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A computational methodology for generating modular design options for building extensions

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ABSTRACT

Adaptation of existing building stock is an urgent issue due to aging infrastructure, growth in urban areas and the importance of demolition mitigation for cost and carbon savings. To accommodate the scale of implementation required, there is a need to increase the efficiency of current design and production processes. Computational methodologies have proven to increase design efficiency by generating and parsing through myriad design options based on multivariate (e.g., spatial, environmental, and economic) factors. Modular Construction (MC) is another approach used to increase efficiency of both design and production. This paper combines these approaches in a novel methodology for generating modular design options for extensions of existing buildings (an efficacious form of building adaptation). The methodology focuses on key architectural design metrics such as energy use, daylighting, life cycle impact, life cycle costing and structural complexity, whereby a set of Pareto-optimal exploratory design options are generated for evaluation and further design development. A functional demonstration is then carried out for the extension of Ken Soble Tower in Hamilton, Ontario. The contribution of this research is the efficient development and evaluation of design options for improving existing residential infrastructure in order to meet required energy improvements using modular extensions.

1. Introduction

Adaptation of existing buildings has increased over the past decade as a response to changing environmental conditions and requirements for reducing energy use and production of construction and demolition waste [1]. Multi-family housing buildings use 20% of all residential energy use in Canada, and 52% of this energy in Ontario being spent of space heating [2]. - Residential towers are the main source of affordable housing in Ontario, with more than 3000 towers built between 1950 and 1990 housing more than 65% of middle-and low-income communities. These buildings were all built with low energy standards and most have reached the end of their useful life [3]. Most of residential towers in Southern Ontario were built as tower-in-the-parks, within urban areas, housing guidelines have changed drastically from former requirements of 90% open space [4]. The increase in density, variation and flexibility within housing units are seen as a strategy to create multi-faceted and diverse tower neighbourhoods, providing much needed affordable housing units.

New infill, providing much-needed housing options for current residents and the city at large, provided both at the grade level or as extensions to the towers, can give better definition and form to the open areas and in-between voids of the tower in the park morphology of tower neighbourhoods. There is a need to reconsider our status-quo linear approach of design and construction with the inevitable end-of-life option of demolition. To move to a circular built environment, there is a need to incorporate adaptation of buildings to facilitate continual loops of resources, products and materials in construction [5].

Implementing Modular Construction (MC) as a building adaptation solution can improve existing buildings' condition while preparing them for a circular future in which unnecessary demolition is avoided, and the building modules and materials can enter multiple cycles of use [6]. The success of MC projects is directly related to appropriate early decision-making due to the planning and coordination focused nature of modular projects. Modular form generation is improved by automated design processes that provide real-time design feedback [7]. MC has proven advantages in life cycle impacts and life cycle costs compared to traditional construction and can contribute to more energy-efficient buildings through the improved quality of construction [8]. Therefore,

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a framework for modular extension to existing buildings and early-stage automation of designs needs to consider multiple factors for optimization.

A literature review highlights the importance of adaptation projects and processes for their improvement. Through early design stage optimization, Kiss and Szalay demonstrated environmental savings of 60–80% compared to traditional design methods. Typical design option optimizations reviewed in literature often consider a limited number of options [9], highlighting the need to consider computational design methodologies for design option generation and simulation for the simultaneous optimization of multiple factors simultaneously. Automated design option generation based on set constraints, energy use, and Life Cycle Analysis (LCA) and Life Cycle Costing (LCC) optimization can be applied using computational tools in early-stage design [10].

Researchers have developed approaches for optimizing building adaptation, constructing with modules, and incorporating design optimization metrics and automated early design decision-making. There are currently no studies contributing a methodology for integrating early-stage design optimization of environmental factors, including energy use and daylighting, Life Cycle Analysis (LCA), and Life Cycle Costing (LCC) in MC computational design processes, specifically for large-scale building adaptation projects. The intent of this research is to develop a computational design methodology for integrating MC in extension to existing buildings and early-stage automation of designs, developing optimal exploratory design options in the process.

The energy cost savings from retrofitting projects in Ontario have 20–30 year paybacks [3], due to low energy costs and lack of carbon taxing. Extra sources of revenue are required to make residential building adaptation projects feasible and scalable. Developing strategies for extensions to existing buildings are required that can address the thermal issues and provide energy savings while reducing the payback period. The proposed methodology's contribution is the integration of computational design strategies for simultaneous analysis of MC metrics, energy and daylighting analysis, LCA, LCC, and structural complexity analysis. The proposed methodology is validated by functionally demonstrating the development of design alternatives to the Ken Soble Tower adaptation in Hamilton, Canada.

2. Background and literature review

In a traditional building adaptation feasibility and early design process, many uncertain factors need to be examined. Project requirements, including budgets, timelines, spatial requirements and performance benchmarks, are taken into account. The analysis of the building's existing conditions, including building geometry, overall condition, and areas for improvement, are also considered. Preliminary exploratory design options are developed by the design team and often analyzed by various consultants who can include energy consultants, LCA consultants and cost consultants, as examples. The design team and specialty consultants go through an iterative process to develop suitable design options, and the results are shared with the client for feedback. This process can take many months to complete depending on project complexity, often leading to suitable, non-optimal design options (Fig. 1).

The extended timeline for the building adaptation feasibility process cannot meet the increasing demand due to key aging urban building stock, requirements for improved energy efficiency and spatial quality, and the need for construction and demolition waste mitigation. For example, more than 3000 residential towers were built between 1950 and 1990, accommodating more than 65% of middle-and low-income communities, as the primary source of affordable housing in Ontario [11]. These buildings were built with low energy standards and have reached the end of their useful life and require adaptation at different scales. In 2019, a ten year CAD 1.3B co-investment fund was set up for Toronto Community Housing Corporation (TCHC) for adaptation, including retrofitting and rehabilitation. Still, only 21 buildings out of the 2100 TCHC buildings were adapted in 2019 [12]. This number alludes to the current low number of buildings being adapted per year. The typical feasibility design process, illustrated in Fig. 1, takes 2–6 months. With the currently available funds, there is an opportunity to expedite the process and increase accessibility to comprehensive feasibility analysis for better decision-making.

In addition, in building adaptation design processes, future adaptability and reusability for improving the built environment's resiliency and circularity are often not considered, which can be addressed using modular construction. This literature review highlights the importance of building adaptation for facilitating a circular economy in the built environment. Strategies and processes for improving the efficiency of this process will be reviewed, including modular construction, computational design methodologies, automated early-stage design using design optimization metrics such as energy use, daylighting, structural efficiency, LCA and LCC.

2.1. Modular construction

Compared to traditionally constructed concrete buildings, prefabricated Modular Construction (MC) can reduce environmental impacts, lead to economic benefits with increased on-site productivity and construction quality [13], improve predictability regarding lifecycle costs, energy performance and environmental impact, acoustic quality, airtightness and thermal performance [14,15]. Designing buildings for reuse using modular construction, instead of recycling at End-of-Life (EoL), can also reduce life cycle impacts by 88% [16], and facilitates maintenance, repair and reuse during different life cycle stages of a building, minimizing waste generation during construction and deconstruction [17]. MC can also improve a building's adaptability through its

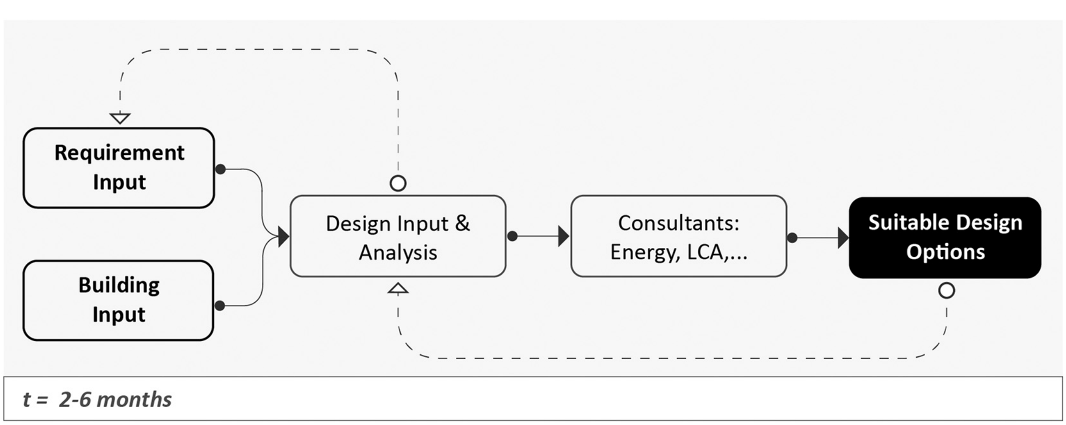

Fig. 1. Traditional design methodology.

life cycle with standardization of interfaces and independently fitted elements, allowing interchangeability and making intensive changes to a building in increments manageable [18].

Prefabrication in controlled factory environments is demonstrated to reduce construction waste by 10–15% on average [15] and up to 52% [19]. Lifecycle greenhouse gas emissions over a 50-year life of a modular building is calculated to be lower on average compared to typical construction [20]. Through a study optimizing for LCA for MC, Kamali & Hewage demonstrated that modular and prefabricated buildings show significantly improved life cycle performance metrics compared to traditional construction [21], and Mao et al. determined the carbon emissions to be lower by 32 $kgCO_2e/m^2$ compared to traditional construction [22]. Effective assembly of prefabricated modular units can also improve on-site construction conditions. These improvements include reduced construction pollution, noise and occupant disruptions making it an ideal strategy for dealing with occupied existing buildings and urban areas [23]. Reduced construction time is also an essential factor, reported from a range of 6-month reduction of construction time in a complex project [24] to a 40% reduction in overall project time with conventional construction and disruption to occupants and neighbourhoods are reduced by 30–50% [15,25].

While MC has been commonly used in buildings four to eight storeys high, implementation in high-rise buildings is slowly gaining momentum. This includes entire modular buildings or a combination of modular and typical construction [26]. Modular structures in high-rise buildings face wind force mitigation requirements, making hybrid structures with a skeletal structure or concrete core common [27]. Therefore, existing concrete towers with their over-designed capacities can be beneficial for modular extensions' lateral support. A study by Du et al. demonstrates that designers and building owners require more developed and detailed technical and financial performance information for considering MC building adaptation projects such as façade retrofits [28]. Through the analysis and integration of MC design parameters, this research aims to bridge this knowledge gap.

2.2. Design optimization metrics

Design optimization is the process of considering and evaluating design alternatives that impact the overall performance of a design. Energy use, life cycle impacts, and structural efficiency are important factors in evaluating a design strategy's success and can be considered adequately in the early stages. Mathematical optimization in building design has been applied extensively in literature to evaluate cost, energy use and thermal comfort [29–31]. Eleftheriadis et al. also demonstrated that optimizing structure and interior layouts in early-stage design for life cycle impacts can reduce carbon emissions by 10–50% and improve cost performance by 2–5% [32]. Ghisellini & Ulgiati suggest the superiority of building adaptation, specifically refurbishing, as an alternative to new construction while implying that a methodology for integrating LCA and LCC and optimizing the design decision making process for building adaptation projects is required [33].

