

BIM-Centric Daylight Profiler for Simulation (BDP4SIM): A Methodology for Automated Product Model Decomposition and Recomposition for Climate-Based Daylighting Simulation

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BIM-Centric Daylight Profiler for Simulation (BDP4SIM): A Methodology for Automated Product Model Decomposition and Recomposition for Climate-Based Daylighting Simulation

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ABSTRACT

Flexible problem formulation is required for product model-based thermal analysis using multidisciplinary design optimization (MDO) environments for cost-effectiveness, accuracy, and scalability in the Architecture, Engineering, and Construction (AEC) industry. The integration of daylighting simulation into an MDO process, however, presents several implementation challenges. In current practice, the process of an architect, engineer, or daylighting consultant to determine how to analyze a given building design for daylighting performance is frequently subjective, time-consuming, and inconsistent. Furthermore, long simulation time requirements for daylighting significantly hinder the realization of many benefits from MDO. The determination of which spaces in a building are sufficiently different to warrant an independent daylighting analysis is based primarily on building physics, building design criteria, and operating schedules (e.g. occupancy schedules). This characteristic of daylighting analysis creates the opportunity to develop intelligent mechanisms to automate the identification of the building spaces for analysis using performance-based methods, simulation of spatial results, and the scaling of spatial simulation results to whole building performance metrics in a fraction of the time it takes in current practice. Such methods would result in enhanced problem formulation and evaluation capabilities for daylighting simulation, and improved cost-effectiveness, accuracy, and scalability for MDO-based daylighting simulation. Currently, no such methods exist in literature or in practice. This paper fills these gaps by presenting a methodology for automated product model decomposition and recomposition for climate-based daylighting simulation using Radiance. The authors validate the research with the method's application to several test cases and a large federal office building industry case study.

KEYWORDS:

conceptual building design; multidisciplinary design optimization (MDO); daylighting simulation; design decomposition; distributed and parallel computing; process integration and design automation

1. INTRODUCTION

To improve design space exploration, researchers developed a class of formal methods for the design of complex products, referred to as multidisciplinary design optimization (MDO). Previous CIFE research has developed a process for product model-based energy and daylighting MDO using Digital Project [1], IFC [2], EnergyPlus [3], and Radiance [4] that supports flexible problem formulation in terms of CADcentric attribution [5-7]. Preliminary results on test cases and several industry case studies have been very promising. However, there has been very limited research into the cost-effectiveness and scalability of MDO to large AEC projects. To investigate this issue, the authors applied the CIFE MDO process to a large industry case study: a 7-floor, 500,000 ft2 federal office building in Washington DC undergoing a major renovation to improve its energy and daylighting performance. Scalability was demonstrated in terms of model size and complexity for geometric attribution, pre-processing, and input for simulation. However, when the building was simulated for annual energy performance in EnergyPlus and annual daylighting performance in Radiance using climate-based daylighting simulation [8-11], the required simulation times on a single processor were 3 hours and 19 hours, respectively, for a total of 22 hours per iteration. One reason for the long daylighting simulation time was the fact that all the daylit spaces were simulated. This result demonstrates that the exceedingly high computational requirements for climatebased daylighting simulation that result from a lack of an effective means to minimize simulation requirements will prevent the scalability and cost-effectiveness of an MDO process for any meaningful trade studies for a building of this size (Figure 1).

Figure 1: While applying the authors' MDO methodology to a large federal office building, it became apparent that despite geometric scalability of the process, it lacked simulation scalability in terms of computational requirements for annual, whole-building climate-based daylighting simulation, resulting in limited scalability and costeffectiveness for large buildings.

To overcome this barrier, an additional type of flexible problem formulation must be enabled: the ability to efficiently select the analysis configuration of an attributed model. This capability would result in more accurate, rapid, and consistent problem formulation capabilities for daylighting simulation, with or without MDO.

1.1. Design Decomposition and Recomposition

Decomposition has long been recognized as a powerful tool for analysis of large and complex systems. By reducing the complexity of the design problem, decomposition improves the reliability and speed of numerical solution algorithms and the multidisciplinary design cycle, enables parallel and distributed computation, reduces programming/debugging effort, and allows for modularity in parametric studies [12, 13]. A decomposition method inherently requires a corresponding recomposition method to extrapolate the subproblem solutions to obtain an overall problem solution, possible using a set of recomposition constraints [14, 15]. A variety of different decomposition/recomposition methods are found in literature [12, 13, 16, 17]. The goal of design decomposition is to systematically decompose the problem into independent or loosely coupled subproblems using decomposition rules to enhance the concurrency of the design process, enable a simple model of recomposition to give an overall design solution, and satisfy demands of parallel computation and availability of computational resources [12, 13, 15, 18].

Decomposition is usually carried out along two lines, either by decomposing according to structure (an object-centered approach) or decomposing according to function (a function-oriented approach) [15, 19]. Object and function decomposition assume a "natural" decomposition of the problem, with most of the previous research using intuitive methods that consider the physics of the system as the prime factor directing the decomposition [12]. Decomposition is best applied to well-understood problems [17]. Though current literature has addressed decomposition/recomposition methods for general design problems, no methods have been proposed for AEC design problems that require thermal analysis.

1.2. Decomposition and Recomposition for Daylighting Simulation

A design decomposition process for daylighting simulation would naturally be based on spaces that have unique daylighting profiles, which would result in a decomposition that was both object- and functionoriented due to the nature of the building components that impact daylighting performance [20], and the convenient fact that the daylighting performance of a given space is independent of the space adjacent to it (unlike energy simulation). The determination of which spaces in a building are sufficiently different to warrant an independent daylighting analysis is based primarily on building physics (e.g. geometry and thermal properties), building design criteria, and operating schedules (e.g. occupancy schedules). Figure 2 below shows just a few examples of the type of information that should be considered in any decomposition process. By minimizing the number of spaces simulated, computational time is minimized more than linearly [21].

Figure 2: A decomposition process for daylighting simulation should consider a range of physical and performancebased criteria (several shown above) to determine which spaces have the potential for unique daylighting performance.

However, due to excessive complexity, data preparation requirements, and simulation times, few designers in current practice actual use daylighting simulation to evaluate the daylighting performance of spaces [22]. In current practice, the process of an architect, engineer, or daylighting consultant to determine how to analyze a given building design for daylighting performance is subjective, timeconsuming, unrepeatable, and with very little formal documentation on the process that guided their design decisions. Precedent-based design, rather than performance-based design, is usually the method of choice through the application of various rules of thumb. Daylighting rules of thumb are simple, numerical expressions that relate a design quantity of interest to one or several design parameters, e.g. the window-head-height, and are pervasive in industry [23-26]. Past research suggests that in current practice designers rely on previous work and rules of thumb during the early stages of design to inform design decisions because they are easy to learn, offer quick advice, and don't require the expertise, time, and financial investment of model-based analysis using daylighting simulation tools [27, 28]. This practice is problematic because rules of thumb are rarely derived from scientific principles or are experimentally validated, with designers liberally applying them to different projects without a necessary understanding of their constraints, limitations, and boundary conditions [22, 27, 29-31]. While some rules of thumb have been partially validated using a simulation-based approach [29, 31, 32], their application is limited and the boundaries of their application and usefulness are not well documented and/or understood. This knowledge gap can result in inaccurate daylighting performance estimates when applied incorrectly, making the process of developing formal decomposition methods very challenging due to design problems that are not well-understood.

