylighting requirements was calculated using a rule of thumb-based design sequence for sidelit spaces by Reinhart and LoVerso [56].

This basic calculation, intended for early design, is given in Equation (3), which was used to formulate the constraints (Equations (4) and (5)). The daylight factor (DF) was set to 2% according to recommendations in the IES Handbook [57]. It was assumed there were no obstructions in case study 1, therefore the obstruction angle θ was set to 90°. The obstruction angle in case study 2 was dynamically calculated as an output of the parametric model (Fig. 5). During geometric optimization, the relative error between the calculated WWR ratio (Equation (4)) and that of the actual design was entered as a formal constraint. Similarly, the relative error between the calculated VT and average VT among all orientations (Equation (5)) was adopted as a formal constraint. Note that Equation (2) is an approximation and accounts only for diffuse daylight contribution. Further analysis would be required for glare considerations in later design, but these constraints help ensure realistic glazing requirements as determined by the architecture [56].

$$WWR > \frac{0.088 \bullet DF}{VT} \bullet \frac{90^\circ}{\theta} \qquad \text{Equation 3}$$

$$\frac{\left(\frac{0.088 \bullet DF}{VT} \bullet \frac{90^\circ}{\theta}\right) - WWR}{\left(\frac{0.88 \bullet DF}{VT} \bullet \frac{90^\circ}{\theta}\right)} < 0 \qquad \text{Equation 4}$$

$$\frac{\left(\frac{0.088 \bullet DF}{WWR} \bullet \frac{90^\circ}{\theta}\right) - VT_{avg}}{\left(\frac{0.88 \bullet DF}{WWR} \bullet \frac{90^\circ}{\theta}\right)} < 0 \qquad \text{Equation 5}$$

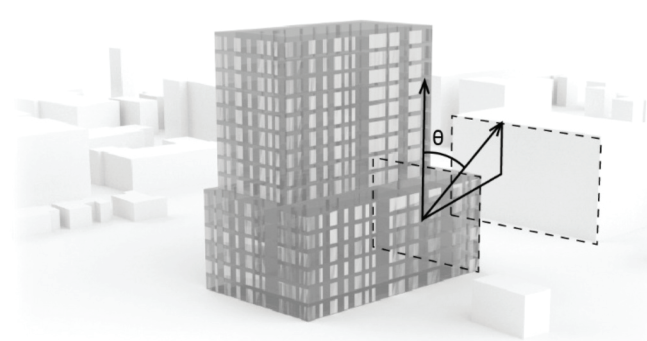

Fig. 5. Case study 2 obstruction angle diagram.

4. Results

In this section, the results of each constrained optimization run are first presented and analyzed to compare potential energy savings from manipulating different variable types. Then, sequentially designing with dynamic façades is evaluated. Finally, relative variable contributions are assessed directly.

4.1. Optimal geometry

The results of the simulated potential energy savings due to geometric optimization only are provided in Fig. 6, offering very little savings (1–2%). The design space was formulated to preserve original design intent, which may have limited savings slightly. However, this result confirms previous evidence that building form itself is not a good indicator of energy consumption [46]. Yet in some cases, 1–2% savings may still be desirable, and the designer must weigh architectural implications while deciding if altering the building geometry is worth it. Despite the small savings, both cases apparently responded to climate and context. Case study 1, located in a suburban setting, took advantage of its ability to fully rotate and oriented the façade with the greatest glazing area toward the south. It is likely that this geometric alteration, in addition to reducing glazing area within the daylight constraint, had the largest contribution to the energy savings. Case study 2 was more geometrically limited to account for the challenges of designing in an urban setting. While case study 1 leveraged solar gains to reduce the heating load, case study 2 attempted to block them. More square footage was distributed to the podium, rather than the tower since the podium receives shade from context. However, during optimization, the model moved away from adjacent buildings to satisfy the daylighting constraint.

4.2. Optimal dynamic glazing properties

Results for optimization of the dynamic properties are shown in Fig. 7. A single dotted line follows the changing monthly setting for a glazing property on one side of the building. Overall savings for each constrained optimization run are provided at the bottom of each column.