Lobaccaro et al. used a computational design approach to optimize multiple factors, including the size of windows and their location on the façade, to optimize daylighting and reducing heat loss and PV placement on the façade for optimized power generation [34]. Ionescu et al. demonstrate energy improvements resulting from a series of combinations of different measures, including thermal insulation, high-performing windows and airtightness measures as examples [35]. This process can easily get complicated even with the consideration of a small number of variables. Each variable will require a series of different values for consideration, such as insulation materials, thicknesses and location as examples [36,37].

Antipova et al. developed a mixed-integer linear program for optimizing environmental impact and life cycle costs of a retrofitting project and determined optimal building designs based on limited metrics. These include varieties of insulation material, window placements and solar panels [38]. Azari et al. developed a multi-objective optimization algorithm for optimizing the design of a building envelope design, considering energy use and life cycle analysis of design options. Following a parametric approach, Hollberg et al. used evolutionary algorithms to optimize the life cycle environmental impact of building designs considering insulation material and thickness, window types and heating systems for a retrofit project [39]. These studies are limited in scope and often focus on single element optimization, rather than complex design option generation.

2.3. Computation and automated early stage design

Design decisions made in the first 10% of projects determine up to 80% of the building operation costs after construction, and computational early-stage design methods can improve the architectural, structural and environmental performance of building designs [26]. Yuan et al. demonstrated that a computational design methodology specific to modular construction could improve constructability and enable design optimization [13]. Kiss and Szalay developed a framework for optimizing early-stage designs for LCA and energy use as part of an automated early-stage design process, leading to savings of 60–80% [9]. Banihashemi et al. proposed a computational methodology for optimizing structural and other material use, reducing waste in the process [40], and Greenbough et al. demonstrated that the integration of computational design tools, in MC specifically, improves the structural engineering design process [41]. Schwartz et al. demonstrated that optimal refurbishment design solutions could be obtained from optimizing LCA in early-stage design through a computational and automated design methodology. Their results prove the increased efficiency and accuracy of a consolidated early-stage design tool [42]. Ciardiello et al. (2020) use computational design and genetic algorithms to generate geometry variations of mid-rise residential towers. The algorithm calculates total annual energy demand, annual energy cost, and carbon emissions caused by building energy use over a year [43]. The study by Ciardiello et al. is the most advanced of its type to date, however, a sole focus has been placed on form generation optimized for energy use. The study also focuses largely on general building form generation.

The consideration of multiple early-stage design factors has become common in the past decade; these include cost, energy, and life cycle performance, amongst others. Granadeiro et al. integrate early design stage automation of building envelope design with energy simulation using grammars [44]. Yu et al. used genetic algorithms and design structure matrix to support automated spatial organization in the early stages of design [45]. Sharafi et al. presented a method for automating early-stage design for modular multi-story buildings by comparing the performance of various forms. This automated methodology supports designers in generating and analyzing multiple design options simultaneously and evaluating optimal design solutions [26].

Computational and parametric design environments enable optimization of building geometry simultaneously with the analysis of various design variations with immediate building performance feedback [7]. Software interoperability is a major step in supporting automated design processes and enabling designers to engage with option generation through real-time performance feedback. In an effective automated early-stage design process, designers in charge must take spatial, structural, environmental performance and life cycle impacts and costs into consideration simultaneously to make optimized decisions. Currently, there are limited studies in supporting an integrated and systematic design process for the design of modular buildings [13] and as modular extensions to existing buildings.

Literature demonstrates examples of applying LCA and energy analysis in a computational tool with geometry represented mathematically or as topologies. Topology optimization is often used in structural design to find an optimized design in a given domain. Design options that do not meet the defined objective are iteratively eliminated after analysis [46]. While energy analysis and environmental performance considerations are becoming common in an automated design process, structural analysis and evaluation are still considered in later design stages.

Multi-objective optimization allows for choosing a suitable solution but is not common in building optimization literature [9]. Obtaining optimal design solutions to complex multi-dimensional and multi-modal problems demands computationally expensive fitness function evaluations, and typical optimization methods cannot address the issue. For example, a single evaluation may require many hours or several days to compute to address a structural optimization problem. A typical genetic algorithm for solving multi-objective solutions creates a reasonably sized initial population that often needs long periods of calculation time, making the task unfeasible [47]. Therefore, it can be more pragmatic to use heuristic methods to constrain the combinatorial variety and create all possible solutions rather than apply genetic algorithm approaches and allow the designer to search the full design space for desirable design solutions.

2.4. Knowledge gap

The success of building adaptation and modular building projects is directly related to appropriate early decision-making due to the planning and coordination focused nature of modular projects and the complexity of building adaptation projects. The following knowledge gaps identified in the literature will be addressed in this research. Computational design methodologies for generating modular exploratory design options and their evaluation using multiple metrics is limited. Most of the work in literature in design option generation focus on energy use evaluation and/or life cycle analysis and fail to consider the multitude of interconnected factors that are necessary for design decision-making. Studies that demonstrate computational design strategies and modular construction mainly consider the evaluation of either structural efficiency or energy use alone. There are no tools or methodologies available that integrate various analysis metrics for the early-stage design automation of modular extension and adaptation of existing buildings. The combination of a rigorous design option generation methodology using energy use, in combination with daylighting measures and life cycle thinking, accounting for LCA and LCC is required. In addition, most studies in literature have been focused on general building form generation. When considering the use of MC, as volumetric modular additions to existing building, a focus at the smaller scale of each module, and its effect on the larger building form, is required.

3. Computational design methodology

The presented computational methodology is based on creating a finite number of design solutions that meet environmental performance requirements and economic constraints, in the process of building extension. The intent is to demonstrate possibility of increasing number of units and variety in unit types. Energy use, daylighting and carbon emissions will be set as system constraints. The remaining design combinations will be analyzed based on their LCC and based on structural efficiency as a proxy for complexity to arrive at a set of Pareto-optimal design solutions for further selection and analysis by the designer.

This methodology is developed in three stages: 1) analysis, parametrization of existing building and development of an algorithm for the generation of exploratory design options, 2) simulation and analysis of generated options for energy use, daylighting, structural complexity, LCA and LCC, and 3) result refinement through a heuristic-guided exhaustive search and selecting Pareto-optimal design solutions. Stage one of the methodology requires manual work and processing from the project designers to process the existing building and define parameters. Through a step-by-step analysis of the building, development of design constraints and user inputs processing, precise design constraints and rules are developed for algorithm input. In the second stage, the developed algorithm generates design combinations, simulates environmental analysis, and analyzes the design combination conditions for life cycle performance and cost. Design options that meet the set criteria are displayed in stage three.

The methodology enables a designer to input preferences for generating and parsing through possible designs for selecting optimal solutions. This methodology suggests possibilities for incorporating external databases and previously analyzed cases to develop databases of all feasible solutions leading to a predictive model of performance feeding the results, to be investigated at a later stage of this work. The first stage requires input from parties involved in the early-stage design process, including the client and designers. The last two stages of the methodology are fully automated and can be processed in real-time (Fig. 2).

The developed computational methodology is differentiated by geometric simplicity, automated processes and simulation tools, and direct manual user input processing in various stages. Genetic algorithms are widely used in computational design; in this methodology, the focus has been to incorporate adaptive strategies (specific vs. generic) and topologic modelling strategies. Existing computational interfaces, plugins and frameworks are used to develop a cohesive tool that integrates existing resources and facilitates integration. The computational design tool is programmed using Grasshopper® visual programming interface, and plugins are used within the interface for energy use simulations and optimization. One-Click LCA® is used for preliminary life cycle emission calculations, and other plugins in Grasshopper®, such as Honeybee® for energy analysis and daylighting, are used. Future development of the methodology will involve incorporating external databases and analytical cases, creating a database of feasible solutions over time and developing predictive algorithms. The Ken Soble Tower in Hamilton, Canada, is selected as a functional demonstration and is used to demonstrate the methodology's functionality in various stages. The computational methodology is functionally demonstrated in section 4.

3.1. Stage 1 – Analysis and parametrization of existing building

The first stage in the methodology is focused on the analysis and parametrization of the existing building and the development of design constraints. The design constraints are developed by processing the existing building information, defining design parameters and determining user inputs and requirements. Design parameters are defined based on the existing building's analysis, existing site conditions, and planning requirements and restrictions. Design input includes adaptation strategies to be considered, such as the extension of the building, recladding of the envelope, re-glazing of the windows and enclosing of existing balconies.

For efficient MC design, the fewest number of structural variants are required. Based on industry partner experience working with z-modular. While modular panelling is feasible with mass customization, variation in 3D modular structures significantly increase the cost of construction.

In the first phase of stage one, the existing building drawings are analyzed, and the geometry of the existing building, including interior spaces and the building envelope, are modelled. The existing structure is analyzed to determine required design parameters, including structural, environmental and spatial shortcomings. The existing building is modelled as zones (b-reps) and aggregated into topological complexes. The building geometry is further discretized into panels and elements at the project designer's discretion, illustrated as step 1 in Fig. 3.

Development of design constraints early in the process, such as a speculative grid for modular design, will limit the design problem's dimensionality, leading to a heuristic approach and increased accuracy of generated exploratory design options. To acquire this information, the existing building geometry is analyzed in terms of dimensional and spatial constraints for extension, and the dimensions of a typical module