1.3. Automated Decomposition and Recomposition for BIM-Centric Daylighting Simulation

Due to the unreliability of the techniques described in the previous section, an *automated* method must be developed for decomposition prior to simulation to provide accuracy, consistency, and speed. An automated decomposition (and recomposition) method for daylighting simulation using a product model, or BIM, could take two different forms. The first is using a knowledge-based system (KBS). Knowledgebased systems, or expert systems, are computer programs containing knowledge about a narrow domain for solving problems within that domain, and consist of a knowledge base (domain knowledge expressed as general facts, rules and heuristics) and an inference mechanism (reasoning engine) [33]. The use of knowledge-based systems for design optimization has many potential benefits, including improvements in cost, accuracy, speed, reliability [34]. Past research has investigated such systems for passive solar design and daylighting [35, 36]. However, a system heavily dependent on heuristics, or rules of thumb, results in the same problems identified in Section 1.2. While simulation-based methods may be used to start to populate the KBS with reference data, which is an improvement over non-simulation-based heuristics, their application is still limited. The second form a decomposition method could take would be to base the spatial assessment process solely on the physics and design criteria for the problem at hand, on a spaceby-space basis, for every instance of a new building alternative. The development of such a method would create a tremendous opportunity to leverage parallel and distributed computing resources [37-40] to drastically reduce simulation time. This potential reduction is made possible by the independence of daylighting performance for a given space from all the other spaces in the model (aside from shading considerations), and would result in improved cost-effectiveness and scalability of climate-based daylighting simulation for MDO. Currently no such automated methods exist for daylighting simulation.

To fill the research gaps, this paper develops, implements, and provides evidence for the power, generality, and scalability of an automated product model decomposition and recomposition methodology for BIM-centric climate-based daylighting simulation called the *BIM-Centric Daylight Profiler for Simulation (BDP4SIM)*. The authors test this method on two test cases and a large industry case study.

2. BIM-CENTRIC DAYLIGHT PROFILER FOR SIMULATION (BDP4SIM)

The goal of BDP4SIM is to accurately decompose and recompose a product model automatically for climate-based daylighting simulation, resulting in significantly reduced simulation time to calculate whole-building daylighting performance metrics while maintaining acceptable simulation result accuracy. The decomposition process systematically evaluates each space sequentially in a product model to determine and group those with "similar" daylighting conditions such that a simulation is only required for one representative space for the group using the authors' Radiance Wrapper referenced in the preceding section. The performance results from the simulated space can then be accurately weighted and applied to the other spaces in the group that were not simulated (recomposition). As BDP4SIM analyzes each new space, it first creates a profile of critical daylighting information for that space then checks the profile against a growing database of daylighting profiles. If the profile is unique, it adds it to the database for future iterations.

Building geometry and all the required analysis attributes for BDP4SIM's space comparison process are obtained from a Digital Project model via IFC and the ThermalSim Plugin show in Figure 1. Details on the rationale and technical workflow for this MDO process are discussed in previous research [6]. Along with general building information relative to site location, climate, and orientation, BDP4SIM also evaluates the relative and absolute geometry and material surface properties of all key objects inside and outside the space (e.g. walls, windows, overhangs, and adjacent buildings), window shading devices and their operating schedules, space occupancy and lighting schedules, lighting controls, and target illuminance setpoints when determining similarity of spaces. If a space does not pass one of the checks, no further checks are performed and the space is identified as unique.

The authors enabled a range of similarity tolerances or "thresholds" that the designer may specify for the space comparison process. This functionality allows the designer to adjust the degree of similarity between spaces for a given evaluation criteria that BDP4SIM uses when determining whether or not to group the spaces together. For example, if the designer desires a $\pm 5\%$ tolerance for window visible transmittance, then two geometrically similar windows with visible transmittance values of 0.70 and 0.74 would not be considered unique during the comparison process, though two windows with values of 0.70

and 0.76 would be unique. The allowable number of "misses" for spherical map pixel comparisons is also a user-definable parameter. Details on specific thresholds are discussed in the relevant sections.

The overall BDP4SIM methodology consists of a range of sub-methods targeted at a specific component of the decomposition or recomposition process. The following sections detail each these sub-methods beginning with the product model decomposition process.

2.1. Spatial Daylight Potential Method

The first check performed determines if the space is daylit or has the potential to be daylit. This check is done by cycling through each of the openings defined for a given space. If there are any exterior windows or exterior glass doors found then the space is known to be daylit. If any interior windows, interior glass doors, or interior voids are found, the space has the potential to be daylit via "borrowed" daylight from the adjacent space if it's on the building perimeter. These spaces are subjected to an exterior spherical map check which filters out spaces adjacent to other spaces with no exterior windows. The method does not attempt to go beyond one space when looking for borrowed daylight.

2.2. Spherical Mapping Method

The authors developed a spherical mapping method to compare relative and absolute geometry, material assignments, and interior/exterior shading elements across the different daylit spaces while eliminating the need to check individual building objects. The method accomplishes this task through the generation of hemispherical maps to take "snapshots" of building's interior and exterior environments using a custom ray-tracing technique via Radiance [41-43]. Rays are emitted from each pixel in the hemispherical map and intersect the surrounding building elements. However, instead of recording the pixel color or luminance as do typical renderings and past spherical mapping techniques [44, 45], the surface property of the geometry that is hit by each ray is recorded. This method enables a hemispherical pixel-by-pixel account of every internal or external surface material that the space is exposed to. Figure 3 illustrates this methodology. Since the method identifies spatial proportions, it is naturally scalable just as light is scalable. For example, if a space is one half the size of another space, but both having identical proportions of height to width to window locations, the spaces will have identical daylight conditions and will been identified as similar by BDP4SIM.

2.2.1. Interior Spherical Maps

Two interior hemispherical maps are generated for each daylit space; one taken upwards from the workplane vantage point and one taken downwards. The upper "half" of the space has a greater impact on the workplane daylight illuminance than the lower "half" of the space (Figure 3a-Figure 3b). Daylight entering in this upper hemisphere can directly strike the workplane. Any daylight entering the lower half of the space requires at least one interior bounce on a surface in the upper hemisphere before striking the workplane. The resolution of the upper and lower hemispheres can be adjusted separately to take advantage of this effect. Often, the downward resolution of the space can be very low and utilized to detect any major differences in surface reflectance/transmittance or significantly low sources of daylighting. The upper hemisphere resolution should be higher to detect any changes in surfaces or daylight sources that directly impact the workplane. If two spaces are found to be similar after the interior spherical mapping comparison including the consideration of any reflectance or transmittance thresholds, any matched up windows are then compared for interior shading devices (type, geometry, control type, and control schedules).

Figure 3: BDP4SIM's spherical mapping method generates hemispherical snapshots of each space directly above a specified workplane height and directly below, as well as outside the building from each exterior window or exterior glass door. Rays generated by Radiance are emitted from each pixel in a hemispherical map and the material property of each ray's incident surface is recorded for the space comparison process.

2.2.2. Exterior Spherical Maps

Exterior spherical maps are generated to compare daylight resource availability for a given pair of spaces. The exterior spherical mapping concept is identical to that for interior mapping with the exception that BDP4SIM generates only a single hemisphere that is normal to the window surface with a vantage point taken from the center of the window (Figure 3c). The designer can adjust resolution of this mapping independently from the interior mapping resolution as often space similarity is much more sensitive to exterior maps than to interior maps. For example, as identical spaces get closer and closer to the ground, even a 3x3 resolution exterior map with no misses will start to identify similar spaces on different levels as unique.

