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A Comprehensive Optimization Approach for Modular Facades: The Case of PULSE Sunshading

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It is well established in literature that computational intelligence-based decision support methodologies are able to efficiently support design decisions in complexity-defined environments. In this paper, we follow a case-based research methodology to develop and propose a comprehensive decision support system for treating complex design problems pertaining to large-scale building facades. The overall approach is based on the well-known combination of geometry generation via parametric models, performance assessments via numeric calculations and/or simulations, optimization via search algorithms. The specific challenge of this case focuses on the high-dimensionality of the decision space, which makes the computational process difficult to manage. The proposed method tackles this challenge in the parametric model and in the performance assessment. Specifically, the proposed method is initialized with parametric design techniques that enable managing the excessive amount of decision variables associated with complex facade design projects. A multi-objective evolutionary algorithm is then used to identify non-dominated solutions to the facade design problem. The performance of the proposed method is shown and validated in an application to a real-world design case study. The case study is a facade design problem for a new building in the university campus of Delft University of Technology. The facade features a striking large glass area protected by an innovative shading elements composed by hundreds of double-curved elements, each one unique and different from the others. The generative parametric model includes inputs from research groups and design professionals collaborating in an extensive research effort. The proposed decision making approach has as a result a range of promising facade configurations in accordance to multi-objective optimization premise that are effective in negotiating indoor daylight conditions, while being economically feasible to the extent allowed by the design space. The paper concludes by discussing some limitations of the proposed method, as well as potential extensions.

Keywords: computational intelligence-based decision support, Modular Façade, Optimization Approach

1. Introduction

It is common understanding that architectural design is characterized by complexity [1]–[3]. Architectural design is expected to solve an architectural design problem comprising a set of requirements and constraints, by creating something new (a new building or built item). Increasingly, this is achieved by means of complex geometries, which on the one hand enable achieving better performance, however on the other hand add further complexity to decision making. Efficiently exploring possible solutions among all possible design alternatives is a challenging task, especially in the early stage of the design process. The architectural design problem can be defined

as a multi-objective optimization problem, since it is characterized by several conflicting objectives and is also subject to challenging constraints.

Within the domain of architectural design, facades are a greatly relevant design topic. Nowadays, building facades are required to respond to a multitude of design criteria. A few of the most important ones are ensuring a comfortable climate indoors and promoting energy conservation. In this respect, shading systems play a crucial role. For instance, in the European Union buildings are responsible for nearly 40% of the total final energy use and 36% of the total emissions of the EU Member States [4]. Thus the European policies aim to improve energy efficiency in order to accentuate energy guarantee and prevent climate change [5], through reduction of green gas emissions to 20% levels until 2050 [4]. In both cases, facade systems are crucial. To provide daylight and more external view, architects and engineers design facades with large, glazed portions, which, however, present a risk of creating high heating and cooling loads [6], [7]. Therefore the use of shading devices is one of the most significant precaution to prevent overheating during cooling periods. In order to provide energy efficiency in the buildings, there are various shading device types such as overhangs [8], external roller shades [9], Venetian blinds [10] and internal shading [11]. In [12], shading device types used in the building sector were reviewed in detail and performance aspects thereof were established through the introduction of different simulation tools. These performance aspects are generally linked with daylight comfort levels, visual comfort and low energy consumption.

In particular, controlling daylight is one of the essential functions of a shading device. Efficient control of daylight may contribute to productivity, energy conservation and overall well-being of the building users. A great deal of studies exist that explore daylight as a primary objective of the design of facades and facade shading elements. Drawing inspiration from such studies, in this paper daylight is the main objective of facade design.

It is common for contemporary buildings to present complex design requirements with respect to daylighting. Complexity in this case stems from the diverse design requirements corresponding to different spaces within the building. A large scale public building may comprise a multitude of spaces of different functions, capacities and locations within the building. To ensure that a suitable distribution of daylight is available in each of the spaces is a challenging design task. Careful planning is needed even for spaces with similar requirements and functions, as other properties such as their location and configuration have an effect on the interior distribution of daylight throughout the operating period of the building. In this study, we aspire to apply our proposed method to complex real-world designs whose requirements with respect to daylight are directly in line with the way of thinking outlined above. Therefore, we wish to establish a model that can give us a concise but accurate figure of whether the daylight distribution guaranteed by a facade is adequate with respect to building requirements.