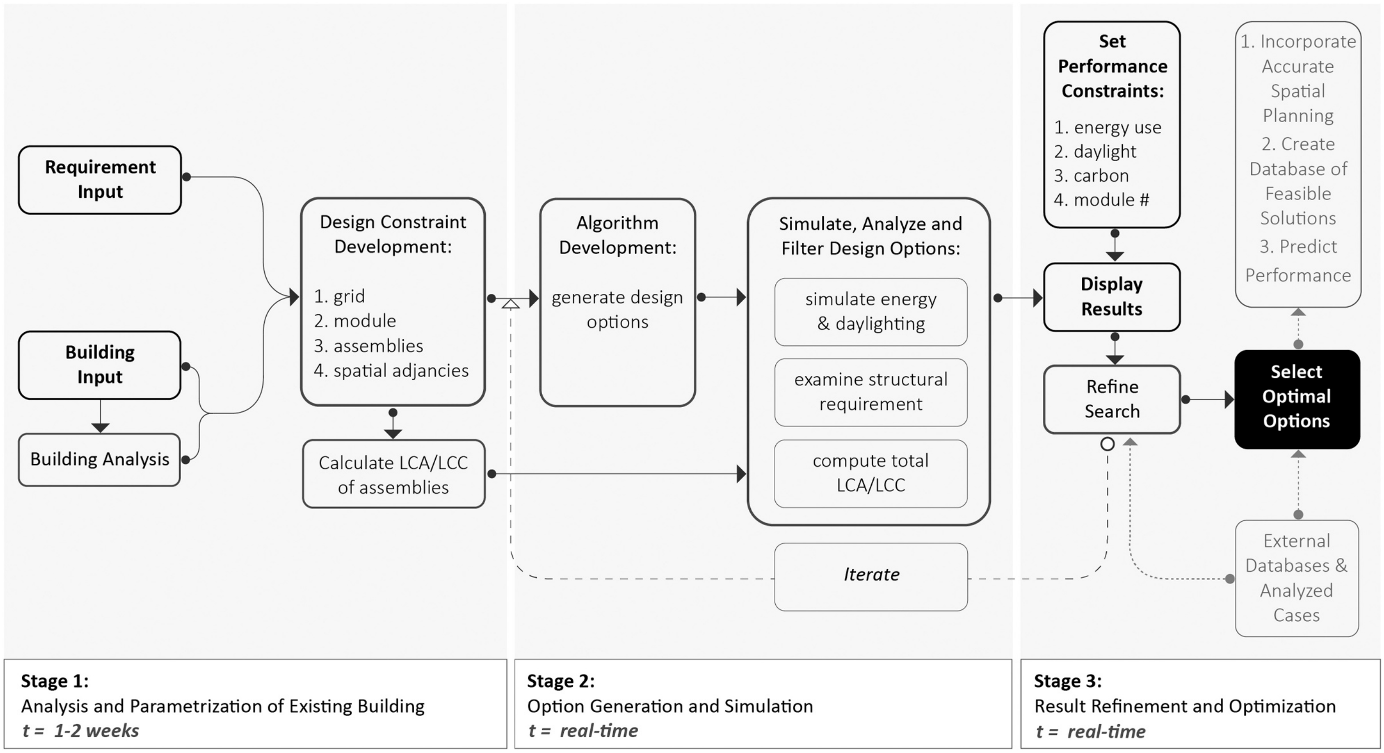

Fig. 2. Computational design methodology.

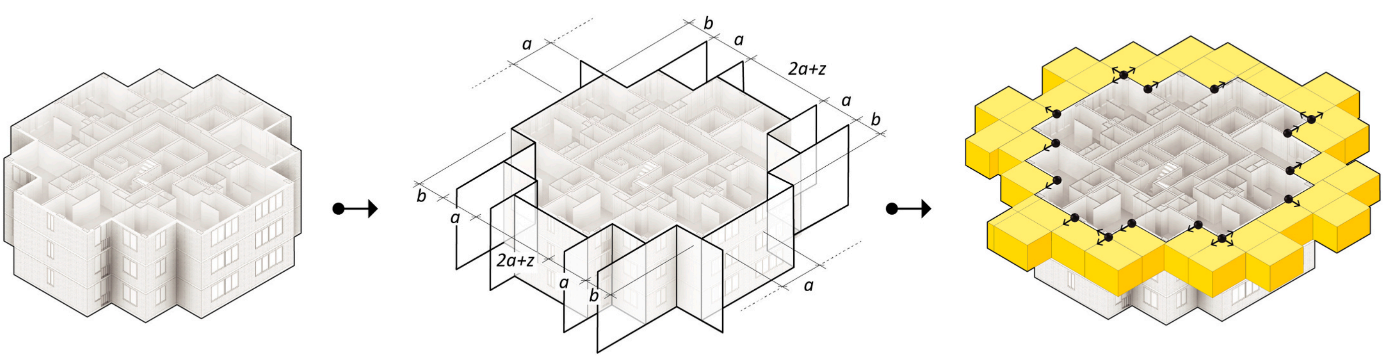

Fig. 3. Step 1 - Existing building analysis (demonstrating the first three storeys): 1) Input existing building geometry, 2) Create speculative grid options, 3) Select grid and define module dimensions, 4) Define growth dimensions, direction and starting points based on modular size and interior layout.

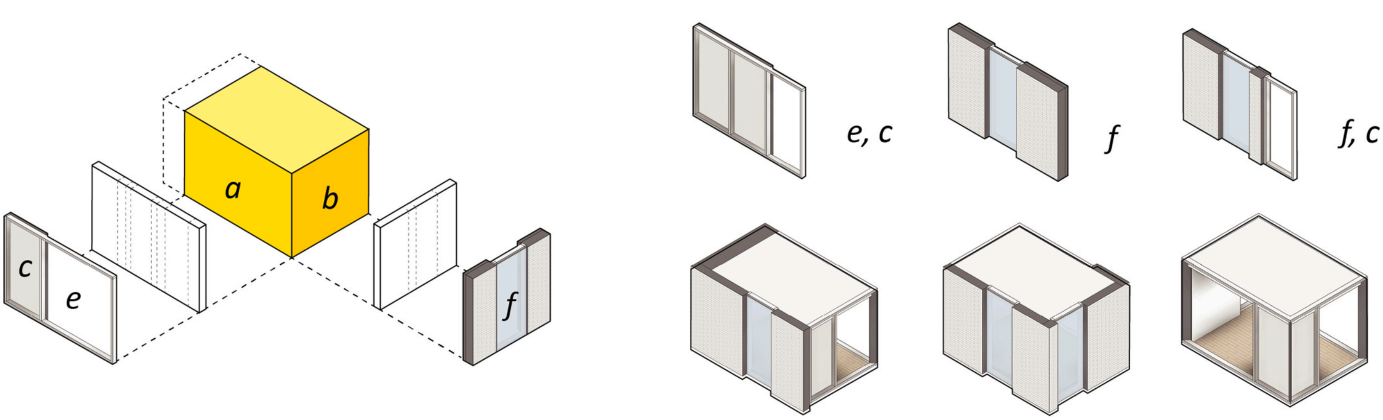

Fig. 4. Step 2 – Module and panel parametrization: 1) Define module parameters, 2) Define panel parametrization, 3) Develop module prototypes.

are determined. For building extension and recladding, for example, the following steps are required: 1) building parameters defining modular extension parameters, module parameters including spatial configurations, connection parameters, and growth patterns and restrictions (Fig. 3); 2) panel parameters including dimensions of panel divisions, the spatial organization of panels and connection details (Fig. 4); 3) Determining rules and patterns for unit growth by testing spatial layout using module and panel types, and defining combination of modules and panels for each existing unit type (Fig. 5).

As part of the existing building analysis in step 4, the LCA of the existing building is determined considering the existing operational energy use standards. After the modules and panels are determined, the life cycle impact (per assembly per m^{2-}) is determined, not accounting for energy use for each of the modules separately using One-Click LCA® (Table 1). The combination of these modules will be used in the algorithm to determine the LCA of the combined design options in real-time following formula (1) and LCC following formula (2). In the framework, the user can input preferences, review and parse through results, and reconfigure priorities based on real-time project data. The user inputs and determines constraints. The user here is defined as the designer, modeller or client evaluating building adaptation strategies. The building analysis results combined with the input parameters are used to feed the developed algorithm for option generation. The building inputs, analysis, design criteria and user inputs are combined to create a detailed breakdown of the design constraints for the development of the algorithm in stage 2.

3.2. Stage 2 - Option generation and simulation

After defining geometry and selecting strategies, a virtual grid of speculative possibilities is computed. The developed algorithm generates exploratory extension design options by positioning modules and assigning states based on the information stored in the grid, previously determined in stage 1. The design options are generated using Topologic® and the developed algorithm within Grasshopper®. Topologic® is a software modelling library enabling hierarchical and topological spatial representations through non-manifold topology [48]. Existing geometry is modelled as b-reps (boundary representation schema) directly modelled or extruded from existing drawings. They are fed as input to the module translating Rhino® 3D b-rep object to topologic cells, organizing them and forming topologic complexes. The set of options is generated through heuristic-guided exhaustive search, being finite and relatively small, allowing for computation and comparison of all the possible options. Invalid combinations that do not meet spatial requirements are further eliminated, for example, long overhangs and inappropriately attached modules (Fig. 6). A topological structure with cells, also known as object-oriented programming, governs the distribution of modules and assignment of states.

Multiple adjacent surfaces must be resolved to analyze the generated design options' performance, and pre-determined building assemblies assigned to each surface in step 6. The attachment of multiple modules results in multiple alignments of horizontal and vertical surfaces, and the solving of these adjacencies will eliminate multiple surfaces for a single alignment per vertical and horizontal surface (Figs. 7 and 8). In step 7, defined assemblies are assigned for every single surface (Fig. 9). With the correct assemblies set, heating energy use (kWh/yr/m^2) and daylighting, Spatial Daylight Autonomy (sDA) is completed in step 8. SDA is defined as the percentage of yearly occupied time with minimum illuminance threshold reached by daylight. It has been cited in multiple studies as an accurate method for quantifying a building's daylighting efficiency [49]. In addition, data from each design combination, including the number of module extensions, panel types, extension area, etc. are extracted from the model at this stage (Fig. 10).

In step 9, the total LCA and LCC of each design option are calculated in real-time. The net environmental impacts for each building adaptation design option consider the LCA of the existing building and consideration of the extension of life by 60 years through building adaptation. The LCA of modules and existing buildings are calculated in line with EN 15978:2011 standards [50] for LCA Modules A1 to Module D. The energy use of each compiled design option is calculated inside Grasshopper® in real-time, using the Honeybee® plugin. Honeybee® supports thermodynamic modelling and creates, runs, and visualizes energy models' results using EnergyPlus® and OpenStudio® simulation engines. The number of extension modules is calculated in Grasshopper® in real-time and calculated using the pre-calculated LCA and LCC of each design option, using the formula (1) for total LCA and formula (2) for total LCC:

$$\mathrm{LCA}_{total} = \mathrm{E}_i[\mathrm{kgCO_2e}] + \sum_A \mathrm{n}_A\,\mathrm{E}_A\,[\mathrm{kgCO_2e}] + \sum_B \mathrm{m}_B \mathrm{S}_B \mathrm{C}_B\,[\mathrm{kgCO_2e}] + U_{total}\,[\mathrm{kWh/yr/m^2}]\left\{\mathrm{U}_{factor}\left[(kgCO_2\mathrm{e})/kWh/yr/\mathrm{m}^2\right]\right\} \tag{1}$$

where LCA_{total} is total life cycle assessment including carbon emissions and operational energy use, E_i is the carbon emission of the existing building excluding operational energy use, n is the area of each assembly in each design option, A is the assembly type used in the design option, $\mathrm{E_A}$ is the emission of type A assembly excluding operational energy use, U_{total} is the total energy use of the building including existing and extension modules, and U_{factor} is the local emission factor, B is accounting for structural impact, m is the number of modules per design option, S is the LCA determined of steel required per module and C is the interpolated complexity score (0.1–0.3) calculated for each design option.

$$\mathrm{LCC}_{total} = \mathrm{E_c}\,(\$/\mathrm{m}^2) + \sum_A \mathrm{n}_A\,\mathrm{F}_A\,(\$/\mathrm{m}^2) + \sum_D \mathrm{m}_D \mathrm{S}_D \mathrm{C}_D\,(\$/\mathrm{m}^2) + \left\{\left[U_{cost}\,(kWh/yr/\mathrm{m}^2)\right]\left[\mathrm{U}_{factor}(kgCO_2\mathrm{e})/(kWh/yr/\mathrm{m}^2)\right]\left[\mathrm{U}_{carbon}(\$/\mathrm{m}^2/kgCO_2\mathrm{e})\right]\right\} \tag{2}$$