4.2.1. SHGC and VT

The existing constrained optimization results account for the relationship between SHGC, VT, and U-value, which was previously established using existing window product data [39]. Case study 1 optimization selected a higher SHGC in the winter months to accept solar gains and decrease the heating load and selected a lower SHGC in the summer months to block solar gains and decrease the cooling load. The case study 2 optimization instead opted for a lower SHGC the majority of the year. The optimal SHGC results are appropriate given case study 1 is located in ASHRAE climate zone 5 (heating-dominated), and case study 2 is located in ASHRAE climate zone 2 (cooling-dominated). For case study 1, the south façade is dominated by the SHGC so it must be varied, whereas the north façade is constrained by the VT variation, which will be discussed in the next section. On the other hand, the east and west façades are varied more for case study 2 due to increased surface area. The north façade maintains a high VT, since it can afford a higher SHGC, with limited solar radiation.

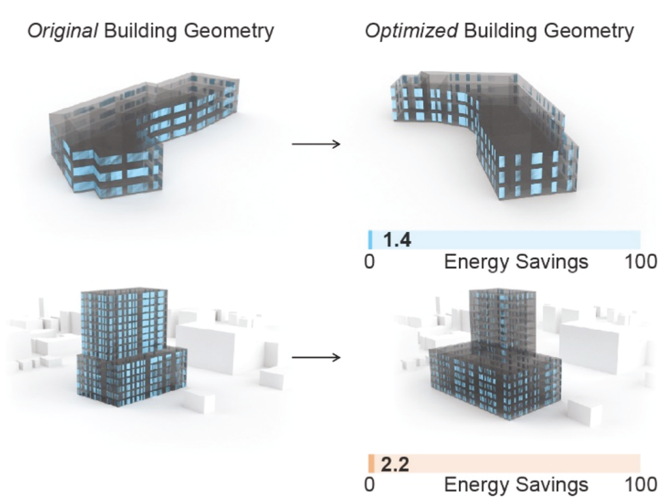

Fig. 6. Original vs. optimized building geometry for case study 1 (top) and case study 2 (bottom).

Overall, the shapes of the existing SHGC graphs for both case studies mimic their respective existing VT graph. This clearly demonstrates the tradeoff between SHGC and VT in existing window products: in order to decrease SHGC, VT must also decrease. Due to this tradeoff, case study 1 was not able to achieve high SHGC values in the winter months. To the same effect, case study 2 only selected low SHGC in the summer for key façade orientations.

Additional investigation following these results present notable features in VT variations. With future technologies, it might be possible to slightly push the bounds towards products with both higher VT and SHGC than in the statistical models used above [39]. We experimented with giving VT more freedom in the simulation, and we expected that the maximum and constant VT would be most beneficial to the energy savings. However, window VT can influence heating and cooling loads as well due to the heat gains generated by the electrical lights. Even with standard-compliant lighting power density (LPD) in the simulations, the high lighting needs in commercial buildings may still enlarge the heat gain effects of electrical lights, which has been reported in other studies [58]. Future studies can test this relationship more rigorously.

In this work, in hot climates (case study 2), such heat gains are not beneficial to save heating and cooling energy, so the VT value was kept at or near the upper bound (~90%) on the south and north façades. Increasing the VT increased daylight levels and consequently reduced the electric lighting load. However, VT was not at 100% in the optimal scenario in heating seasons (case study 1), which is mainly constrained by the low U-value in the winter. To achieve a higher insulating ability of windows, low-e coatings and/or additional window panes are required, which typically reduce the VT value. As mentioned previously, VT is sacrificed in both existing runs to achieve desirable SHGC values. This allows for a high light-to-solar gain (LSG) ratio, thus demonstrating the effectiveness of the algorithm.

4.2.2. U-value

It is widely known that highly insulating windows reduce heating and cooling loads consumption, and the results of the dynamic glazing optimization runs generally agree. For case study 1 and case study 2, the optimal U-value was the lower bound for nine and seven of twelve months, respectively. However, a higher U-value was selected for the summer months in climate zone 5 and shoulder months in climate zone 2. During these mild weather periods, strong solar heat gains may significantly enhance the building cooling loads. Such increased heat gains can be offset by the high U-value of the building window systems because the outdoor temperature conditions at most times are desirable or beneficial to the heat release from the interior. For window orientations with higher solar heat gains, a higher U-value was selected. Further, if the simulations were conducted on an hourly resolution, a lower U-value would be selected during the day, and a higher U-value would be selected during the night. While additional studies can investigate these phenomena in more detail, the optimization still largely gives intuitive results that would be helpful at the early stages of design.