In very broad terms, a designer wishes to ensure that all spaces within a building receive at least the minimum amount of daylight required for the function associated with each space, for the maximum amount of time possible. This constitutes a good use of daylight which promotes conservation of energy and is associated with the well-being of building tenants [13], [14]. On the other hand, extreme amounts of daylighting is generally avoided, as they are associated with visual or thermal discomfort [15], [16]. A desirable level of daylighting thus lies in a range that is dependent on the function of the space. Sun-shading elements in the facade contribute mainly to this end, mediating the extremes of sunlight intake while ensuring the minimums are met for the longest time possible. As the sun position and climate are subject to constant change, daylight distribution for a fixed site is subject to perpetual temporal fluctuations. It is important, therefore, to consider temporal, as well as spatial, distribution of daylight in assessing a space.

The introduction of new manufacturing techniques enable the design to depart from traditional concerns of standardization, and embrace a condition where fine-grained component variability is desirable, though more complex. In addition, the use of accurate tools for estimating facade behavior allow a better prediction of the resulting performances. However, this implies also the understanding of the highly non-linear relationships between design decisions and resulting performances. Each of the design aspects outlined above introduce additional design complexity that leads to challenges throughout the design decision making process in general, while in the case of facade design additional design aspects that will be outlined throughout the rest of the paper intervene and increase complexity. With the aim of addressing these issues, in this study we present a method for addressing complex design problems with application to facade design. We acknowledge and adopt the general framework introduced in [17] comprising “form generation”, “performance evaluation” and “optimization”, available in Figure 1. The proposed method comprises innovative techniques pertaining to form generation and performance evaluation, and couples those with advanced multi-objective computational optimization algorithms namely the Hyper volume Estimation (HypE) algorithm. The proposed method is applied and validated on a real-world complex facade design problem.

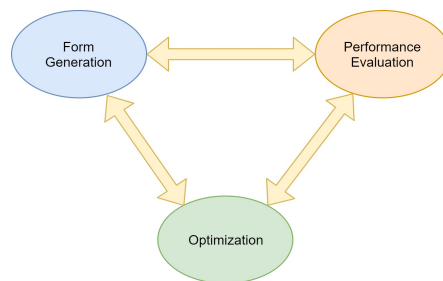


Figure 1: The loop of the Performance Driven Conceptual Design (Sariyildiz, 2012)

The rest of this paper is organized as follows. In section two, the state of art in computational optimization for facade and shading design is briefly reviewed. In section three, the proposed method is elaborated. In section four, the proposed method is applied on a complex real-world shading device design problem, and results are discussed. Section five concludes the paper.

2. Computational Optimization for Facade Design - State of Art

Several studies exist that focus on performance-based design of shading devices and computational decision support and optimization. In [18] authors highlight the importance of investigating design alternatives for facades in the early stages of architectural design. In [19] authors highlight the effectiveness of shading devices to reduce unwanted solar loads rather than focusing solely on window to wall ratio. They also highlight that for achieving proper daylight, the choice of slat angle and solar cut-off angle of a fixed exterior slat shading system is a non-trivial problem. In [20] authors advocate a similar standpoint, by highlighting that computer-assisted parametric techniques can be advantageous for daylighting design compared to design considerations based solely on prior knowledge and experience. The authors compare conventional design approaches with indoor lighting conditions obtained by adjusting louver shapes and window patterns using genetic algorithms. In [21] the author used a Genetic Algorithm for identifying promising solutions to fixed shading device for an office room with south facade. In [22] authors propose a performance based