2.2.3. Spherical Mapping Resolutions

As introduced in the previous sections, the designer is able to vary the resolution of both the interior and exterior spherical maps. For a very small map, such as a 4x4 in resolution, only 16 sample rays will be sent out. This resolution will likely account for any major elements in a given space but could start to miss smaller windows and/or interior reflecting elements. A resolution of 64x64 (still very small relative to rendering standards) sends out 4,096 sample rays and requires spaces to be nearly identical before they are considered similar. As only a first level of ray-tracing is required for this method, these maps can be generated very quickly. A 16x16 pixel map (256 samples) has been implemented as the default resolution, and has been shown in the case studies to adequately detect similarity for most daylit spaces. Figure 4 shows an 8x8 pixel map (64 samples), 16x16 pixel map (256 samples), 32x32 pixel map (1,024 samples) and 64x64 pixel map (4,096 samples) for comparison. Figure 5 shows various resolutions of the three spherical mapping types for the federal office building case study.

Figure 4: The figure shows four different resolutions for the interior spherical map and the resulting frequency of object type hits for the space depicted in Figure 3.

Interior Spherical Mapping (Down)

Exterior Spherical Mapping

Figure 5: This figure shows the interior and exterior spherical maps at four different resolutions for a space in the GSA office building with core-facing atrium windows (8x8, 16x16, 64x64, and 256x256). A mapping resolution that is too low could results in important detail being missed by BDP4SIM during the space comparison process.

In addition to variable spherical map resolutions, two spherical map "miss count" parameters are available for adjusting the similarity criteria for the space comparison. A "miss" between two compared spaces results when the returned surface reflectance/transmittance for a given pixel from one space does not match the same relative pixel of another. Upward and downward miss counts can be specified separately as upward misses are likely more critical than downward misses for the same reasons used for the justification of separate upward and downward spherical map resolutions.

2.2.4. Spherical Mapping Types

There are a number of different methods for mapping hemispherical information into a discrete set of points and values. Three common mapping types are hemispherical, angular, and stereographic (Figure 6). Hemispherical mapping follows the cosine of the viewing angle, hence the highest resolution is normal to the surface and the lowest resolution is at the perimeter. This is a reasonable approach for a lighting simulation since bright sources with a low incidence angle (perpendicular to the surface) have a greater contribution to space illuminance than sources at the perimeter. However, for daylighting applications often the daylight resource is located on the perimeter of the space and much of the ambient daylight delivered to the workplane comes from the architectural surfaces around the perimeter of the space, particularly the ceiling adjacent to the windows. An angular (equidistant) mapping samples the hemisphere equally according to incidence angle. This approach gives a more balanced sampling of the space (close to a true equi-solid angle sampling) but still may not adequately sample the perimeter walls of the space that often contain the main daylight resource (windows). Finally, a stereographic mapping samples the perimeter of the space with greater resolution than the previous techniques, resulting in the walls being sampled heavier than the ceiling.

Hemispherical mapping

Angular mapping

Stereographic mapping

Figure 6: Three types of hemispherical mapping algorithms are available in BDP4SIM: hemispherical, angular, and stereographic. The most appropriate mapping for a given space is dependent on the geometry and configuration.

In Figure 6 the area of walls is roughly 3x that of the ceiling. In the hemispherical image, the ceiling is the most pronounced. In the angular image the ceiling to wall ratio is much closer to the 3:1 ratio. In the stereographic image the walls are most pronounced. Even though the most common daylight resources are side windows, the system will have to correctly handle top lighting (skylight) strategies as well. Hence, the angular mapping type may be the most appropriate for interior and exterior mapping. However, the designer can specify the spherical mapping type as any of the three methods to account for unique situations. The authors explore this concept further for BDP4SIM's validation in Section 3.

2.3. Common Capture Point Method

In order to use the concept of a spherical material map to properly compare the geometric and material assignments of two different spaces in a building with different absolute spatial coordinates, there must exist a systematic way to determine an identical vantage point for the maps. The vantage point must adequately "see" the entire space in question. The floor of each space can be any given shape and will have three or more corners, or "nodes", to the shape. The vantage point location is determined based on the number and coordinates of these nodes using the following logic:

- For "non-dented" spaces with any number of nodes, BDP4SIM places the vantage point at the center of the space's x and y extents.
- For spaces 5' (1.52m) and taller, the vantage point is always located at a workplane height of 2.5' (0.757m). Using this workplane height allows for a spherical map to be comprised of an upward map and a downward map that BDP4SIM treats separately.
- For spaces shorter than $5'(1.52m)$, the height of the workplane is half of the space height.
- For dented spaces, the vantage point is located halfway (rounded down) between the $1st$ found dented corner and the node halfway across from this reference corner. For dented spaces 4 nodes and less, this method will always locate the point in the exact same location and will see the entire room. For dented spaces with greater than 4 nodes, the vantage point may start to miss some "legs" of the space, particularly if there are parts of the space that are long and skinny and protruding away from the main body of the space.
- BDP4SIM fixes the orientation of the spherical maps based on the positive y-axis being 0 degrees (assumed to be true north). By fixing the orientation of the hemispherical maps the method will identify differences in orientations for spaces that are otherwise identical.

BDP4SIM generates the vantage point using this same algorithm for all spaces, ensuring that the vantage point relative to the space will always be the same (Figure 7). Spaces with a large number of dents and greater complexity may be incorrectly identified using this method. However, this situation will simply result in the space being marked as unique and then simulated individually.

Figure 7: These vantage point diagrams show how the number and location of common capture points vary by space shape.

2.4. Annual Daylighting Simulation Method

BDP4SIM conducts a spatial comparison of illuminance setpoints, lighting schedules, and conditioning schedules to further refine the list of unique spaces for simulation. The conditioning schedules are included in the spatial comparison due to the authors' approach of averaging hourly daylighting performance metrics for annual metrics only for hours that the space is conditioned. Hours outside of the conditioned time periods are assumed to be unoccupied. Once the final list of unique spaces has been determined, the Radiance Wrapper introduced in Figure 1 conducts the annual daylighting simulations. Details of the Radiance Wrapper annual daylighting simulation methods are discussed in previous

research [6]. The metrics generated by the Radiance Wrapper are Daylight Autonomy (DA) [10], Daylight Saturation (DS) [11], Maximum Daylight Autonomy (DAmax) [10], Useful Daylight Illuminance (UDI) [46], Daylight Glare Probability (DGP) [47, 48], and Daylight Factor (DF) [9, 49]. These metrics are calculated both on a sensor-averaged basis as well as spatially using a threshold-basis for the space sensors [50, 51]. The latter method accounts for spatial uniformity (or lack thereof) of daylight in the space by reporting the fraction of a space determined point-by-point that exceeds a certain threshold for a given metric.