Although U-value is not strongly correlated to SHGC and VT [39], there are still losses to address by manipulating this glazing property: to

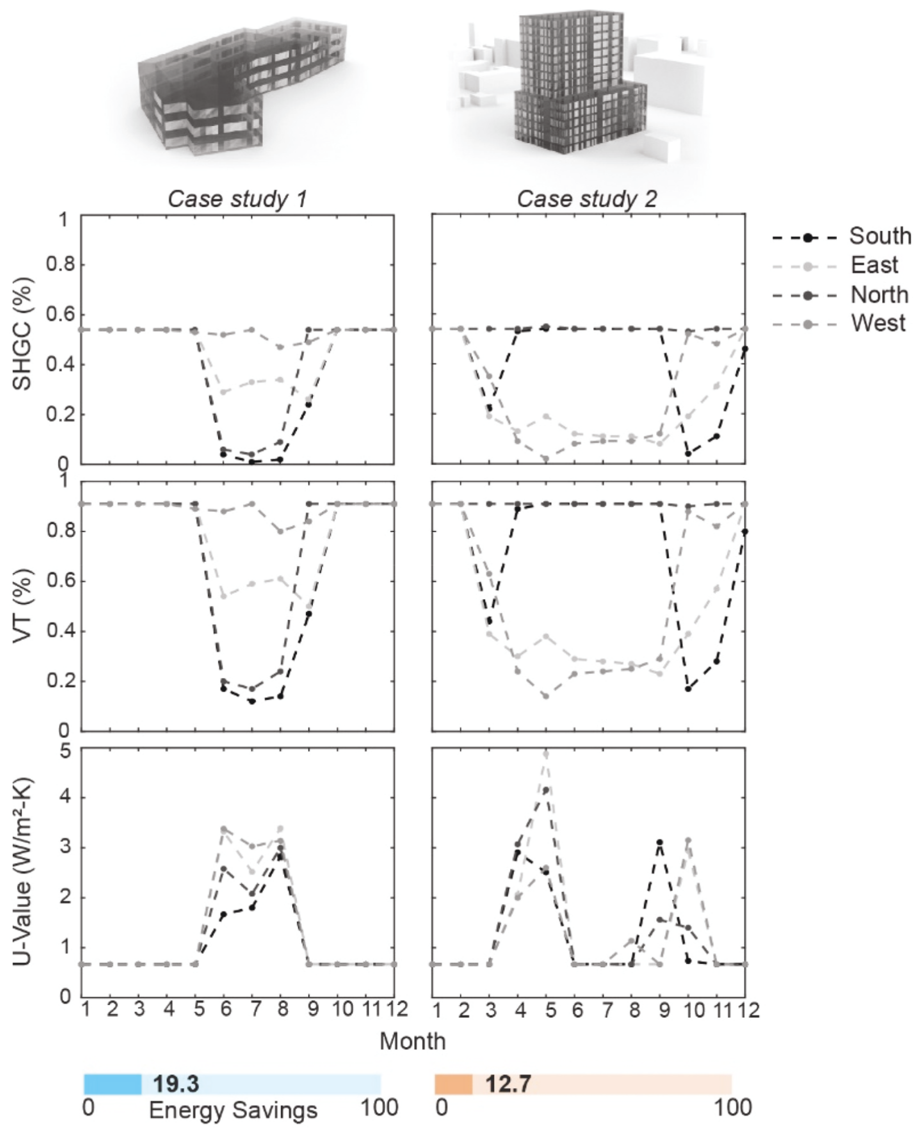

Fig. 7. Optimal glazing properties on a monthly resolution.

increase the thermal insulating ability of glazing systems, VT and SHGC will be somewhat reduced due to the addition of glazing layers or low-e coatings.

Since most months optimized to the lower bound, it was difficult to understand if modulating the U-value contributed to energy savings. To answer this question, a "high-performance" static baseline model was used to quantify the savings due to the dynamic aspect alone. The high-performance glazing adopted the lower bound of the U-value from the optimization and maintained the ASHRAE recommended SHGC value. The high-performance static model performed better than the baseline, but the dynamic model exceeded it by 5% and 3% respectively for case study 1 and case study 2. This suggests adopting dynamic glazing is a viable step in reducing building energy consumption. Energy savings comparisons are discussed further in the next section.