parametric design approach for the design explorations of shading device, which could optimize daylight and block the excessive amount of solar heat gain. In [23] authors employ reduction of building overheating, maximization of visual comfort and minimization of energy consumption as objective functions, formulating a bi-objective optimization problem. In [24], authors investigate the effect of alternative shading types, namely Venetian blinds and roller shades, in a school building situated in a cold climate region. Authors formulate an optimization problem with variables of orientation, room depth, corridor depth, window-to-wall ratio of different interfaces, glazing materials and shading type. They also formulate objectives of minimizing energy use for heating and lighting, minimizing summer discomfort time and maximizing useful daylight illuminance. Finally, they use a genetic algorithm to optimize the shading device design. In [25], authors optimize a louvre system in hot climate based on daylight metrics and energy consumption, using a genetic algorithm. In [26], authors focus on daylight admission in an open-plan indoor space. The admission was optimized using genetic algorithm alerting the external and internal widths, external tilt angles, and specularity of light shelves with or without overhangs. The objectives were to maximize the spatial daylight autonomy and minimize the annual sunlight exposure. In [27], authors focus on the optimization of external shadings for visual comfort and energy efficiency in a typical office space; the research tackles solutions popularly adopted in standard practices, such as blinds and overhangs. In [28], authors consider the optimization of rectangular louvers for thermal performance using genetic algorithms to alternate the angle of rotation, spacing, projection length, and inclination. In [29], authors compare the performance of four different optimization algorithms to optimize building design, including exterior shading, for daylighting performance to minimize lighting loads. The results indicate the region of optimal performance is found quickly by all algorithms, but the convergence has shown it can be slow. In [21], authors focus on the optimization of an external fixed inclined panel combined with deployable internal Venetian blinds for an office room with a south exposed window. Their research focuses on an algorithm designed to deal with problems involving long simulation times, based on the combination of a Multi-Objective Genetic Algorithm (MOGA) and response surfaces, in which starting from a dataset of initial designs, different meta-models are trained.

Most of the above studies focus on rather standard shading device geometries. Several other studies focus also on complex and/or non-standard geometries for shading systems. In [30], authors use Genetic Algorithms to optimize an external shading screen based on a modular system gradually changed throughout the façade. In [31], authors propose the design of a high performance concrete static shading system using a parametric design approach based on radiation control, outdoor view, daylight indexes and energy performance. Optimization by genetic algorithms is used in order to define the openness and the cutting angle to minimize solar radiation throughout the year, while maintaining view to the outside. The result includes geometries with gradient changes and smooth transitions. In [32], the author presents a set of designs based on optimization of complex architectural facades using generative algorithms for daylight and structural analysis, with explicitly focus on the value of ornament. In [33] authors focus on Origami-inspired geometry to generate modular patterns. They first study and then optimize a set of kaleidocycle rings using Genetic Algorithms, which can be morphed to change the daylight performance in interior spaces.

Although the above works propose optimization-based approaches to optimizing facade and shading element performance, the efforts are limited to facade configurations that are relatively homogeneous and comprise relatively few parameters. On the contrary, the contribution of the present work lies in that it proposed a comprehensive optimization approach that is applicable to modular facades where each of the facade elements may be unique, and therefore the number of decision variables is excessive for direct application of an optimization approach. To the best of the authors' knowledge, this important topic has not been extensively treated up to this point.

3. Proposed Method

It is noted beforehand that the method outlined in this paper has been developed with application in a computational optimization context in mind, forming a comprehensive decision support system. Within this context and as already outlined in the introduction, the general outline of the proposed method comprises three elements: Solution instantiation and form generation, performance evaluation, and finally multi-objective optimization. In the subsections hereafter, each of these components are outlined in detail.

3.1. Form generation

In the proposed method, the form generation is conceived as a process that accepts an abstract description (an encoding) and generates detailed geometry for the needs of evaluating performance based on simulation. The main aim of the proposed geometry generation method is to minimize the required input, thereby reducing the dimensionality of the search space. In the context of facade design, the proposed method achieves exactly that, and is further elaborated in the following section.

3.1.1. Design Considerations: Modularity

Most facade systems are based on modules (being the modules all equal or different from each others). Consequently, in the proposed method, we consider the general architectural facade problem definition, where the facade comprises a set of elements or building blocks E placed according to a predetermined regular arrangement. Common cases may refer to rectangular, hexagonal or rhomboidal arrangements of elements; however any regular arrangement is possible without limitation. The physical elements are held together by any means of interlocking (e.g. mechanical, chemical etc.) and may have an underlying support structure, whether visible or not. The elements may form any part of the facade; for instance, they may be shading elements, or they may be integrated elements including glazing, shading and even specialized devices.