2.5. Product Model Recomposition Method

After BDP4SIM decomposes the product model into a set of unique spaces and the annual daylighting simulation is run for each of these spaces in the Radiance Wrapper, the results must be recomposed in some manner to determine a single daylighting performance metric for the entire building. BDP4SIM accomplishes this task by scaling the metrics from Section 2.4 generated for each space to the remainder of the spaces that were determined to be similar to that space during the initial decomposition process. This scaling is done on an area-weighted basis. The Radiance Wrapper calculates the area-weighted annual daylighting metrics for the total simulated area (TSA), total daylit area (TDA), and total building area (TBA). The algorithms used for the averaged whole building metrics are shown in 1-4 for DS:

$$
DS_{TSA} = DS_1 * \frac{A_1}{A_{simulated}} + DS_2 * \frac{A_2}{A_{simulated}} + ... \tag{1}
$$

$$
DS_{TDA} = DS_1 * \frac{A_1}{A_{daylit}} + DS_2 * \frac{A_2}{A_{daylit}} + \dots
$$
 (2)

$$
DS_{TBA} = DS_1 * \frac{A_1}{A_{building}} + DS_2 * \frac{A_2}{A_{building}} + \dots
$$
\n(3)

where: $DS_x =$ Daylight Saturation for Space X, $A_x = A$ rea of Space X, $A_{simulated} = Total$ Simulated Area, $A_{davlit} =$ Total Daylit Area, Abuilding = Total Building Area

$$
SDS_{TSA} = SDS_{1, TI_{1}, DS_{1}} \star \frac{A_{1}}{A_{simulated}} + SDS_{2, TI_{2}, DS_{2}} \star \frac{A_{2}}{A_{simulated}} +
$$
(4)

where: $sDS_x = Spatial$ Daylight Saturation for Space X, TL_x= Target Illuminance for Space X, DS_x= Target Daylight Saturation for Space X

If the similarity checks by BDP4SIM are effective in identifying similarly daylit spaces, this recomposition method should result in three very accurate whole building climate-based daylighting metrics.

2.6. BDP4SIM and Distributed/Parallel Computing Environments

The fact that the daylighting performance of a given space may be evaluated independent of the adjacent spaces creates the opportunity to utilize distributed and parallel computing resources [42, 52, 53] to reduce the overall simulation time of a design alternative. This reduction in simulation time is made possible by simulating the building's spaces in parallel for a given design alternative as compared with series simulation of the spaces on a single core, as is most common in practice today. While some research is exploring multi-threaded applications using Radiance (e.g. simulating a single space with multiple processors) [54-56], simulating spaces in parallel for a given design alternative is the viable use of parallel computing in practice for daylighting in the short-term. Future advances in multi-threaded Radiance functionality will only enhance any spatially-based methods.

After BDP4SIM has decomposed the product model and identified the unique spaces to be simulated, the spaces may be "split up" and run in parallel to speed up the overall simulation process for a given design alternative. After simulating all the required spaces, product recomposition is achieved using the same methodology discussed in Section 2.5. This overall distributed and parallel computing methodology using BSP4SIM could reduce the simulation time required for the federal office building from 19 hours to 0.5 hours (run time for BDP4SIM + 1 space), or a reduction of 97% (Figure 8).

 (c)

Figure 8: This figure shows the overall product model decomposition and recomposition method for distributed and parallel computing. The method requires (a) product decomposition using BDP4SIM to determine which spaces have unique daylighting characteristics and should be simulated (and what non-simulated spaces they are similar too); (b) the processing of simulation inputs for each of the spaces identified in (a) and their scheduling to separate processors on a distributed cluster or cloud computing platform for simulation; then (c) product recomposition via the acquisition and scaling of the results from the simulated spaces to the non-simulated daylit spaces to determine annual daylighting metrics for the entire building.

The time and financial value of such a methodology is dependent on the nature of the computing resource being used, scheduling and run management techniques, and the magnitude of any computational overhead encountered during the process. For example, assume a requirement to simulate 500 design alternatives with each single-threaded run consisting of 100 spaces and a computational requirement of 15 minutes/space. Excluding any computational overhead for the selected computing methodology, this scenario results in a computational requirement of 12,500 core-hours, regardless of whether each space for a given design alternative is simulated in series or in parallel. If the number of processors available to the designer is fixed and larger than the number of single-threaded runs required (e.g. 100 nodes, 8 cores/node), then the time value of such a methodology is clear since there are unused computing resources that may be leveraged. If there does not exist unused computing resources (e.g. 10 nodes, 8 cores/node), then the time value of running spaces in parallel is significantly reduced, or even eliminated.

Simulating spaces in parallel for the above example may result in a negative time savings value, or even a negative financial savings value if a core-hour rate structure exists, if the computing methodology results in significant computational overhead. Computational overhead for parallel space simulation compared with series may result from (1) generating more input files and instances of the required analysis executables, along with their respective data transfer requirements; (2) data management requirements to schedule, track, and reunite the individual space runs over the distributed environment to ensure the spaces used in the recomposition process are the same as those generated during the decomposition process for a given design alternative; and (3) latency issues resulting from the recomposition process having to wait for the longest space simulation to complete. Validation of this distributed and parallel computing methodology is beyond the scope of the paper and is planned for future research.

3. VALIDATION CASE STUDIES

Section 2 identified the goal of BDP4SIM as accurate product model decomposition and recomposition for climate-based daylighting simulation that significantly reduces simulation time to calculate wholebuilding daylighting performance metrics while maintaining acceptable simulation result accuracy. As simulation time continues to decrease, eventually simulation accuracy will be reduced beyond acceptable levels. Identifying the conditions under which this correlation occur using BDP4SIM is one objective of the method's validation, as well as identifying input parameter sensitivity and effectiveness for determining spatial uniqueness. Table 1 below lists functions of BDP4SIM and their respective parameters. The designer may define these parameters for a given project to provide a balance between reduced simulation time and simulation accuracy. The last set of functions in Table 1 does not have a respective set of parameters as these functions have either little to no impact on overall simulation time.

Table 1: This table shows the various functions of BDP4SIM and their respective user-definable parameters.

To validate the overall performance of BDP4SIM, the authors tested the functions under a range of values for their respective parameters using a Design of Experiments (DoE) to determine how each impacts simulation time and accuracy. The functions that do not have dependent parameters are checked to ensure correct implementation by BDP4SIM. The validation process evaluates the simulation results for each configuration of parameter values in the DoE both on a building level and a spatial level to ensure integrity of the parameter DoE results. The authors test BDP4SIM using two test cases and a large federal office building industry case study.

3.1. Validation Metrics

The authors developed several validation metrics to evaluate BDP4SIM's performance in the decomposition process, the reduction of overall simulation time, and simulation accuracy. The metrics are:

Design Decomposition Effectiveness (DDE): Design Decomposition Effectiveness is the ratio of unique spaces identified by BDP4SIM for a given configuration of parameters to the total # of daylit spaces in the building. DDE indicates the percentage reduction in simulated spaces.

Simulation Time Ratio (STR): STR is the average time spent per design alternative (hrs) using BDP4SIM divided by the time required to simulate all spaces. The authors predict that the values of DDE and STR will be quite similar as simulation time is primarily a function of the number of spaces simulated. However, as STR is a time metric and includes the run time of BDP4SIM, there may be significant differences between DDE and STR when the BDP4SIM and spatial simulation run times are of the same magnitude. Simulation time reduction equals 1-STR.

Daylight Saturation Error (DSerr,TSA/TDA/TBA): Daylight Saturation Error is the error in DS predicted by BDP4SIM for the entire building relative to the baseline DS (TSA, TDA, and TBA) calculated without using BDP4SIM (i.e. all the daylit spaces were simulated) using the same sensor grid resolution, illuminance setpoints, lighting schedules, etc. The authors have defined a "significant" difference in DS as an error over 2%. Target performance is less than 2% Daylight Saturation Error.