4.3. Comparing sequential optimization results

After determining potential savings from each category separately (runs 1, 2, 5, and 6), existing dynamic glazing properties were optimized using the optimal geometric configuration (runs 3 and 7) and an additional constrained optimization was conducted on the building geometry with the existing dynamic glazing optimal settings (runs 4 and 8). Fig. 8 shows the results of these two design procedures. Case study 1 achieved 1% reduction in heating, cooling, and lighting load energy from the geometric optimization and up to 19% reduction from the dynamic glazing optimization. Similarly, case study 2 achieved 2% reduction in heating, cooling, and lighting load energy from the geometric optimization and up to 13% reduction from the dynamic glazing optimization.

Designers might assume that combining the optimal variable settings from each constrained optimization run would yield the highest energy savings. However, because the geometric optimization altered the building orientation and form, thus altering many aspects of the fenestration, the combination did not lead to greater savings (runs 3 and 7). Compared to the existing dynamic glazing optimization, the energy savings values differed by 3% for case study 1. The relationship between dynamic glazing and building geometry is also demonstrated by the additional sequential optimization run (runs 4 and 8). For these runs, the optimal existing dynamic glazing settings were set, and the building geometry was optimized. For case study 1, optimizing the building geometry with the optimal existing glazing settings resulted in a loss of about 5% savings compared to the dynamic glazing optimization alone. This suggests the performance of dynamic glazing is not only dependent on the climate zone, but also the effects of window orientation, self-

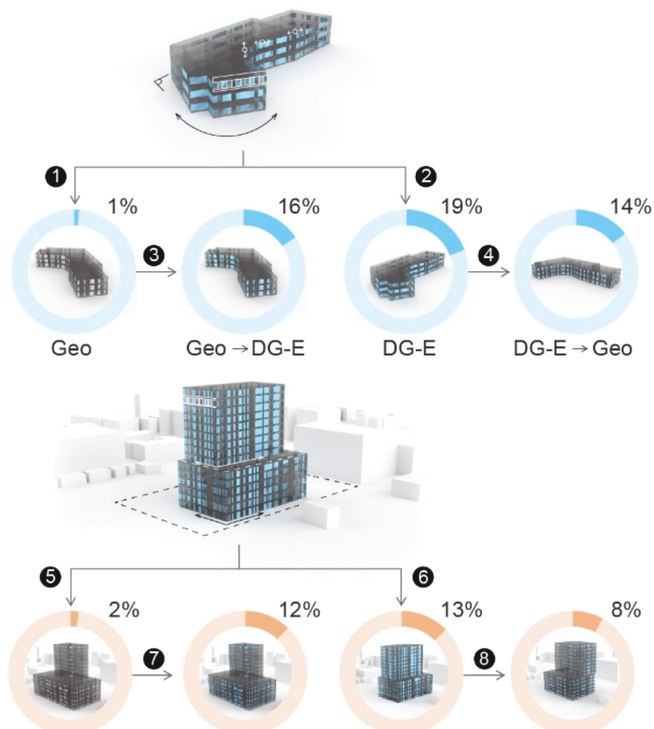

Fig. 8. Combining optimal settings for sequential optimization. Run numbers correspond with Table 1.

shading, and radiant heat exchange in relation the building shape. A direct comparison of the energy use reduction for each procedure is provided in Fig. 9.

The results show that making geometric adjustments warrants a new set of optimal dynamic glazing settings, and vice versa. Therefore, to truly understand the full potential of dynamic glazing in architect-designed buildings with atypical geometries, an additional optimization run would need to be conducted with all 16 variables and 18 variables for case studies 1 and 2, respectively. We predict that building geometry and dynamic façade materials must be considered simultaneously to achieve the optimal geometric-material combination for minimal energy consumption. Unfortunately, limitations in existing engineering software prevent exploration of complex geometry, and limitations in parametric environments prevent the full customization of dynamic materials. This suggests an avenue for extensive tool development and future research, towards a future in which designers use simulation to specify dynamic materials that can adapt to necessary conditions, along with building geometries that afford the most flexibility for achieving future energy savings through dynamic properties.