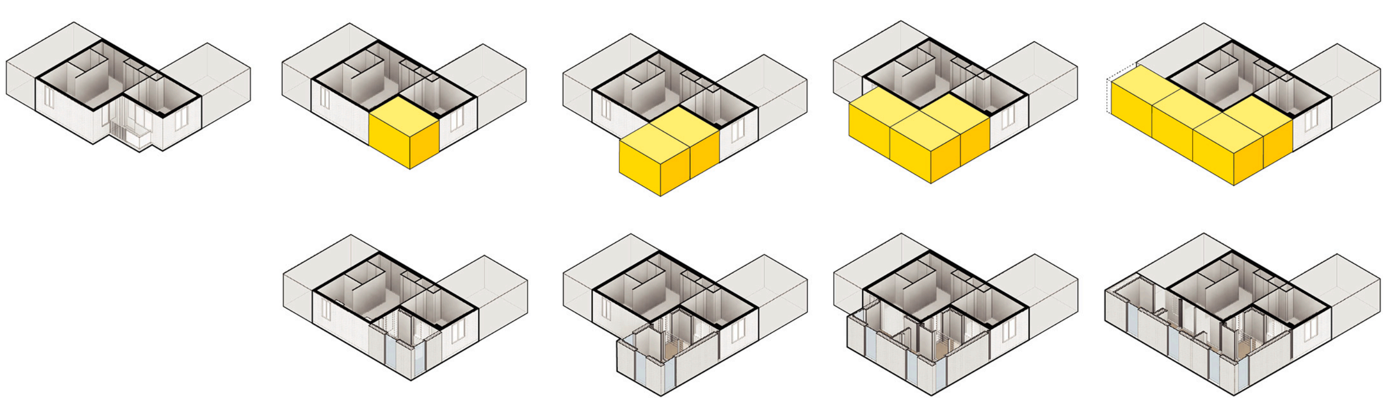

Fig. 5. Step 3 – Unit growth patterns: 1) Test spatial layout using module and panel types, 2) Define a combination of modules and panels for each existing unit type.

Table 1
Stage 4 – LCA/LCC of Building Assemblies: 1) Define all building assembly types, 2) Calculate LCA/m^2 for each assembly, 3) Calculate LCC/m^2 for each assembly.

Assembly	GWP (kgCO2e)/m^2	Life Cycle Cost ($)/$m^2$
Connecting Module Floor *- Hardwood flooring, prefinished* *- Concrete, ready mix, 0–2500 psi* *- Plywood, generic, 4–50 mm, 620 kg/m^3* *- Glass wool insulation panel, unfaced, generic, 25 kg/m^3* *- Gypsum board, wallboard, type X, 16 mm)*	51.5	325.5
Exposed Floor (Soffit) *- Hardwood flooring, prefinished* *- Concrete, ready mix, 0–2500 psi* *- Plywood, generic, 4–50 mm, 620 kg/m^3* *- Glass wool insulation panel, unfaced, generic, 25 kg/m^3* *- Gypsum board, wallboard, type X, 16 mm)* *- Flexible waterproofing membrane, from thermoplastic elastomer, on CMU, 2.4 kg/m2* *- Styrofoam insulation, 1.3–3.0 pcf (Dow)* *- Western red cedar bevel siding, clear grade, painted, 1inx6in*	100.0	504.8
Exposed Roof *- Roll formed metal wall and roof panels, 1.0127 lbs/ft2* *- Flexible waterproofing membrane, from thermoplastic elastomer, on CMU, 2.4 kg/m2* *- Oriented strand board (OSB), 0.37in (APA)* *- Glass wool insulation panels, unfaced, generic, 25 kg/m3* *- Styrofoam insulation, 1.3–3.0 pcf (Dow)* *- Gypsum board, wallboard, type X, (16 mm)*	78.2	130.3
Exterior Wall (Solid) *- Gypsum board, wallboard, type X, (16 mm)* *- Glass wool insulation panels, unfaced, generic, 25 kg/m3* *- Plywood, generic, 4–50 mm, 620 kg/m3* *- Styrofoam insulation, 1.3–3.0 pcf (Dow)* *- Plywood, generic, 4–50 mm, 620 kg/m3* *- Air and water barrier system, mechanically fastened, 0.184 lbs/ft2, Tyvek* *- Clay brick, 3.625 × 2.25 × 7.625 in, 37.1% fly-ash*	56.8	187.8
Exterior Wall (Glazing) *- Window wall curtain wall aluminum framing, 5.9 kg/m2*	51.9	880.2
Recladding *- Plywood, generic, 4–50 mm, 620 kg/m3* *- Styrofoam insulation, 1.3–3.0 pcf (Dow)* *- Plywood, generic, 4–50 mm, 620 kg/m3* *- Air and water barrier system, mechanically fastened, 0.184 lbs/ft2, Tyvek* *- Clay brick, 3.625 × 2.25 × 7.625 in, 37.1% fly-ash*	46.1	158.2
Connecting Interior Module Wall *- Drywall system with steel studs, incl. Mineral wool insulation, painted*	22.0	3.0

where LCC_{total} is total life cycle costing including carbon emissions and operational energy use, E_c is the cost of the existing building excluding operational energy use, n is the area of each assembly in each design option, A is the assembly type used in the design option, F_A is the cost of type A assembly excluding operational energy use, U_{cost} is the operational energy cost of the building including existing and extension modules, U_{factor} is the local emission factor, U_{carbon} is the local cost of carbon, D is accounting for structural cost, m is the number of modules per design option, S is the LCC determined of steel required per module and C is the complexity score calculated for each design option.

In step 10, the structural complexity of each module is evaluated. While the development of a computational methodology could include a comprehensive structural design component (i.e., where each module could have its own unique structural system), this methodology adopts a more pragmatic approach of assessing the structural complexity as a function of module topology. A score for structural complexity is a proxy for adding the additional materials required at connections to ensure certain module configurations can be achieved from a structural design standpoint. For instance, a suspended or cantilevered module to another module or the existing building will require additional supports (e.g., larger connections, bracing or awning-type cables). These additional materials not only increase the project cost by adding design complexity and more materials, but they contribute to the overall life cycle inventory (e.g., more volume and mass of materials). As such, the overall LCA and LCC values are increased by a linear factor of the structural complexity, as determined by formulas (**1**) and (**2**). A larger structural complexity score will increase the life cycle impacts of a given module configuration. The structural complexity scoring details are explained for the functional demonstration case and shown in Fig. 11.

3.3. Stage 3 – Result refinement and optimization

The results of option generation and simulation are visualized for review of all the generated and evaluated options. The user can refine the search for the most viable option by limiting the scope of the investigation (Fig. 12). After initial refinement, LCC and structural complexity are compared, and Pareto-optimal results are highlighted (Fig. 13) for further analysis.

4. Functional demonstration – Ken Soble tower

The Ken Soble Tower is a 16-storey multi-unit concrete residential tower built-in 1967 in Hamilton, Ontario. A regional shortage of adequate, affordable housing and the need to reduce energy use and carbon production has led to the adaptation of the tower to Passive House standards currently under construction. In the adaptation, all balconies have been demolished, the envelope has been recladded, and the HVAC systems have been decentralized. In this study, alternative strategies of extension and recladding are investigated as a functional demonstration of the developed computational methodology. Due to computation limitations, only the first three storeys of the building are considered in this analysis.

A heuristic method is used to constrain, combine, and generate all possible solutions, allowing the user to explore the created design space. According to a set of predefined design constraints, the developed tool in this research creates over 600 exploratory design options in a 2-week simulation period. The breadth of the design space is relatively small due to the imposed constraints. Heuristic methods are applied to minimize the dimensionality of the problem at hand. An extended amount of computation is required for performing simulations to assess each resulting design option's performance.

4.1. Stage 1: project parametrization and analysis

The typical module dimension and the spatial analysis lead to the determination of rules for extension. Fig. 3 demonstrates the points of "growth" in black, and the direction of permitted extension determined by the designer. The grid is determined as derivatives of a, b and z (an exception of envelope extension to a. At the level of the determined module size, panels are broken down and analyzed in terms of joining conditions that include: 1) attachment of a new module to the existing building (e), 2) connection of two modules together (c) and 3) exterior façade (f). Through multiple design exercises, the number of required panel divisions for each panel of a and b are determined for each condition of e, c and f. In the Ken Soble Tower project, the variation of module connections leads to 16 different possible configurations of e, c and f for panel a, seven different possible configurations of e, c and f for

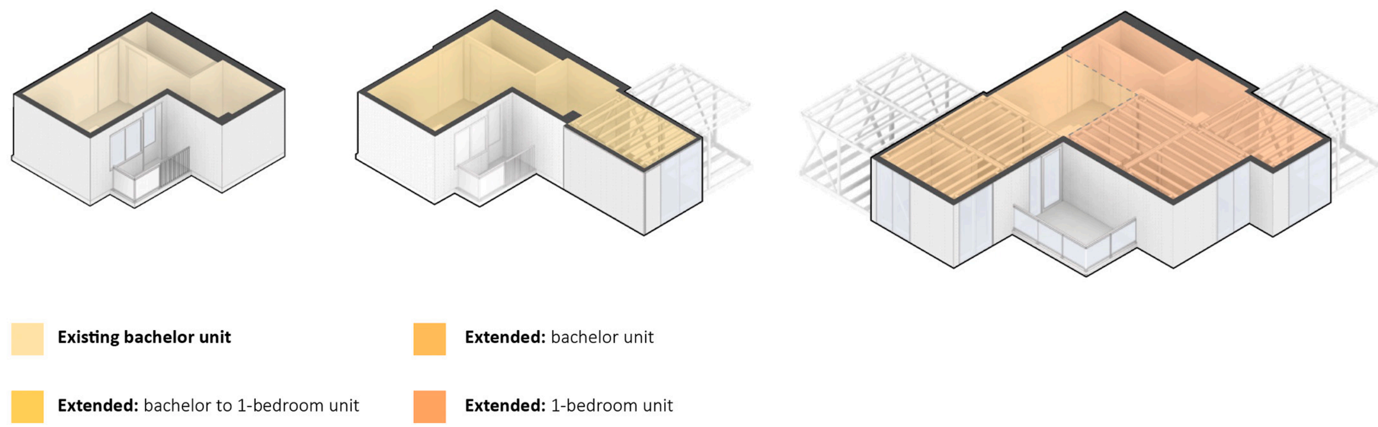

Fig. 6. Example of addition of units through extension.