DS_{err} for TSA is significantly higher than for TDA and TBA since it does not take into account the differing areas for the non-simulated spaces that should be weighted to a given simulated space. For this reason, the authors assert that the TDA metrics are not appropriate to assess BDEP4SIM. DS_{err} for TDA and TBA are generally quite similar, though absolute values of DS are lower for TBA since non-daylit space areas are included in the total value. As the relative area of non-daylit area to daylit area can vary widely building to building, the TDA metrics are the most appropriate for this research and DS_{err} is assumed to refer to TDA for the remainder of this research unless explicitly stated.

3.2. Test Case #1: Simple Office Building

Test Case #1 is a simple but very common building type: a multi-story office building with nearly identical perimeter offices and punched windows lining all sides for a total of 196 spaces (Figure 9a). All non-geometric properties of the buildings space and interior/exterior spaces are the same. Before examining the actual simulation results, it is useful to visualize the expected intuitive or theoretical results to establish some sort of reference for the data analysis. There are 8 space groups, 4 defined by orientation and 4 defined by corners. With little to no ground effect and a lack of exterior shading, the building could theoretically be simulated with 8 unique spaces (Figure 9b). However, with ground effect, 8 spaces would misrepresent the building. If BDP4SIM considers ground contribution as similar for floors 1-2, 3-4, and 5-7, then $8x3 = 24$ unique spaces should be identified (Figure 9c). If BDP4SIM considers each of the 7 floors as unique due to the varying impact of ground reflection with height, then $8x7 = 56$ unique spaces should be identified (Figure 9d). The case of 84 unique spaces could result due to the presence of a rectangular and finite ground plane surrounding the building model (Figure 9e).

Figure 9: The building model in (a) could theoretically result in a range of unique space configurations, ranging from a low degree of differentiation (b) to a high degree of differentiation (e).

3.2.1. Test Case #1 Results – Building Level

The goal of Test Case #1 is to evaluate how BDP4SIM behaves for a range of parameter values for differing space heights off the ground plane, orientation, and to a lesser degree space geometry (only 2 different spatial layouts). The authors ran a DoE with the range of parameter values shown in Table 2, resulting in a design space of 540 alternatives. The simulations for the DoE were run in parallel using the Windows Azure cloud computing platform [43]. The parameter limitations identified in this test case, as well as in the remaining validation cases, are intended to be general guidelines that will allow the designer to obtain a certain degree of accuracy with a very high degree of probability. Outliers certainly may exist that are valid, particularly when generating a large number of alternatives.

Parameter		Parameter Range	Size of Design Space (Param./Total)	
	Interior Map Resolution (up/down)	$16/16$, $14/14$, $12/12$, $10/10$		
	Exterior Map Resolution	16, 14, 12, 10, 8, 6, 5, 4, 3		540
	Interior/Exterior Mapping Type	Hemispherical, Angular, Stereographic		
	Interior/Exterior Miss Ratio	0.0, 0.02, 0.05, 0.10, 0.15		

Table 2: A DoE with the above range of BDP4SIM parameter values resulted in a design space of 540 parameter configurations.

Figure 10 shows the Daylight Saturation Error vs. the number of unique spaces identified by BDP4SIM for TSA, TDA, and TBA. The results show that the majority of the runs identified a number of unique spaces within the estimate of 8-84 spaces from Section 3.2. There were, however, runs with a predicted number of unique spaces above and below this range. The highest number of unique spaces (110) was

likely a result of the effect described for the case in Figure 9e. The lowest number of spaces (3) was surprising since there are 4 orientations, which certainly should result in at least 4 unique spaces. Section 3.2.2 examines this result in more detail.

The data does clearly show the lower limit in the number of unique spaces after which significant DS errors are introduced. Figure 10 shows that the DS_{err} is never larger than $+/1.5%$ until the number of unique spaces approaches the 24 unique space grouping. A grouping of 35 unique spaces or greater seems to ensure an overall DS_{err} less than the target threshold of 2% for TDA and TBA. As expected, the error for TSA started to exceed this threshold at a much higher number of unique spaces, confirming the authors' assertion that it is an inappropriate metric to use to evaluate BDP4SIM. In this case, 35 unique spaces results in a DDE of 18% and an STR of 33% (19% excluding the runtime for BDP4SIM). As expected, the DDE and STR excluding the BDP4SIM run time are similar, but quite different when the BDP4SIM run time is included due to its similar run time to the spatial simulation (0.1 hrs vs. 0.14 hrs, respectively).

Figure 10: This figure shows the relationship between the Daylight Saturation Error (TSA, TDA, and TBA) and the number of unique spaces identified by BDP4SIM for the DoE in Table 1. The DS_{err} increases exponentially as the number of unique spaces decreases below approximately 35.

A sensitivity analysis of the data set in Figure 11 indicates that the two main parameters impacting the DS_{err} and DDE are the Interior/Exterior Miss Ratios, with the Exterior Map Resolution also having a significant impact on the DDE. These results show that as DDE becomes increasingly small, the result is typically a loss in simulation accuracy. However, the results also show that the Exterior Map Resolution can effectively reduce the number of unique spaces without incurring a significant cost in simulation accuracy.

Figure 11: A sensitivity analysis reveals that Interior/Exterior Miss Ratios have the greatest impact on DS_{err} and DDE. Exterior Map Resolution also significantly impacts DDE.

Figure 12 shows the impact that the Interior/Exterior Miss Ratio and Exterior Map Resolution have on DS_{err} and DDE. Miss ratios of 4% or less typically result in DS_{err} less than 2%, though errors as high as 4% still do occur. Miss ratios of 10% and above all have a DDE below 10% and thus a high potential for significant errors. Additionally, as miss ratios are reduced below 4%, the Exterior Map Resolution begins to have a significant impact on DDE (though not DS_{err}). From these results, the authors conclude that the miss ratio generally should not be 10% or higher and that miss ratios of 4% or less should result in errors in DS of 4% or less and the ability to lower Exterior Map Resolution to reduce DDE without introducing significant error.

Figure 12: This figure shows the impact on DS_{err} and DDE by Exterior Map Resolution and Interior/Exterior Miss Ratio. The acceptable ranges for each are shown in (b) and (d), respectively.

3.2.2. Test Case #1 Results – Spatial Level

An examination of the DoE results on the spatial level reveals that the majority of the runs do fall within the 8-84 range of predicted number of unique spaces and display the uniqueness profiles predicted in Figure 9, though the runs in the lower spectrum of this range start to have high DS_{err} . To further investigate the cause of the large number of runs with high DS_{err} , the authors analyzed the DoE data in terms of spherical mapping type in Figure 13. The analysis revealed at low Interior Map Resolutions and high Interior Miss Ratios, the spherical map comparisons were sometimes failing to identify the windows. Since the windows determine orientation, BDP4SIM was identifying spaces of similar space geometry but different orientations as similar. The grouping of spaces of different orientation, and therefore different DS values, results in the large DS_{err} values shown for the low range of unique number of spaces. This error occurred with all the spherical mapping types, but was most pronounced with the hemispherical mapping type. This result makes sense given the analysis in Section 2.2.4, which shows that the hemispherical approach results in the least amount of pixilation for walls and windows. The best performing run from the DoE identified by BDP4SIM has 24 unique spaces and a $DS_{\text{err}} = 0\%$, an STR = 0.31, and a DDE = 0.12 .

Figure 13: The hemispherical mapping type resulted in the highest average DS_{err} for runs with a number of unique spaces outside the 2% DS_{err} threshold. This result reflects the failure of the hemispherical mapping type to identify exterior windows in some spaces due to high miss ratios, low map resolutions, and low wall/window pixilation.