4.4. *Considering variable importance directly*

To analyze which individual variables were most influential in predicting building energy usage, a random forest regression model was built to first predict energy consumption and then calculate feature importance. This secondary analysis complements the findings of the overall optimization procedure by attempting to understand variables at a more granular level. To create this data model, case study 1 and case study 2 design spaces were sampled at a rate of n = 1000 using the Latin Hypercube Sampling method. The dependent variable was the combined annual heating, cooling, and lighting load (converted to secondary energy) divided by the gross square footage. The training and validation data were split at a ratio of 0.6. The random forest module from scikit learn [59] was implemented and tuned before calculating feature importance, reaching an 87.2% accuracy on the case study 1 test set and an 83.6% accuracy on the test set for case study 2. Fig. 10 shows the collective influence of the four main categories of variables: percentage of opaque panels variable, other window geometry variables (sill height and head height), and window performance (SHGC, VT, and U-value). Both case study 1 and case study 2 identified the single most important variable as the percentage of opaque panels, which most strongly influences WWR. Note that there were three variables affecting fenestration size: percentage of opaque panels, sill height, and head height. The collective influence of the three variables that together dictate WWR was the most important category in predicting building energy usage, followed by window performance.

It is noteworthy that control points from case study 1 (v_1, v_2, v_3) are not important features based on this model, reinforcing the notion that energy is not frequently "form-giving" for design. Likewise, the length: width aspect ratios in case study 2 (v_2 and v_3) were also deemed unimportant. However, because dynamic glazing does not yet outperform opaque construction, the amount and configuration of glazing matters most. This furthers the importance of exploring building geometry and façade materials in early design, as many geometric decisions are still relevant.

5. Discussion

The results demonstrate that a sequential design process is not necessarily fit for dynamic façade technologies. Because dynamic façades are sensitive to orientation, self-shading, and radiant heat exchange in relation to the building shape, simply applying the optimal values for the climate zone can lead to potential missed savings.

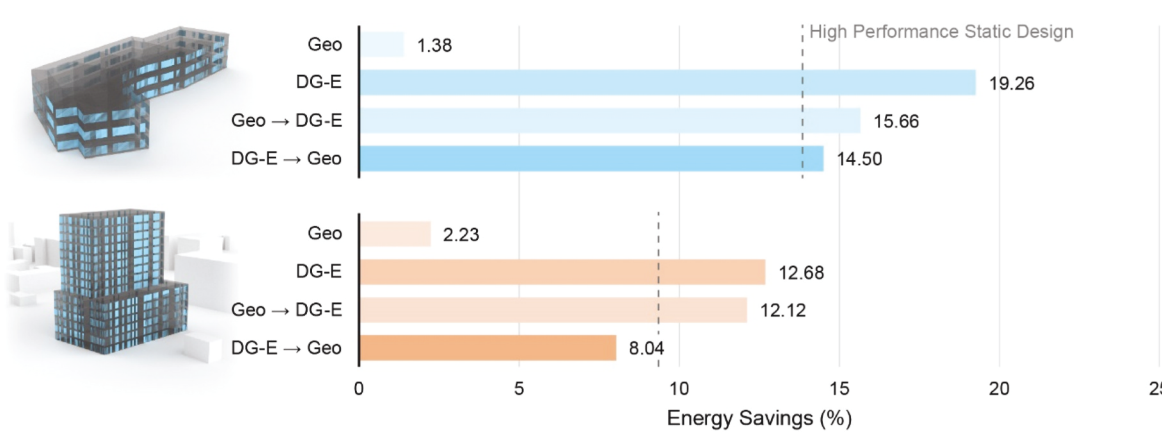

Fig. 9. Energy savings comparison.

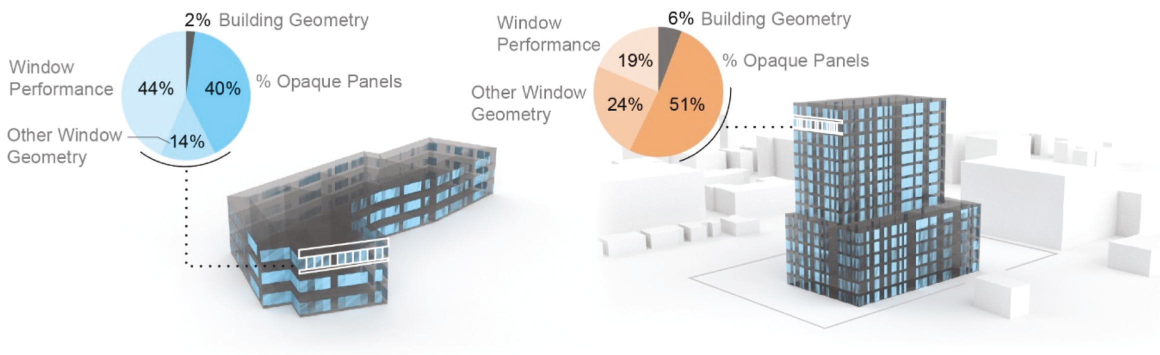

Fig. 10. Random forest variable importance.