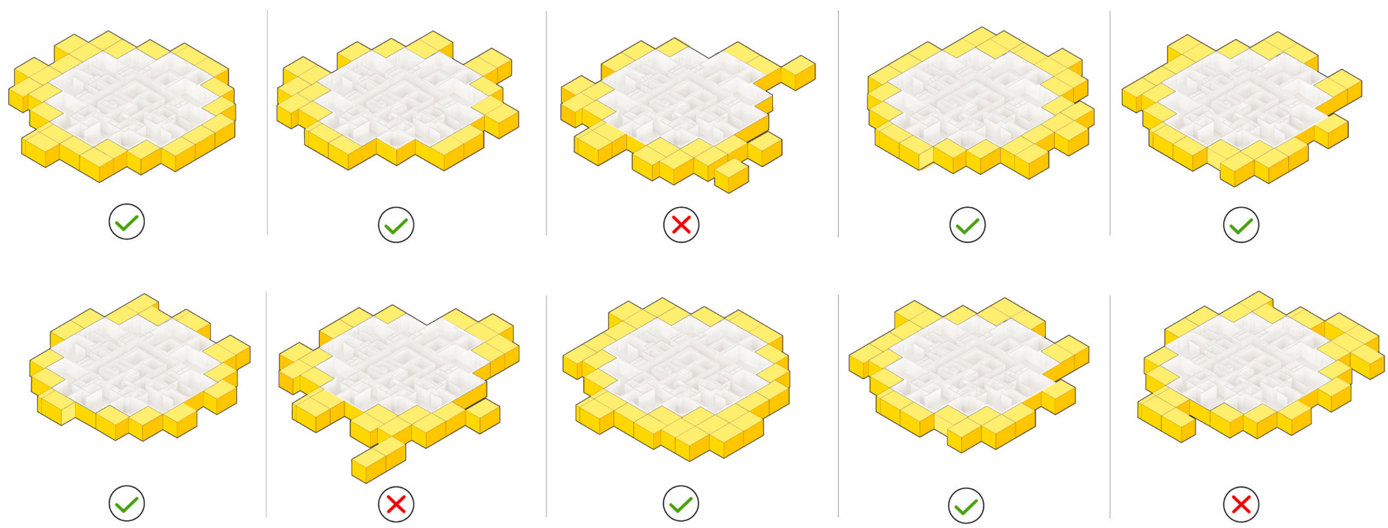

Fig. 7. Step 5 – Generate combinations and eliminate invalid configurations: 1) Generate all possible design combinations based on design parameters, 2) Eliminate combinations that do not meet spatial requirements.

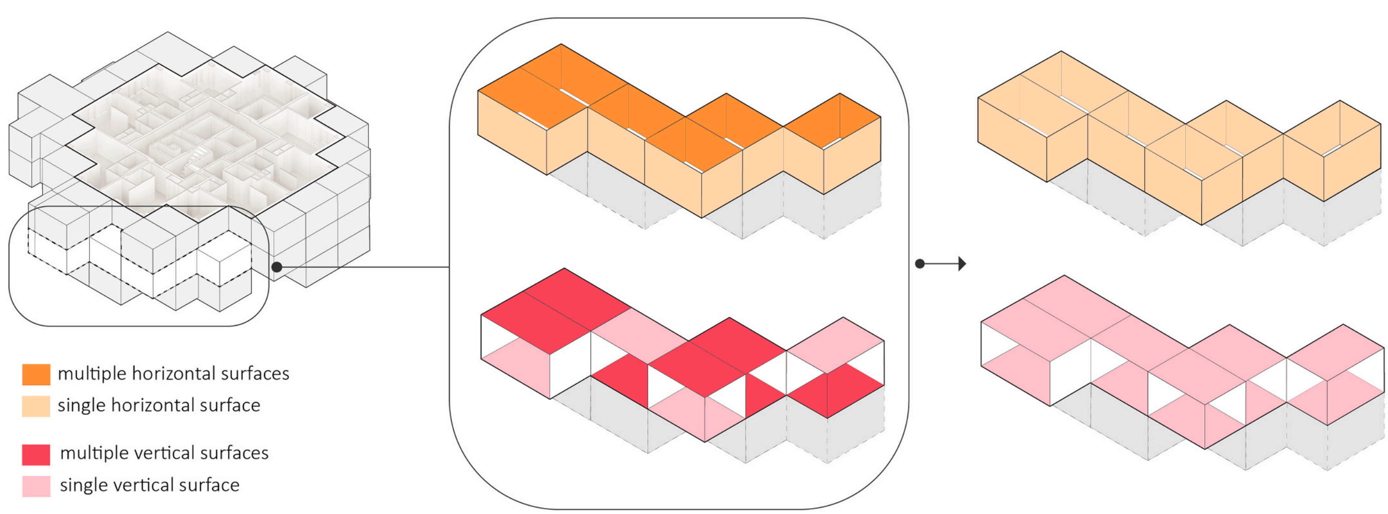

Fig. 8. Step 6 – Solve Adjacencies: 1) Identify multiple alignments of horizontal and vertical surfaces in each design combination, 2) Eliminate multiple surfaces and arrive at a single alignment per vertical and horizontal surface.

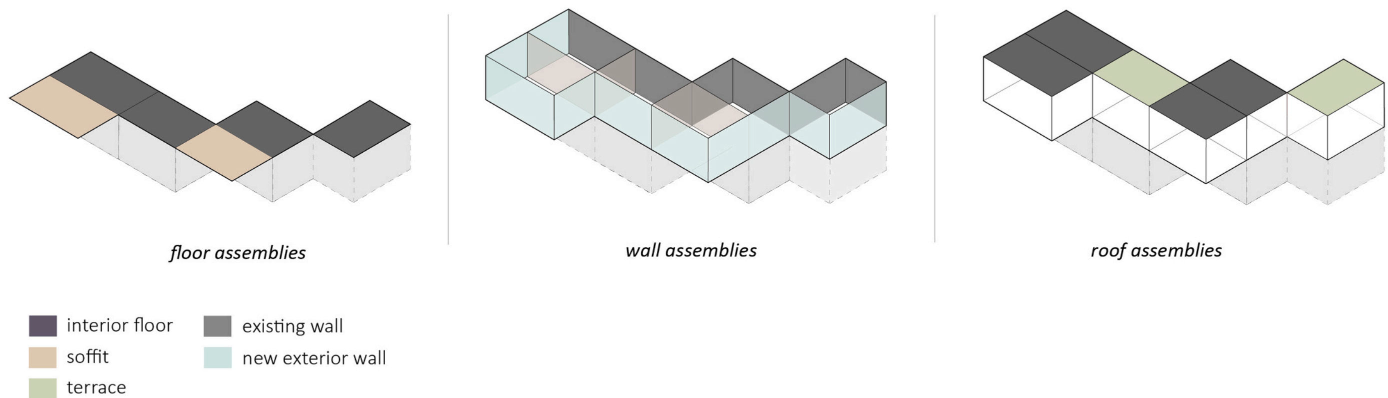

Fig. 9. Step 7 – Assign Materials: 1) Assign material assemblies to solved zones in each design combination.

panel *b* as demonstrated. The user also determines unit growth patterns by testing spatial layouts for each existing unit using the defined module size and defining a combination of possible extensions using modules and panels for each unit (Fig. 5). All the different building assembly types used in the study are defined in Table 1 and assigned for each surface. These assemblies include: 1) connecting module floor, 2) exposed floor; 3) exposed roof, 4) exterior wall (solid), 5) exterior wall (glazing), 6) recladding, or 7) connecting interior module wall (Fig. 9). The LCA and LCC per unit area (m^2) are calculated for each assembly to be used in real-time LCA and LCC analysis in stage 2 of the methodology (Table 1).

4.2. Stage 2 - Option generation, simulation and analysis

Possible design combinations are generated within a designated temporal limit for simulation based on set constraints, and combinations that do not meet set spatial requirements are further eliminated (Fig. 6). After the design combinations are finalized for further analysis, the geometric adjacencies are resolved. Multiple alignments of horizontal and vertical surfaces in each design combination are identified and eliminated to arrive at a single alignment per vertical and horizontal surface (Fig. 8). For each resolved surface is identified per assembly type and identified in Table 1. The assembly is assigned to enable environmental, LCA and LCC simulation and analysis (Fig. 9). Using the prepared geometry, the algorithm simulates and calculates heating energy use (kWh/yr/m^2) and daylighting simulation using Honeybee® for Grasshopper®. Spatial Daylight Autonomy (sDA) is used for daylighting analysis of generated design options. Further, data is collected from each design combination, including module numbers, panel types and numbers, extension areas for further analysis (Fig. 10).

4.2.1. Structural complexity

The scoring system employed in this work is shown in Fig. 11 and is based on the following conditions. First, as the number of modules supported above a given module increases, so does the structural complexity score. A linear factor of $(+n)$ is assigned to a module for the n number of modules supported above. Effectively, this means that lower modules in a stack will require more support than modules at the top of a stack. For modules at ground level, a score of $(+1)$ is assigned to account for the materials required to tie-into the foundation (i.e., anchor bolts, grout, etc.) Next, complexity is assigned to a module based on the vertical load transfer. No additional scoring is applied when a module is continuously supported from below (i.e., the bottom face of a module is coincident with another module or the existing building). For modules that are not continuously supported, complexity is based on the number of supported vertical faces. For rectangular shaped modules with all four sides supported, no additional scoring is assigned as the number of supported vertical sides decreases, the structural complexity increases. A factor of $(4\text{-}f)$ is used for rectangular panels to denote the number of supported vertical sides f. Based on this framework, the lowest structural complexity score would be a value of 0 (for a module on top of a stack, continuously supported below). The highest value for a story height of 6 would be a value of 8 (4 modules supported above, and which is only supported below by one of its vertical faces). The sample scores for a given configuration is shown in Fig. 11.

4.3. Stage 3 – Result refinement

Results for the 600 generated design combinations are demonstrated in Fig. 12. Constraints are determined for embodied carbon (KgCO2e/m^2), energy use (kWh/yr/m^2) and sDA(%). Based on Toronto Green Standards, a 25% reduction of energy use intensity from the status quo for the achievement of tier 2 is required. The standard is a measure for facilitating sustainable site and building design in the region [51]. The existing building has a heating energy use of 243 kWh/yr/m^2 [52]; therefore, the heating energy use is constrained to below 193.8 kWh/yr/m^2. According to LEED v4, complete points are awarded for a 20% reduction in embodied carbon compared to a reference building. Therefore, the design options are constrained to the ones having 80% of the lowest embodied carbon at 180,000 (kgCO2e/m^2). Also, the minimum average sDA value required for regularly occupied floor areas to qualify for LEED is 40% [53]. Design options are therefore constrained to sDA of 40% and higher.

Generated design options are further analyzed in terms of LCC, encompassing LCA and structural complexity, as a proxy for overall building form complexity. The filtering of results by acceptable ranges or required targets allows the narrowing down of optimal results. Fig. 12 demonstrates all the 600 generated options presented for refinement by the user, and the filtered results primarily by number of module extensions, daylighting and energy use, and in addition by LCA and LCC. After the set constraints, the remaining results are presented in Fig. 13, with the Pareto-optimal frontier design options marked including options 74, 169, 223, 117, 513, 264, 322 and 500. The eight Pareto-optimal design options are visualized in Fig. 14 for further design exploration by the project designer. Secondary options that perform close to the optimal frontiers are also presented as further design guidance.