With respect to the individual elements, we assume that each one may vary in shape within certain boundaries that do not violate design requirements as set forward by the facade and element definition. In addition, we consider that each element is defined by its Cartesian position on the facade plane. Thus any facade element is uniquely defined by $e = \{V_e, P_e\}$, $e \in E$. The vector $V_e \in R^n$ comprises parameters that completely define the shape of a single element according to a geometry-generating function $g(V_e)$ defined parametrically. The vector $P_e \in R^2$ corresponds to the position of the element on the facade plane. Due to the regularity of the facade described previously, the shape of the elements is dependent solely on V_e and does not otherwise depend on their position on the facade P_e , or on features of neighboring elements. In addition, we assume that g is defined so that the domain of valid V_e value combinations results in elements that do not in any way break geometrical continuity of the facade. This last requirement may be easily achieved by defining g so that geometrical features close to interface points remain constant and independent of V_e .

Under these assumptions, the dimensionality of the search space may be easily calculated. As an example, we will consider a facade comprising elements in a rectangular grid with h elements in the horizontal dimension and v elements in the vertical. This gives the cardinality of E as $|E| = hv$. If each element comprises n parameters as described above, it is easy to see that the dimensionality of the search space would be $d = |E||V| = hvn$. This may easily turn out to be an extensive search space, as the values of the variables h and v may easily range into the hundreds for moderate to large size facades. Such search spaces may turn out to be challenging to search, due to combinatorial explosion. Therefore, it is often desirable that constraints pertaining to decision variable composition are established so that the effective dimensionality of the search space is reduced.

To investigate potential strategies for reducing dimensionality, we refer to aesthetic properties of architectural facade designs. It may be empirically observed that the vast majority of real-world facade design cases exhibit regularities that may be exploited to reduce search space. Such regularities are often the result of stylistic or aesthetic preferences and are established as part of the overall facade concept. Through considering these regularities, it is possible to stipulate that at any given time, only a very small subset of possible design alternatives is of interest to the decision makers, even before having any knowledge regarding facade performance. An example of aesthetic preference that can be seen in many recent architectural design examples, is facade designs where the composition of element parameters gradually varies along the facade plane. This seems as a preferable design direction for many real-world design applications. Some recent architectural examples of this type of facades are demonstrated in figure 2.



Figure 2: Recent examples of facades that follow a module-based approach. a. Al Bahar Towers, AEDAS, Image Credit: AEDAS; b. Nanjing International Youth Culture Centre, Zaha Hadid Architects, Image Credit: Khoo Guo Jie; c. Nantong Urban Planning Museum, Henn Architekten, Image Credit: Bartosz Kolonko/HENN

Another example would be facades that exhibit periodicity of the element-defining properties over their surface. Considering a facade with specific assumptions with respect to the distribution of decision variable values over its surface allows us to impose constraints that may help in reducing the dimensionality of the decision variable space and therefore enable more efficient search in more relevant regions of the search space. A relevant strategy is proposed in the next section.

3.1.2. Managing Complexity through Inducing Localized Module Transitions

In order to alleviate combinatorial complexity due to the factors discussed in the previous section and focus on a more relevant subset of the search space, in this section we identify constraints that

may be applied to the decision variable distribution of the facade elements. In particular, and as already stipulated, we wish to maintain smooth formal transitions between neighboring elements throughout the search space, while maintaining the expressiveness of the model to allow facade design professionals expressive power. We propose a model where the decision variable corresponding to elements' properties becomes a dependent variable that varies in accordance to the element's proximity to a set W of control nodes spatially distributed along the facade area. Similarly to the facade elements' definition, the control nodes are defined by $w = \{V_w, P_w\}, w \in W$. $V_w \in R^n$ is a decision variable value vector, with each of its values corresponding to one facade element parameter. Each node is additionally characterized by a vector $P_w \in R^2$, which denotes their position on the facade plane. The control nodes act to "affect" the parameter composition of each of the facade's elements, with a magnitude that varies according to some function c of the Euclidean distance between an element and a node. As an example one may consider that the effect of a node on an element varies inversely proportional to the Euclidean distance between them. In this case, $c(e, w) = \frac{1}{|P_e - P_w|}$, and the effect that a node has on an element is maximized the closer the element is to the node.