3.3. Test Case #2: Complex Office Building

Test Case #2 is a more complex version of Test Case #1 (Figure 14). The goal of Test Case #2 is to test the behavior of BDP4SIM for a range of building configurations not addressed in Test Case #1. The additions to Test Case #2 to test BDP4SIM's performance across *trends* in parametric variations for external and internal geometry are: (a) overhangs of varying depth to assess the impact of attached shading objects (PW1); (b) an adjacent building to assess the impact of detached shading objects (PW2); (c) a north wing to assess the impact of building self-shading (PN1, PE2); (d) increasing space depth with constant space width and window size (PE1); (e) increasing space width with constant window size and space depth (PS1); and (f) increasing space width with variable window size and constant space depth (PS1) to assess the impact of parametrically varying internal geometry. The additions to Test Case #2 to test BDP4SIM's performance for *instance* variations in space or surface properties are: (g) a unique space illuminance setpoint (PW1); (h) a unique conditioning schedule (PW1); (i) unique window transmissivities (PN1); (j) unique internal window shading (PE1); (k) an interior window (PS1); and (l) a skylight on the core roof.

Figure 14: The authors modeled Test Case #2 in Digital Project and successfully processed it through the IFC2ThermalSim Plugin, AMS, and EnergyPlus/Radiance Wrappers. The reference directions shown in yellow are in place as an aid in clarifying where the spatial level parametric variations (trends) and differing object properties (instances) reside for testing purposes.

3.3.1. Test Case #2 Results - Building Level

The authors ran a DoE with the range of parameter values shown in Table 3, resulting in a design space of 1600 alternatives. As with Test Case #1, the simulations for the DoE were run in parallel using the Windows Azure cloud computing platform. The authors' intuition is that the angular or stereographic mapping types are likely the most appropriate for these buildings and would result in the identification of the correct populations of unique spaces within the target accuracy using the "loosest" BDP4SIM parameter value limits and therefore better STR and DDE. However, the authors chose to use the hemispherical mapping type for both Test Case #2 and the federal office building industry case study to identify the most conservative BDP4SIM performance estimates, the "tightest" parameter value limits, and to further explore under what conditions the missed window phenomena identified in Section 3.2.2 most frequently occurs.

Parameter		Parameter Range	Size of Design Space (Param./Total)	
	Interior Map Resolution (up/down)	64/32, 32/16, 16/8, 14/7, 12/6, 10/5, 8/4, 6/3		
	Exterior Map Resolution	32, 16, 12, 10, 8, 6, 4, 3		1600
	Interior Miss Ratio	0.0, 0.01, 0.02, 0.04, 0.10		
	Exterior Miss Ratio	0.0, 0.01, 0.02, 0.04, 0.10		

Table 3: A DoE with the above range of BDP4SIM parameter values resulted in a design space of 1600 parameter configurations for Test Case #2. The authors chose to use a hemispherical mapping type.

Figure 15 shows DS_{err} and STR for TSA, TDA, and TBA. As STR decreases, the errors in the TSA continue to increase, as was the case in the first two test cases. However, while the TSA continues to diverge, the TDA and TBA numbers vary around a 0% error. This result shows that BDP4SIM is correctly decomposing, simulating, and recomposing unique spaces. With no limitations applied to the parameter value ranges, the worst case error is 7.7% which occurs when the Interior Miss Ratio is 10% and the Exterior Map Resolution is 3, supporting the results of Test Case #1 that these parameters values are likely cause significant errors in accuracy.

Figure 15: This figure shows the relationship between STR and simulation accuracy (TSA, TDA, and TBA) for all the BDP4SIM parameter configurations in the Test Case #2 DoE.

A sensitivity study of the input parameters in Figure 16 indicates that, similar to Test Case #1, the Interior Miss Ratio has the greatest impact on DS_{err} . However, since the Interior Miss Ratio is now decoupled from the Exterior Miss Ratio, the results show that the latter has a relatively small impact on accuracy. Interior Map Resolution significantly impacts simulation accuracy as well, with further analysis of the data revealing that this effect is in part due to BDP4SIM missing windows at low resolutions and high misses. On the contrary, the Exterior Map Resolution and Exterior Miss Ratio are the dominant drivers of DDE, which makes sense given the added complexity of exterior building interactions such as selfshading, overhangs, and detached shading objects. Similar to Test Case #1, the results also show that the Exterior Map Resolution can effectively reduce the number of unique spaces without incurring a significant cost in simulation accuracy.

Figure 16: A sensitivity analysis for Test Case #2 reveals that Interior Miss Ratio has the greatest impact on DS_{err} while the Exterior Map Resolution has the most significant impact on DDE.

Figure 17 reveals the appropriate limitations for map resolutions and miss ratios that ensure a probability of > 99% that accuracies will be within 2% and 1% for Test Case #2. The plot uses the maximum DS_{err} for each run to ensure all spaces for a given run would fall within the stated range. These results align with the results of Test Case #1: the Interior and Exterior Miss Ratios should be limited to 4% or less. The results also indicate that Interior Map Resolutions less than 10 can result in errors greater than 2%. Imposing this first level of limits brings almost all results to within the defined 2% error range. The authors explored a second tier of limits as an option to reduce the accuracy error to 1% or less using the next highest priority parameters: the Exterior Map Resolution and Exterior Miss Ratio. By limiting the resolution to 8 or greater and the miss ratio to less than 4%, almost all the remaining runs have a DS_{err} of less than 1%.

Figure 17: These 2-dimensional plots in (a) for Interior Map Resolution and Interior Miss Ratio and (b) for Exterior Map Resolution and Exterior Miss Ratio clearly identify the parameter setting limits required to obtain a maximum DS_{err} of 2% and 1%, respectively, for Test Case #2.

Figure 18a below shows the scatter of BDP4SIM performance after applying the limitations of $\leq 4\%$ for Interior Miss Ratio and ≥ 10 for Interior Map Resolution. With these limitations applied, almost all the resulting runs fall within the 2% error range. The best case scenario that results is one that provides an STR of 14% and a DS_{err} of 1.3%. Figure 18b shows the scatter of BDP4SIM performance after applying the limitations in Figure 17b. With these limitations applied, almost all the resulting runs fall within the 1% error range. In this scenario, the best performing option results in a STR of 32% and a DS_{err} of 0.3%.

Figure 18: This figure shows the relationship between STR and simulation accuracy (TSA, TDA, and TBA) with (a) a 2% error limitation applied and (b) a 1% error limitation applied to the DoE for Test Case #2.