5. Discussion and application

This paper's main goals were to demonstrate a computational methodology for generating design options and integrating and evaluating MC in building adaptation projects. The aim was to improve the quality of design options and the speed of evaluation in building adaptation projects. It was demonstrated that the energy use and LCA of generated options are linearly correlated across all generated design

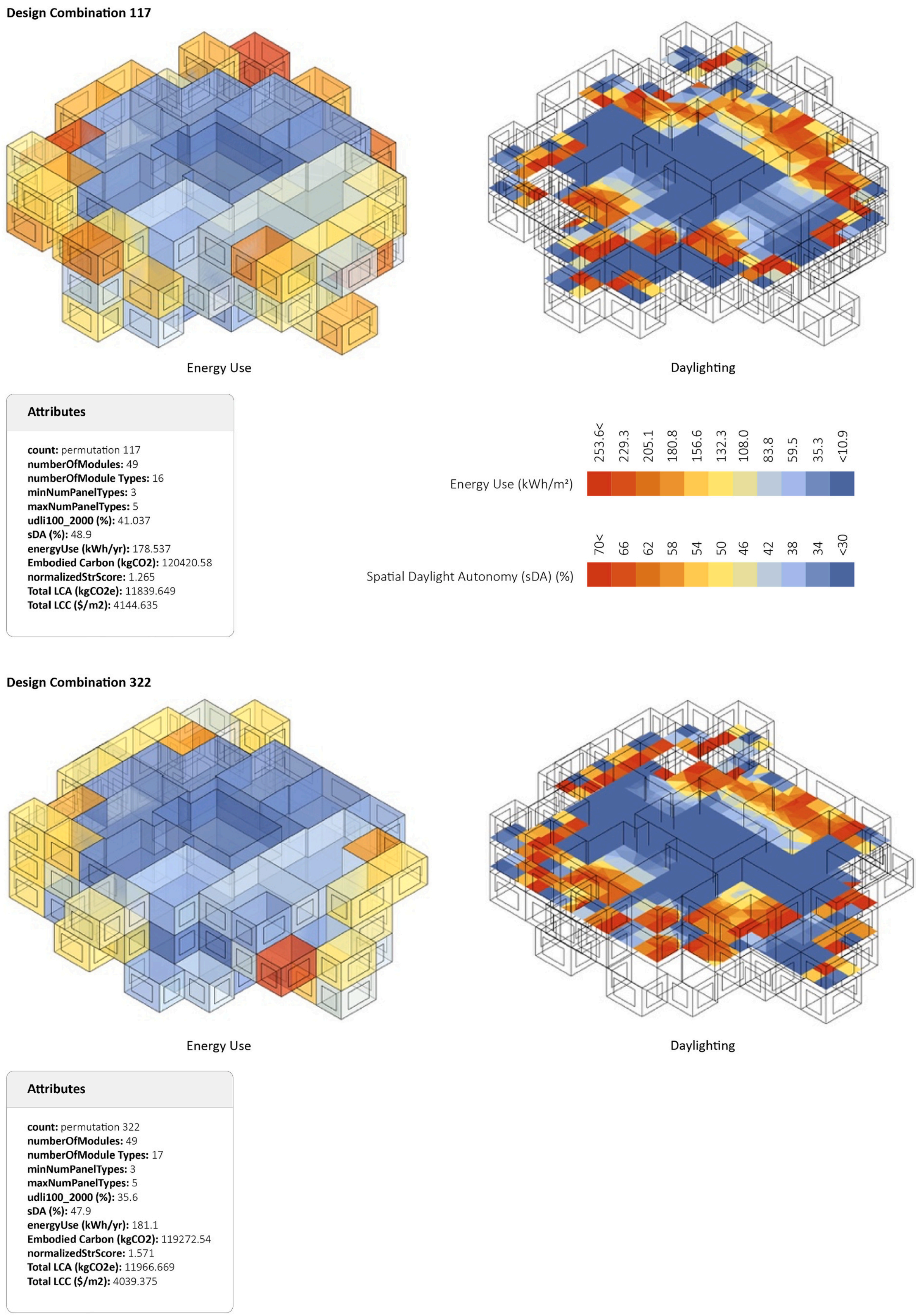

Fig. 10. Step 8 – Simulations and Data Generation: 1) Conduct energy simulations and calculate heating energy use (kWh/yr/m^2), 2) Conduct daylighting simulation and calculate sDA (%), 3) Collect data from each design combination including module numbers, panel types and numbers, extension area.

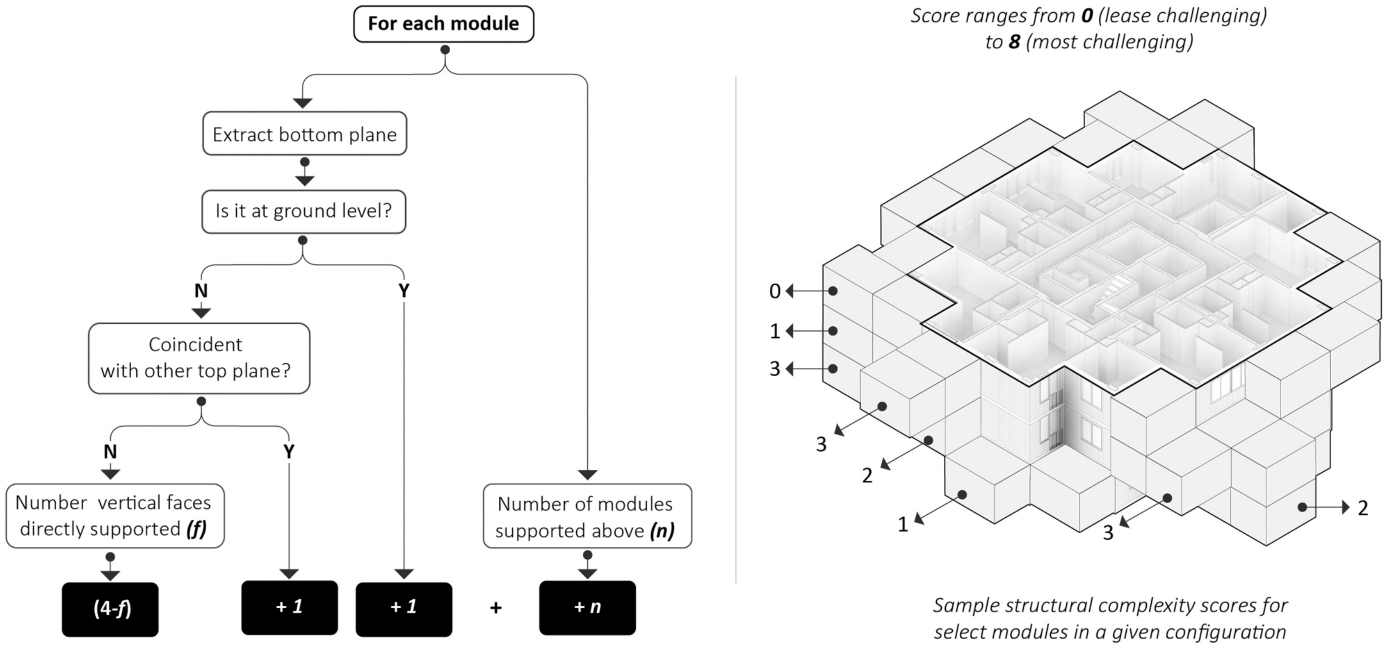

Fig. 11. Step 9 – Workflow for calculating structural complexity score: 1) Rank each module in design combination in terms of structural complexity, 2) Combine all scores and normalize for each design combination.

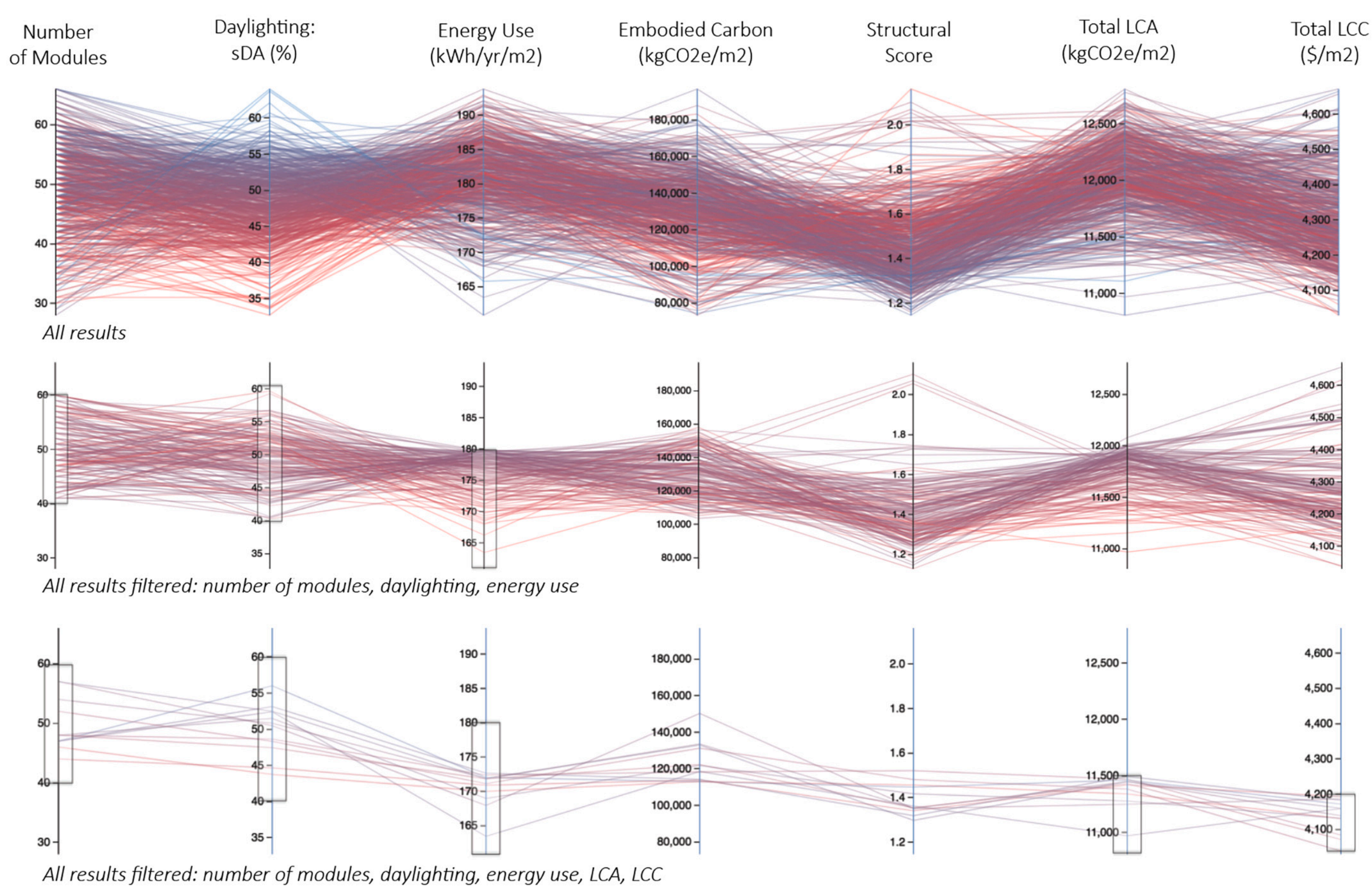

Fig. 12. All results presented for refinement by user for 1) Number of Modules, 2) Daylighting, 3) Energy Use, 4) Embodied Carbon, 5) Structural Score, 6) LCA and 7) LCC. The filtering of results by acceptable ranges or required targets allows the narrowing down of optimal results.