Due to the fact that each element's parameter composition is affected by each node on the facade, the effect of all nodes needs to be taken into account when defining the element's final decision variable composition. Towards this end, an aggregation function that considers the magnitudes of each of the nodes' effects and the decision variable composition corresponding to each node would be sufficient to determine all of the elements' compositions, and as such their final forms. A straightforward aggregation function, although not unique as will be seen later on, is a weight-proportional summation of decision variable values, with node magnitudes as weights:

$$V_e = \frac{\sum_{w \in W} c(e, w) V_w}{\sum_{w \in W} c(e, w)}$$

The resulting V_e is a vector in decision variable space that corresponds to a single facade element. Together with the element's position vector P_e , the element is completely defined. Repeating the same process for all facade elements allows us to obtain a definite composition of the facade.

The effect of the above approach on managing search space complexity can be seen in the reduction of the effective multiples of the vector V that need to be determined for a complete facade definition. It has been mentioned previously that the search space dimensionality in the case of unconstrained element control is $d = |E||V|$. On the contrary, in the constrained case the search space dimensionality would be $d = |W||V|$, where W pertains to the set of control nodes. If the assumption is made that the control node cardinality ranges at most in the tens, then we have $|W| \ll |E|$, because $|E| = hv$, which as previously mentioned may well range in the thousands, and as such is orders of magnitude greater than $|W|$. It is thus evident that the proposed method offers a competent way of managing complexity of facade designs.

It is clearly seen that the above mathematical formulation may be easily adapted in a geometry-generating parametric model of the facade. Most parametric platforms offer tools that allow the high-level expression of the above mentioned relations while iteration over facade elements and control nodes is handled internally by the parametric program's data structures.

As mentioned in the beginning of the section, the technique presented above is generic applicable to any facade design that comprises regular patterns of individual modules. As an example of a simplified parametric model, a Grasshopper definition is presented in the figure 3.a, which makes

use of a total of three control nodes and 18 parameters in total to adjust the properties of a facade comprising 66 facade elements, with four parameters each, for a grand total of 264 parameters. This definition translates to facade available in figure 3.b, and demonstrates a few alternative arrangements of modules corresponding to varying attributes.

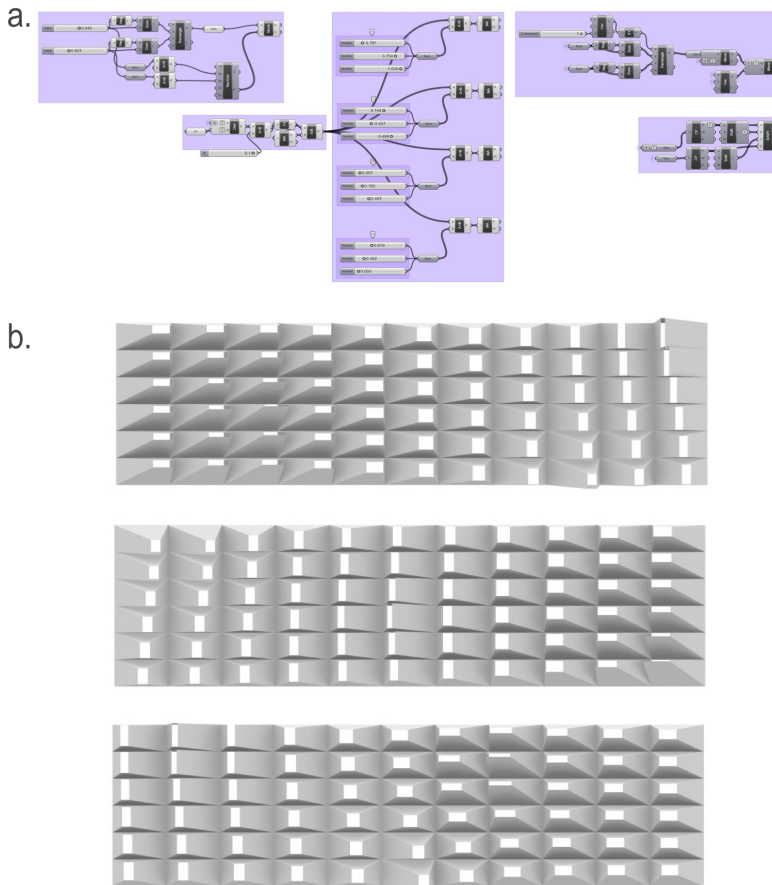


Figure 3: (a) An exemplary parametric definition demonstrating the methodology presented in section 3., that allows a facade comprising 264 parameters in total to be varied using three control nodes and a total of 18 parameters, (b) three example facade configurations.