Dynamic façade technologies introduce a unique opportunity to explore building geometry and envelope materials in early design to find the optimal geometric-material combination. However, it is currently difficult in conceptual design to structure an optimization problem with different resolutions using current design tools—building geometry is optimized on an annual basis, and dynamic façades are optimized on a monthly or hourly resolution. At minimum, we conclude that to maximize the potential savings of dynamic glazing or dynamic building envelope materials in general, it is important to consider building geometry and orientation while developing proper control algorithms. Further, the design lessons learned here suggest fundamental changes in the early design process when working with dynamic façades and encourage further computational tool development. Given the cutting-edge and often open-source nature of digital design tools, it is likely that further modifications to existing software could make simultaneous optimization of geometry and façades increasingly accessible to designers in practice.

Furthermore, many previous studies on building energy optimization use rectangular buildings or prototypical models. This study provides an example of geometry optimization for more expressive architectural designs. While it is possible to achieve 2% energy savings in these examples, drastic geometric changes often influence performance in other engineering domains or substantially alter the original design intent. For example, the optimal geometric configuration for case study 1 required the building to rotate 117° clockwise. While this is a simple parametric adjustment, it would have huge implications for how the massing relates to the site. In case study 2, the shifting of the tower on the podium would likewise have considerable influence on the structural performance. Because decisions related to building geometry require consensus between architects and other engineering disciplines, implementing these changes may or may not be beneficial to the whole project. On the other hand, assuming dynamic envelope materials become more commercially available, the high energy savings potential from dynamic glazing creates a compelling argument for their importance in design.

There are several notable limitations to this study. Although a monthly resolution was sufficient to demonstrate the geometric-material relationship, future studies at a higher resolution (daily or hourly) across multiple climate zones would provide a more robust understanding of dynamic façade performance in various design settings. As advanced simulation tools and advanced geometry tools are futher integrated, it will likely be possible in the future to conduct this framework in another platform and increase the resolution. Further, a simulation-based daylighting constraint could offer a more thorough treatment of daylight compared to the analytical constraint applied in this study. Nevertheless, the case studies were modeled with current, appropriate design variables and simulation resolution for early design, which reveals significant implications for both architecture and building performance.

6. Conclusion

In this study, we investigated the implications of automated sequential optimization while designing with dynamic glazing materials. While geometric optimization alone achieved only 2% energy savings, dynamic material optimization savings reached up to 19%. However, when combined in sequence, around 5% potential energy savings are lost. The paper also determines the relative importance of different decision categories in early design. The results are in accordance with previous findings or assumptions about the building design process established by studying these properties separately, such as the limits of geometric optimization on savings compared to façade materials [46] and the relative importance of WWR [60]. However, by using repeated constrained optimization runs that consider geometry, façades, and realistic design constraints altogether, the data in this paper provides a comprehensive analysis of these interrelated building features and how they are manipulated during design.

This study leaves several areas for further research. More extensive simulation of modern building geometries and types requires increasing access for designers and allowing for customization of dynamic components in parametric environments. Other issues to address include increasing the resolution of the simulation and allowing for continuous transitions, rather than state-to-state. Additionally, there are opportunities for multi-disciplinary optimization (MDO) [61–63] and further studies with multi-objective methodologies, as opposed to constrained optimization. Such studies could provide new insight into early design strategies for balancing adjacent objectives in conjunction with operational energy use. As daylighting simulations become less computationally expensive, including a daylight objective such as spatial daylight autonomy (sDA) or a glare metric will also provide more detailed information. Finally, a more extensive treatment of simultaneous optimization for flexible geometric variables and façade characteristics should be conducted for geometries outside the typical rectilinear prototypes, once tools are developed to make this accessible within design software.

While dynamic façades show considerable promise for improving the sustainability of future buildings, several barriers remain to their frequent adoption in architecture, making them a topic of ongoing research. As the fundamental material and technological questions surrounding dynamic façades are being answered, it is critical that digital design approaches develop to make these technologies accessible for design practitioners. This paper hopes to stimulate further investigation into how dynamic façade considerations can be better incorporated into advanced design approaches, including parametric design and optimization.

CRediT authorship contribution statement

Laura E. Hinkle: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Julian Wang:** Writing – review &

editing, Writing – original draft, Methodology. **Nathan C. Brown:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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