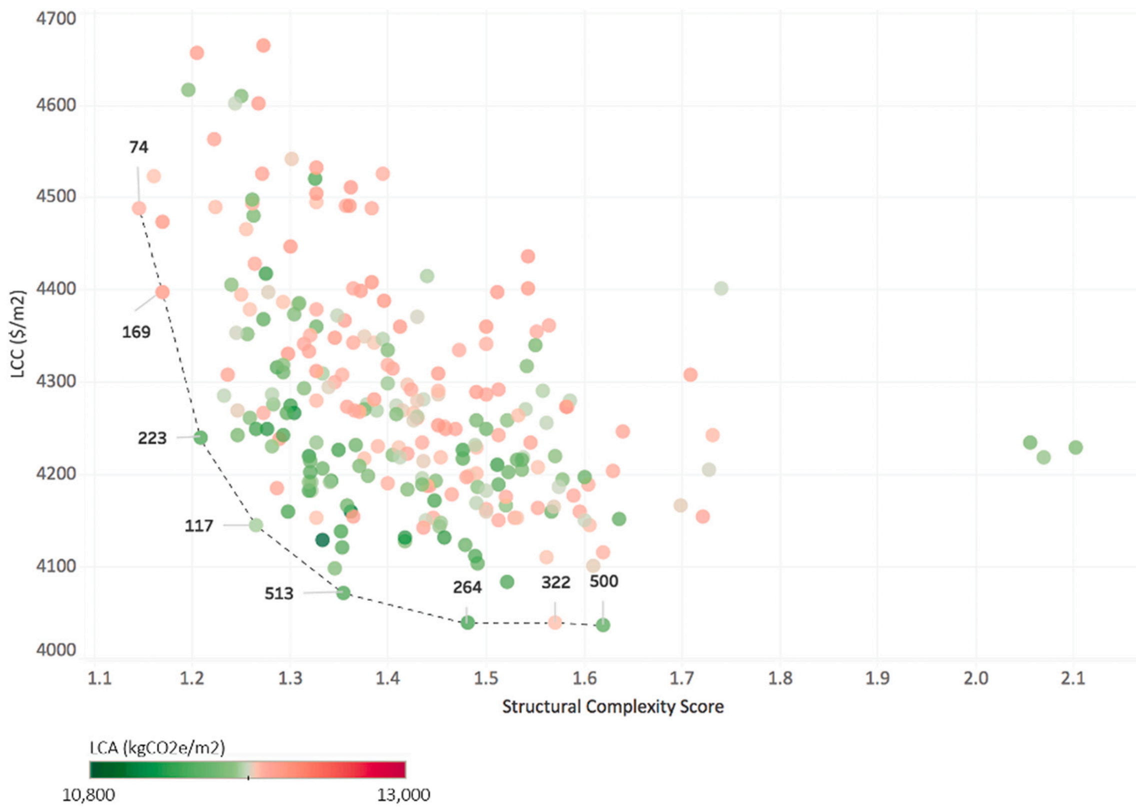

Fig. 13. LLC ($/m^2$), Structural Complexity, and LCA (KgCO2e/m^2) of Design Permutations (represented by colour range), filtered by selected ranges of embodied carbon, energy savings, daylighting requirements and range of extension. Pareto-optimal design permutations per cost (74, 169, 223, 117, 513, 264, 322, 500). Grey represents all other results.

options, as was expected due to the significance of operational energy use in a building's overall LCA. However, for design options with a similar LCA, there are significant variations in LCC. For example, for LCA of around 11,760 (KgCO2e/m^2), there are over 25 design options with a range of LCC; from \$4098/m^2 to \$4616/m^2 (Fig. 15). The variations in LCC correspond to the effect of different materials and assemblies used instead of energy use factors. The variations in data-driven design option analysis for early-stage design, and the resulting variety of LCC per range of LCA highlight the importance of this investigation and multi-objective analysis. Without using a computational methodology for design optimization with simulation feedback, there is a potential loss of opportunity in achieving savings in embodied carbon and life cycle impact and environmental performance criteria that are dependent on geometric form generation and material use in MC.

When searching for optimal results based on LCC and Structural complexity score, all other results are filtered based on set requirements, including embodied carbon, energy savings, daylighting and range of extension (number of modules).

Based on these measures, the Pareto-optimal results do not show a changing pattern in LCA with increasing LCC and a higher complexity score. Design options with the highest LCA of close to 1300 (kgCO2e/m2) have been filtered out by the other set criteria but the none of the Pareto-optimal options embody the lowest LCA amount of 10,800 (kgCO2e/m2) and the primary and secondary solutions are in the mid-range of LCA results, between 12,000 and 12,500 (kgCO2e/m2).

The structural complexity score is also validated by the primary and secondary design permutations demonstrated in Fig. 14. The options with the lowest complexity scores of 1.15–1.22 (permutations 74, 169 and 223), are design options with the least amount of cantilevers, variations in height and numerous repetitions per floor layout. The options with the highest complexity score, 322 and 500, demonstrate higher variability per floor layout and more cantilevered modules. The life cycle cost of each design permutations is highly dependent on energy use and operational costs. With the variety of unit depths enabled by the more complex unit types, it is anticipated that optimal energy performance and daylighting in contributing to the lower LCC in these two options in comparison to the others, that provide deeper floor plates.

Fig. 16 demonstrates the existing building case demonstration and four options from the primary and secondary pareto-optimal options explored in Fig. 13 and Fig. 14. The exploratory work presented in this research aims to guide designers and architects gain perspective on the implications of possible design options and does not seek to replace a rigorous design process. The representations in Fig. 16 are suggestive of possibilities and do not reflect architectural design qualities. In Table 2, the Sustainability Return on Investment tool [54] was used to analyze the financial feasibility of one of the design options. The design of permutation 513, a 230-module addition, will require a capital expenditure of \$1.9 M at \$8.3 k per 10 m^2 module. This addition can add up to 45 new units, yielding to \$672,000 of extra revenue per year, a payback period of 8.2 years, an IRR of 8% and a profit increase of 191%.

The impact of the methodology described is in its versatility and flexibility, making it accessible for designers to use in various contexts, as demonstrated in the functional demonstration. It also has the potential to be used as a preliminary design tool for asset managers who manage existing, aging building stock. The implemented methodology has a modular architecture and can be customized to meet the demands of different investigations. In this paper's functional demonstration, it was decided to constrain the generated exploratory design options based on embodied carbon, energy savings, daylighting requirements, and the number of modular extensions and select Pareto-optimal frontier based on LCC and structural complexity. In this investigation, it was important to understand the correlation between LCC and structural complexity as a proxy for design complexity and to select complex design options that

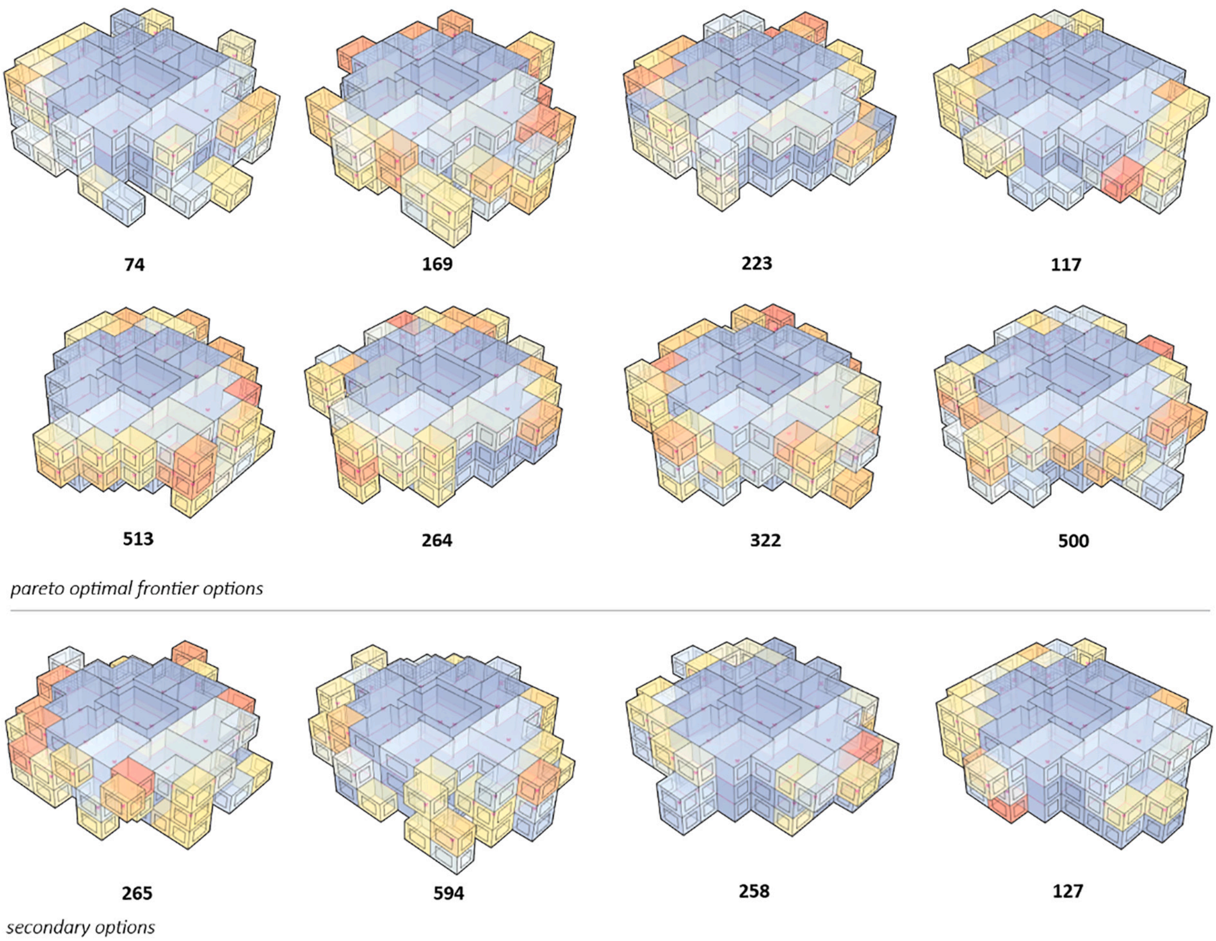

Fig. 14. Pareto-optimal design permutations (74, 169, 223, 117, 513, 264, 322, 500). The option generation algorithm is limited to three-storeys due to computation limitations.

are financially feasible and meet the set requirements in terms of performance. However, it is possible to customize the methodology in different ways for designers to improve their workflow based on various objectives. The modules of the methodology can be adjusted to constrain and analyze for any sets of performance criteria. These include optimizing for the lowest cost and most energy-efficient options, or the most cost-effective intensive extensions, as examples.