3.2. Daylight Indicators & Modeling

In order to respond to the daylighting requirements as stipulated in the previous section, the proposed method considers a model with a two-level hierarchy that is as follows: In the lowest level, an accurate daylighting simulation offers information regarding the distribution of daylight within a single space, for each relevant space of the building. Given these results, the highest level comprises an aggregation scheme that combines individual results into a single figure, which is subsequently used in computational optimization as an objective.

In order to outline the proposed model, we begin by laying out the assessment criterion. The widely adopted Useful Daylight Illuminance (UDI) [15] metric is used as a base evaluation metric for building our comprehensive daylight evaluation scheme. The definition of UDI begins by defining illuminance ranges with respect to the level of comfort associated to them [15]:

- Daylight illuminances less than 100 lux are generally considered insufficient to be either the sole source of illumination or to contribute significantly to artificial lighting.
- Daylight illuminances in the range of 100- 500 lux are considered effective either as the sole source of illumination or in conjunction with artificial lighting.
- Daylight illuminances in the range of 500-2000 lux are often perceived either as desirable or at least tolerable.
- Daylight illuminances higher than 2000 lux are likely to produce visual or thermal discomfort, or both.

With the above assumptions and considering a single point that is on the horizontal plane of a workstation, a simple piecewise function may be devised that allows one to quantify the above reasoning scheme at any given point in time:

$$UDI(p, t, g) = \begin{cases} 0 & , \text{ if } L(p, t, g) < 100 \\ \frac{L(p, t, g) - 100}{400} & , \text{ if } 100 \leq L(p, t, g) < 500 \\ 1 & , \text{ if } 500 \leq L(p, t, g) < 2000 \\ 0 & , \text{ if } L(p, t, g) > 2000 \end{cases}$$

In the above formula, $L(p, t)$ corresponds to a function that outputs horizontal illuminance in lux for a given point indoors and time within the year. UDI , thus, is a dimensionless figure that takes the value zero if current daylighting conditions do not serve the purpose of the workstation corresponding to the indoors measurement point, one if conditions fully serve said purposes, while in between values denote intermediate conditions. Given the above formula, it is possible to derive a figure that corresponds to the time throughout a year during which daylighting for a particular indoor point is useful:

$$UDI_a(p, g) = \int_0^y UDI(p, t, g) dt$$

In the above equation, y denotes the final time point within the year, and depends on the unit of measure of time. If the assumed unit is hours, then $y = 8760$. Figure 4 presents a visual depiction of the UDI calculation over a year. For practical purposes, the above definition may be discretized with an hourly interval as follows:

$$UDI_{a,h}(p, g) = \sum_{t=0}^y UDI(p, t, g)$$

The above figure gives the annual Useful Daylight Illuminance for a single indoor point. However, in our case we need to be able to characterize multiple points of relevance within a single space (e.g. multiple workstations), as well as multiple spaces with varying requirements. Therefore, the UDI definition needs to be extended so that is is possible to:

- Obtain an aggregate figure of the daylight performance for multiple points within a single or within different indoor spaces, and,
- Be able to specify alternative thresholds for minimum illuminance in the UDI formula.

The rationale behind the requirement for varying illuminance thresholds comes from the function of each space. An open, public space may warrant a more atmospheric lighting solution compared to a strictly functional space such as e.g. a reading room or a laboratory. It is therefore appropriate to adjust one's expectations regarding the quantity and type of daylight that is experienced. In order to accommodate the above requirements, we begin by reformulating the UDI definition with additional parameters for the minimum thresholds as follows:

$$aUDI(p, t, g, m_l, m_u) = \begin{cases} 0 & , \text{ if } L(p, t, g) < m_l \\ \frac{L(p, t, g) - m_l}{m_u - m_l} & , \text{ if } m_l \leq L(p, t, g) < m_u \\ 1 & , \text{ if } m_u \leq L(p, t, g) < 2000 \\ 0 & , \text{ if } L(p, t, g) > 2000 \end{cases}$$

This extension allows for a detailed specification of the UDI gain slope at the lower illuminance levels. The high-end threshold has not been modified as it has been considered a reasonable value for avoiding undesirable side effects of extreme illuminance. However, it is trivial to add a parameter for that in the above formula.