3.3.2. Test Case #2 Results - Spatial Level

The validation of BDP4SIM's performance on a spatial level is important for further understanding and verifying the building level results. Section 3.3 identified the additions to Test Case #2 used for the spatial level validation. Additions (a)-(f) shown in Figure 19 will test BDP4SIM's performance across *trends* in parametric variations for external and internal geometry (external $=$ (a)-(c) and internal $=$ (d)-(f)), while (g)-(l) will test BDP4SIM's performance for *instance* variations in space or surface properties. The results of the spatial level validation are as follows:

- a) *Variable Overhang Depth*: The overhang depth is decreased from left to right for PW1, and from Floor 7 to Floor 4. Values are as follows: 2.0m, 1.9m, 1.8m, 1.7m, 1.6m, 1.5m, 1.4m, 1.3m, 1.2m, 1.1m, 1.0m, 0.9m, 0.8m, 0.7m, 0.6m, and 0.5m. Floor 3 overhangs are the same as Floor 4 overhangs. BDP4SIM captures the variable overhang depth on Floors 6-7 at an Exterior Miss Ratio \leq 4% and an Exterior Map Resolution \geq 12. Identification of the variable overhang depth on Floors 4-5 requires a resolution \geq 14 and a miss ratio \leq 1%.
- b) *Adjacent Building Shading:* All the spaces on the PW2 wall are the same, though they have different views of the adjacent building (and ground). The adjacent building is 50% the height of the main building to evaluate to what degree the upper spaces catch its effect. The effect of the adjacent building shading both vertically and horizontally is clearly evident for the first 6 spaces (north to south) on Floors 1-6 at Exterior Map Resolutions ≥ 8 and Exterior Miss Ratios $\leq 4\%$. BDP4SIM does not identify the shading for Floor 7 until resolutions are ≥ 10 and miss ratios are \leq 2%. Beyond the first 6 spaces, BDP4SIM requires much higher resolutions (\geq 16) and lower miss ratios (\leq 1%) to identify any impact from the adjacent building shading.

c) *Building Self-Shading:* The effect of the building self-shading for PN1 and PE2 both vertically and horizontally is clearly evident for the first 5 spaces east or north of the intersection of the 2 wings for Exterior Map Resolutions ≥ 6 and Exterior Miss Ratios $\leq 4\%$. Beyond these first 5 spaces, BDP4SIM requires much higher resolutions (≥ 10) and lower miss ratios ($\leq 2\%$), with BDP4SIM showing spaces at the far east and north ends of the wing as not having any selfshading effects at any resolution or miss ratio.

Figure 19: The behavior and performance of BDP4SIM for a range of parameter values in capturing parametric variations on the spatial level for (a) increasing overhang depth; (b) adjacent building shading; (c) building selfshading; (d) increasing space depth; (e) increasing space width; and (f) increasing window width was evaluated to further validate the building level results.

- d) *Variable Perimeter Space Depth, Constant Perimeter Space Width, and Constant Window Size:* All the spaces on Floor 7 of PE1 have a depth of 12m (all the way to the core). Starting on Floor 6, the space depth decreases by 1.0m each floor down to Floor 3, resulting in space depth variations of 12m, 11m, 10m, 9m, and 8m. The rest of the space characteristics are the same. BDP4SIM captures this variable space depth at an Interior Miss Ratio of \leq 2% and an Interior Map Resolution ≥ 12 . A resolution less than 12 results in the aggregation of several floors. At an Interior Miss Ratio $\geq 2\%$, the geometric variation is lost, even at high resolutions.
- e) *Constant Perimeter Space Depth, Variable Perimeter Space Width, and Constant Window Size:* The top floor of PS1 has all the same windows sizes, but the space width increases starting on the west side then going east along the floor until you reach the second to last space. Widths are 5.0m, 5.5m, 6.0m, 6.5m, 7.0m, 7.5m, and 8.0m. Figure 20a shows the DS decreasing as the width increases, as is predicted. Interior Map Resolutions ≥ 12 and Interior Miss Ratios $\leq 1\%$ capture this variation.

f) *Constant Perimeter Space Depth, Variable Perimeter Space Width, and Variable Window Size:* Floor 6 of PS is the same as Floor 7, but the window width increases with space width to maintain the same window-to-wall ratio. As expected, Figure 20a shows a relatively constant DS along this floor. BDP4SIM considers all these spaces as similar until a high Interior Map Resolution of 64 and an Interior Miss Ratio $\leq 1\%$, at which point it identifies two groups of similar spaces.

Instance checks for (g)-(l) validate BDP4SIM's ability to correctly identify differences in space illuminance setpoints, conditioning schedules, window transmissivities, internal window shading, and the existence of interior windows and skylights. In all these cases, BDP4SIM correctly identified the appropriate spaces as unique. For instance, in Figure 20b, the two red spaces on Floor 7 and Floor 6 of PN1 have higher transmissivities than the surrounding windows. Additionally, Figure 20b shows two black spaces on Floor 1 of PE1. These spaces were assigned interior window blinds, thereby significantly reducing light penetration. The Floor 1 corner space in Figure 20a was assigned a different conditioning schedule then the space above it, resulting in fewer hours being sunlit in the morning, and thereby increasing the daily average illuminance levels. In all of these instance checks the spaces are identified by BDP4SIM as being unique with no other spaces considered similar to them (Figure 20d).

Figure 20c and Figure 20d show which spaces BDP4SIM determined to be unique given the best performing run from the DoE. An examination of the unique spaces identified by BDP4SIM reveals that there are no significant DS performance variations or trends in Figure 20a or Figure 20b that do not have a representative space in the BDP4SIM sampling shown in Figure 20c and Figure 20d. There are 34 spaces that are unique and therefore simulated, resulting in a $DS_{\text{err}} = 0.3\%$, an STR = 0.24, and a DDE = 0.23.

Figure 20: This figure shows the actual DS for each space in Test Case #2 in (a) and (b), and the minimum number of unique spaces identified by BDP4SIM during the DoE that has a DS_{err} < 1%. An examination of the unique spaces identified by BDP4SIM reveals that there are no significant DS performance variations or trends that do not have a representative space in the BDP4SIM sampling shown in (c) and (d).

3.4. Industry Case Study: Federal Office Building

The industry case study is a large federal office building in Washington D.C.: a 7-floor, 500,000 ft2 building undergoing a major renovation to improve its energy and daylighting performance. The renovation includes a new 105,000 ft2 south-facing glass atrium. The project is targeting LEED Silver certification. Some of the measures that will be implemented are (1) replacing the historic punched windows; (2) adding internal shading devices; (3) installing low-e vertical atrium glass filled with argon; (5) installing photovoltaic glass on the horizontal skylights; (6) adding horizontal external shading devices to the atrium wall; (7) installing daylight controls; and (8) increase wall and roof insulation.

The authors constructed a Digital Project model of the planned renovation using project drawings and a Revit model provided by the design team, and successfully exported, pre-processed, and attributed the IFC file in the ThermalSim Plugin and converted to analysis models by the EnergyPlus and Radiance Wrappers (Figure 1). The parametric model took approximately 2 weeks to build, while the conversion process to analytical models for EnergyPlus and Radiance took approximately 1 week to implement. With the technical implementation complete, the actual processing time from Digital Project to both EnergyPlus and Radiance takes under 3 minutes.

3.4.1. Industry Case Study Results – Building Level

The authors ran a DoE with the same range of parameter values as Test Case #2 (Table 3), resulting in a design space of 1600 alternatives. As with Test Case #1 and Test Case #2, the simulations for the DoE were run in parallel using the Windows Azure cloud computing platform. The mapping type used is again hemispherical.

Figure 21 shows DS_{err} and STR for TSA, TDA, and TBA. Rather than a trend of increasing errors in the TSA calculation with decreasing STR, the errors are scattered around 0%. However, like the previous test cases, the TDA and TBA errors are all close to 0%. This result shows again that BDP4SIM is correctly decomposing, simulating, and recomposing unique spaces. With no limitations applied to the parameter value ranges, the worst case error is 4.1% which occurs when the Interior Miss Ratio is 10% and the Exterior Map Resolution is 3, which is the same as for Test Cases #1 and #2. Another worst case scenario is a run that results in the smallest STR, 77%, but still results in a high error of 2.9%. This result is likely due to the high Interior Miss Ratio of 10% along with the high Exterior Map Resolution maintaining many unique spaces. Unlike the other test cases, there are several instances where the TSA results are actually more accurate than the TDA and TBA results for some parameter settings. This occurrence is likely due to the many large and symmetrical spaces in the federal office building causing the TSA number to more likely be weighted to appropriate non-simulated spaces. The runs with high TDA and TBA DSerr likely result from a significant number of non-simulated spaces incorrectly being weighted to the simulated spaces during the recomposition process due to a failure to identify the appropriate windows for low resolutions and high miss ratios. This phenomena was identified in the previous two test cases due to the hemispherical mapping type.