In this study, it can be summarized that early design stage multi-objective analysis of various performance criteria, as demonstrated, can enable designers to better understand the design option parameters and conditions that can lead to better-performing designs as the designs develop. As presented in this paper, simulation-based computational methodologies help supplement a designer's abilities in developing optimal exploratory design options. It is demonstrated in the functional demonstrations that the use of the methodology can improve the performance of a range of design options on multiple metrics and highlighting relationships between various performance metrics. The exploratory design methodology presented in this research has been useful for our industry partners in providing more comprehensive building adaptation services. Building adaptation and new build clients have been interested in exploring feasibility design alternatives being suggested through the use of this methodology. The continuation of this work with the industry partners includes the adaptation of the methodology to be used with new build projects as part of master planning consulting work.

In further development of selected designs, the methodology can be refined and optimized with designer feedback and according to varying project requirements. With extensive use of the methodology and the creation of databases of feasible solutions, it will be possible to use data science and machine learning algorithms to begin to predict the performance of design options in the early stage of design processes, limiting the computational time and improving the quality of generated design options. Also, external databases and previously analyzed cases can be incorporated to improve the overall analysis process. From the stages of the design requirement analysis and constraint development to final selection and design development, the creative process and designer experience are crucial in developing successful building projects. The application of this research in residential multi-family adaptation projects can mitigate unnecessary demolition and promote improvements to affordable housing assets at increased rates.

6. Conclusions

6.1. Contributions

Adopting modular construction in building adaptation projects, specifically as extensions to existing buildings, is an essential step in moving towards a circular built environment and facilitating the continual use of resources in construction. Parameters and limitations in modular design and the opportunity for design optimization highlight the importance of incorporating computational design tools in the design of modular buildings. This research contributes to improving data-driven design generation and multi-objective analysis of early-stage design by developing a computational design methodology. The methodology also contributes to the improvement in MC's design process, specifically in the integration with building adaptation projects.

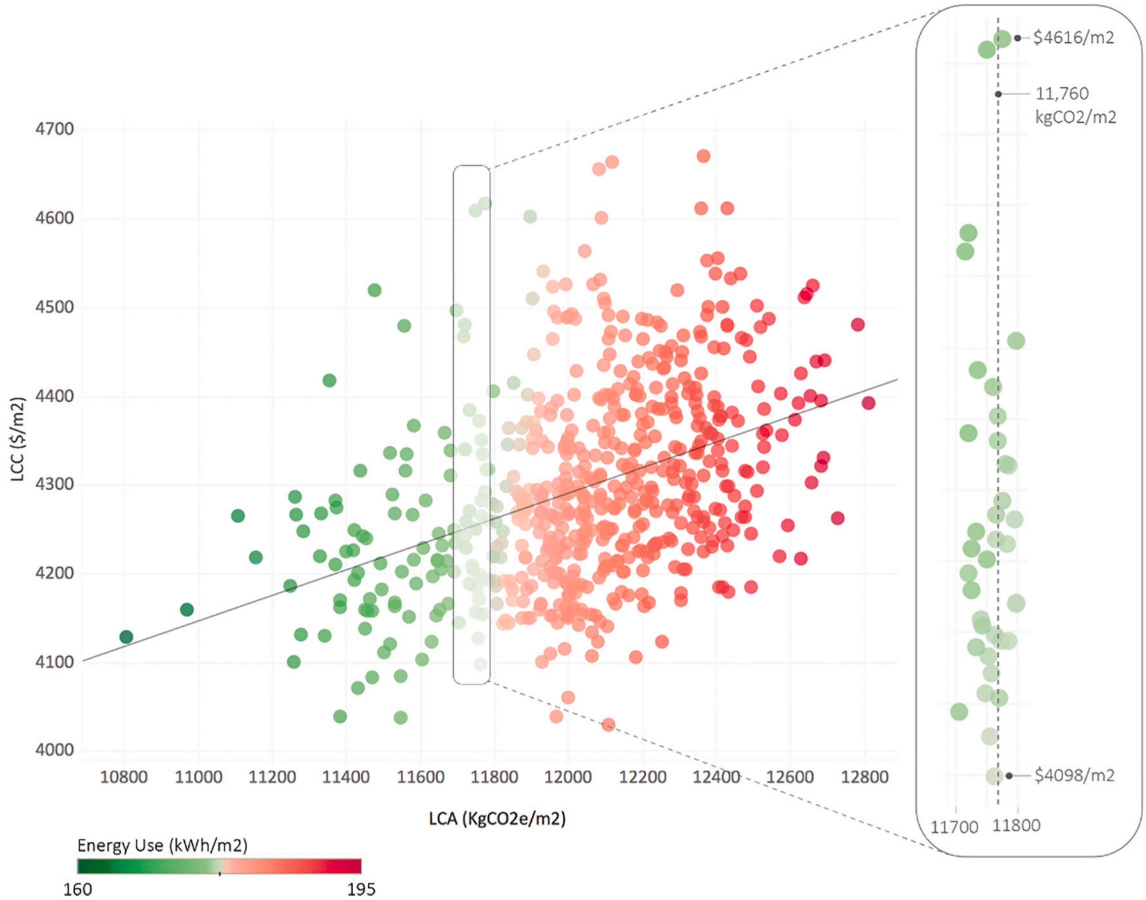

Fig. 15. LCA (KgCO2e/m^2), LCC (\$/m^2) and Energy Use (kWh/yr/m^2) (represented by colour range), all results. Energy use and LCA are linearly correlated; for design options with a similar LCA, there is a variation in LCC from \$4098/m^2 to \$4616/m^2.

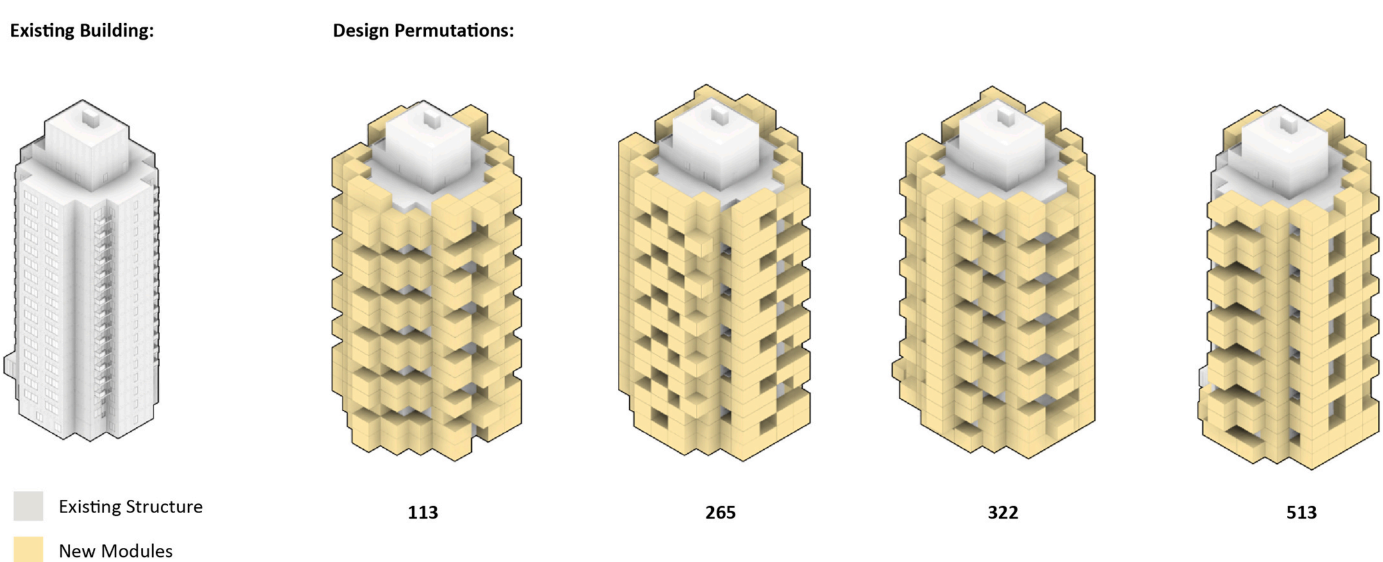

Fig. 16. Visualization of existing building and sample of primary and secondary pareto-optimal design permutations for LCC and structural complexity (based on Figs. 13 and 14).

A heuristic method for creating a finite number of exploratory design options that meet defined design criteria is primarily developed. Then, simulation tools are used to analyze the performance and characteristics of each design. Design solutions are further constrained based on an acceptable range of performance set by the user, and final Pareto-optimal frontiers are determined for further design development. The methodology's efficacy is shown in a functional demonstration of an existing residential tower adaptation in Hamilton, Canada. The advantages of the methodology include improved early-stage design workflow, the possibility of enhancing the quality of design decision-making

Table 2
Financial Analysis of Design Permutation 513. A 230-module addition will require a capital expenditure of $1.9 M at $8.3 k per 10 m^2 module. This addition can add up to 45 new units, yielding to $672,000 of extra revenue per year, a payback period of 8.2 years, an IRR of 8% and a profit increase of 191%.

New Units				Total new modules	Added annual revenue	Capital expenditure	Payback period (years)	Internal rate of return (IRR)	Profit increase
Studio	1 Bedroom	1 Bedroom +1	2 Bedroom						
15	20	5	5	230	$672 k	$1.9 M	8.2	8%	191%

and the increased speed of evaluations. The steps described in the methodology are not bound to specific software mentioned in this study and can be implemented within various computational design interfaces.

6.2. Limitations and future work

This methodology's limitations include a limited analysis of spatial layouts after generation and the ability to account for the addition of units, enabling a calculation of increased revenue and return on investment rates; essential factors for feasibility analysis of building adaptation projects. This study's other limitations include calculation time and computation capacity, highlighting a need to optimize the algorithm for faster analysis in the future. In this study, only one module variant was used. In more complex projects, the number of module sizes might need to differ, adding complexity that needs to be considered in the algorithm. The methodology can also be improved by incorporating a user interface for designer input, parsing of data and design option visualization for better accessibility.

Future work will address the limitations mentioned and complete the proposed steps in the methodology not comprehensively investigated in this research—integration of external databases, linking to other analyzed cases, and creating an internal database. Selected options are combined to form a database of feasible options that will then be used to build a predictive model and support the assessment of viable options. External database of analyzed cases – relevant examples are retrieved, and comparison with selected options is possible. Future work will require financial analysis for each design permutation to be developed simultaneously for improved results. The scope of this work was limited to a preliminary design option generation and did not take into account the future adaptability and life cycle transformation options enabled by modular construction. The authors acknowledge the importance of considering adaptability from the early stages of a project for achieving optimal circular designs. This limitation will be addressed in future developments of this work.

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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