The second extension builds on the previous one by allowing integration of multiple measurements in different spaces each with their own requirements in daylighting levels. We consider a set of spaces S , each of which include a set of measurement points P_S .

A set of requirements R contains a tuple of required illuminance levels indexed by elements in S . Under these assumptions, the formula is defined as follows:

$$sUDI(S, R) = \frac{1}{\sum_{s \in S} |P_s|} \sum_{s \in S} \sum_{p \in P_s} aUDI_{a,h}(p, g, m_{l,s}, m_{u,s}), (m_{l,s}, m_{u,s}) \in R_s$$

The formula above may be used to comprehensively compare different designs with respect to satisfaction of daylighting requirements. One limitation stems from the dependence of $sUDI$ on the cardinality of the measurement points, such that naturally a greater number of points will generally yield higher values. This may be addressed by adding a normalization factor to the formula above, so that the output becomes a factor instead of absolute values.

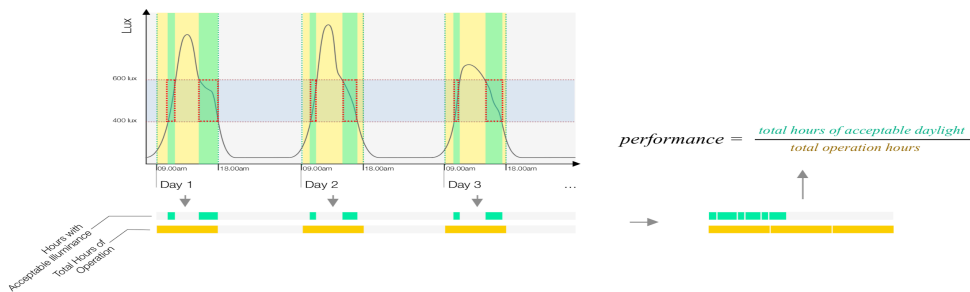


Figure 4: Visual diagram of the UDI calculation for daylight performance

3.3. Computational Complexity

The daylighting evaluation outlined above requires accurate indoor illuminance distribution figures which can be obtained using simulation. One of the most widespread daylighting computation software is the RADIANCE tool [34]. RADIANCE is an advanced ray-tracing software that is able to accurately determine the illuminance values at the required indoors measurement points, for different times of the year and outdoor skylight distributions. In our case, we utilize software that allows the use of RADIANCE from within a Parametric Modeling environment, namely the DIVA software [35]. The use of simulation enables the accuracy of the proposed method, however it contributes significantly to the computational complexity of the proposed method. In relation to the use of simulation there are, in fact, several factors that contribute to computational complexity:

- Complexity of indoors and facade geometry affects daylighting model execution time.
- Multiple indoors measurement points require separate computations.
- In the context of computational optimization which is the main concern of this study, a multitude of evaluations of varying facade configurations.

In order to alleviate issues related to computational complexity there are mainly two approaches: The first is to exploit any potential for parallelizing that the selected optimization scheme may offer, in order to augment the available computational power. The second is to develop surrogate models of the design performance and utilize those in evaluating different design solutions throughout optimization. Surrogate modelling for fitness approximation is a widely adopted approach in computational optimization [36], with applications in architectural daylighting [37], [38]. In the present study we do not consider surrogate modeling, which is left as a promising perspective for extending the work described herein. On the contrary we do consider a parallelization scheme that is compatible with both the simulation software at use and the population based optimization algorithm that will be outlined hereafter.

The proposed scheme consists of two levels of parallelized computation:

- The first is offered by the RADIANCE program and concerns the use of multiple processors in the same computer, in order to accelerate daylighting computations. As the daylighting computations are by far the most computationally intensive task in the proposed method, use of multiple processors translates into a computational gain that is nearly proportional to the number of processors at use in a single machine.

- The second layer concerns the use of multiple machines to distribute the computation pertaining to individual solutions within a population. A simple queueing scheme allows for the use of heterogeneous infrastructure where each machine may receive one or more tasks depending on its capabilities and the computational complexity of each task. A compute cluster size of up to the population size of the tasks for each population can be used for parallelization.

A diagram of the proposed scheme is available in figure 5.