Figure 21: This figure shows the relationship between STR and simulation accuracy (TSA, TDA, and TBA) for all the BDP4SIM parameter configurations in the DoE for the federal office building.

A sensitivity study of the input parameters in Figure 22 indicates that, similar to both previous test cases, the Interior Miss Ratio has the greatest impact on DS_{err} . The Exterior Miss Ratio has a major impact on DDE (as well as STR) due to the complexity of the exterior building envelope. Similar to previous results, this parameter has the least impact on accuracy. Consequently the lowest acceptable parameter setting of 4% will yield the best results in terms of simulation time and accuracy. Exterior Map Resolution has the greatest impact in Test Case #1 due to the greater variety in exterior shading conditions whereas in this case study the spaces are so large and symmetrical on the various facades that low resolutions are adequate at identifying unique conditions and higher resolutions are unnecessary.

Figure 22: A sensitivity analysis for the federal office building reveals that the Interior Miss Ratio has the greatest impact on DSerr and the Exterior Miss Ratio the greatest impact on DDE.

Figure 23 reveals the appropriate limitations for map resolutions and miss ratios that ensure a probability of > 99% that accuracies will be within 2% and 1% for the federal office building. These results align with the previous two test cases: the Interior and Exterior Miss Ratios should be limited to 4% or less and the Interior Map Resolution should be ≥ 10 . Imposing this first level of limits brings almost all results to within the defined 2% error range. By limiting the Exterior Map Resolution to ≥ 4 and the Exterior Miss Ratio to \leq 4%, almost all the remaining runs have a DS_{err} of less than 1%. The reduction in the Exterior Map Resolution limit from Test Case #2 makes sense due to the larger spaces and high degree of symmetry on the various facades, both of which allow lower resolutions to identify unique conditions.

Figure 23: These 2-dimensional plots in (a) for Interior Map Resolution and Miss Ratio and (b) for Exterior Map Resolution and Miss Ratio clearly identify the parameter setting limits required to obtain a maximum DSerr of 2% and 1%, respectively, for the federal office building industry case study.

Figure 24 below shows the scatter of BDP4SIM performance after applying the 2% and 1% error limitations from the preceding paragraph. The best case scenario within a 2% error is one that provides an STR of 43% with a DS_{err} of 0.2%. The best case scenario within a 1% error range has a STR of 50% and a DSerr of -0.6%. This scenario utilizes a 4% Interior Miss Ratio, a 0% Exterior Miss Ratio, and an Interior/Exterior Map Resolution of 4. Both scenarios show significant reductions in simulation time while maintaining accurate simulation results.

Figure 24: This figure shows the relationship between STR and simulation accuracy (TSA, TDA, and TBA) with a 2% error limitation applied (a) and a 1% error limitation applied (b) to the DoE for the federal office building.

3.4.2. Industry Case Study Results – Spatial Level

The federal office building provides an ideal case study for BDP4SIM for the building is perfectly symmetric through the building's north/south centerline (except for the top floor). Figure 25a-d show that the DS values for the building follow this geometric symmetry, both horizontally and vertically. BDP4SIM should theoretically only identify one space for all the symmetric spatial pairings, and recompose the simulation results using the same pairings.

Figure 25e and Figure 20f show which spaces BDP4SIM determined to be unique given the best performing run from the DoE using the parameter limits in Section 3.4.1 as guidelines. An examination of the unique spaces identified by BDP4SIM reveals that there are no significant DS performance variations or trends in Figure 25a-d that do not have a representative space in the BDP4SIM sampling shown in Figure 25e and Figure 25f. There are 79 spaces that are unique and therefore simulated, resulting in a $DS_{\text{err}} = -0.1\%$, an STR = 0.40, and a DDE = 0.42.

Figure 25: This figure shows the actual DS for each space in the federal office building in (a)-(d), and the minimum number of unique spaces identified by BDP4SIM during the DoE that has a DS_{err} < 1%. An examination of the unique spaces identified by BDP4SIM reveals that there are no significant DS performance variations or trends that do not have a representative space in the BDP4SIM sampling shown in (e) and (f).

4. DISCUSSION AND CONCLUSIONS

The theoretical contribution of this research is a methodology for automated product model decomposition and recomposition for climate-based daylighting simulation. The authors validate this methodology, the BIM-Centric Daylight Profiler for Simulation (BDP4SIM), with two test cases and a large industry case study. The intent of the test cases and industry case study is to evaluate the functional capabilities of the methodology for different building scenarios relevant to daylighting performance and a range of different parameter settings that impact the method's behavior and performance through a Design of Experiments (DoE) simulated over the Windows Azure cloud computing platform. Validation metrics to evaluate the simulation results for accuracy (DS_{err}) , simulation time reductions (STR), and design decomposition effectiveness (DDE) are defined and applied. The test cases and industry case study vary in size and complexity, both geometric and non-geometric. Nonetheless, the method's performance trends and parameter limits recommended to maintain acceptable accuracy are similar across all the validation cases, providing evidence of the method's generality and scalability.

The application of BDP4SIM to Test Case #1, Test Case #2, and the industry case study resulted in a decomposition and recomposition process with accuracies (DS_{err}) of 0%, 0.3%, and -0.1% and reductions in simulation times of 69%, 76%, and 60%, respectively. These results provide further evidence of the method's generality and scalability while also demonstrating the power of BDP4SIM and its potential impact on practice by clearly demonstrating the method's accuracy and reduction in simulation time requirements for climate-based daylighting simulation.

Section 1 identified several major problems with daylighting analysis encountered in practice: subjective, time-consuming, and inconsistent decomposition of daylighting analysis problems. BDP4SIM directly mitigates these issues by enabling an automated daylighting decomposition process based purely on building physics and building operating characteristics that is rapid, consistent, and repeatable. Combined with the corresponding recomposition method, the overall BDP4SIM methodology with its proven accuracy and speed enables drastically improves problem formulation capabilities for climate-based daylighting simulation in MDO environments. These enhanced problem formulation capabilities result in the improved cost-effectiveness and scalability of climate-based daylighting simulation for MDO, particularly for large buildings such as the federal office building. Further validation of Test Case #2 and the federal office building using the angular and stereographic mapping types, as well as the inclusion of several additional industry case studies, is necessary to identify potential strengths, weaknesses, and limitations of the methodology beyond the cases used for the validation of the authors' research presented in this paper.

Future research beyond that described in the preceding paragraph will include implementation and validation of the distributed and parallel computing methodology discussed in Section 2.6 and the investigation of methods for automated decomposition and recomposition for BIM-based energy simulation. A robust methodology to accomplish the latter goal is very challenging due to the dependency on spatial energy performance with characteristics of adjacent spaces and mechanical systems that serve multiple spaces. However, it may be feasible to accomplish such a task given a limited set of heating, ventilation, and air-conditioning (HVAC) configurations.

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