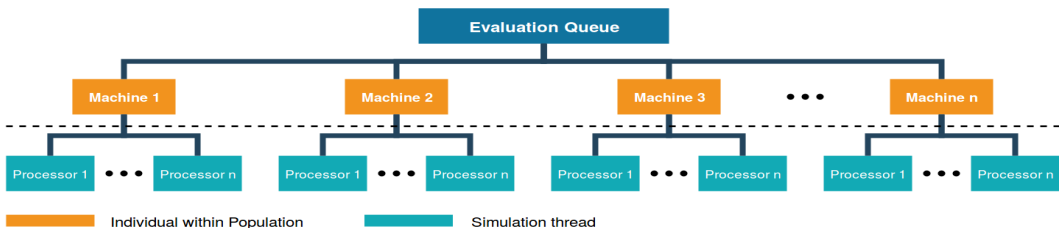


Figure 5: Hierarchical organization of available compute infrastructure: Each individual in a population is assigned to a machine where the relevant simulation is performed on multiple threads.

3.4. Multi-Objective Optimization

In an optimization problem, a function of decision variables is maximized or minimized, subject to hard or soft constraints. Optimization problems fall into two broad categories:

- Single objective optimization problems (SOP) that involve a single objective function,
- Multi-objective optimization problems (MOP) that involve more than one objective functions.

Single objective problems can be solved by exact methods to achieve optimal solution for the problems with small-size and a strict mathematical formulation, however this does not match with complex problems occurring in real-world scenarios [39]. Realistic optimization problems usually entail more than one decision-making criteria and formulated as MOP. In most of the cases, multiple objectives are conflicting with each other e.g. a satisfactory solution for one objective could be unsatisfactory solution for another objective. Therefore, it is difficult to explore optimal results for each objective simultaneously. Instead, there usually exists a solution set to be achieved as best trade-offs. Beyond the conflicting goals, decision variable type (real or discrete) and existence of constraints are important considerations that affect the problem formulation and algorithm selection. Architectural design problems usually require a large number of continuous (real) design variables and several constraints due to changing building program, user expectations, or environmental impacts. In our approach, building facades have a big potential to respond several aspects in designing performative buildings.

In order to deal with these complex types of MOPs, we employ Multi-Objective Optimization (MOO) techniques. The earliest MOO method in the literature is to convert the multiple goals into one single function by considering a weighted summation of individual objectives [40]. In the application of these approaches, it is difficult to decide the importance degree of each objective whether it is previously determined (weighted-sum method) or during the search process (boundary intersection method) [39]. Considering the drawbacks of these approaches, we refer to metaheuristics algorithms. These algorithms are capable of searching for near-optimal solutions. Another advantage of these approaches is to solve large-size MOPs in a reasonable time. Metaheuristics algorithms have been developed by inspiring from behaviors and communication

mechanisms in nature, such as biology-inspired algorithms, physics-inspired algorithms, geography-inspired algorithms, and social culture inspired algorithms [39].

In architectural domain, metaheuristics have attracted a lot of attention of researchers in recent years. The most popular and extensively used ones are biology inspired algorithms (e.g. swarm and evolutionary algorithms), which have many architectural form-finding applications reviewed in [2]. Evolutionary algorithms (EAs) are inspired from the survival of the fittest process of natural ecosystems [39], [41]. Several examples of EAs are Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [42], Differential Evolution Algorithm (DE) [43], *Hypervolume Estimation Algorithm (HypE)* [44], and etc. Swarm algorithms (SAs) are inspired from social nature and the collective behavior of swarms [39]. Several examples of SAs are Particle Swarm Optimization Algorithm (PSO) [45], Ant Colony Optimization Algorithm (ACO) [46], Artificial Bee Colony Algorithm (ABC) [47], among others.

All of the algorithms above are possible to be used in our approach. However, according to No Free Lunch theorem [48], the choice of algorithms is a difficult task for optimization of a specific problem. Because each algorithm performs different and affect eventual set of design solutions based on case to case specifics. Although our approach allows using different types of algorithms, Hyper-volume Estimation Algorithm is selected as one of the most recent multi-objective real-parameter constrained optimization algorithms during the optimization phase of this study to get best-trade-off façade design solutions (e.g. Pareto optimal results).

Hyper-volume Estimation Algorithm

Hyper-volume Estimation Algorithm, called HypE, was developed by Bader and Zitzler [44]. It is based on an effective fitness assignment strategy. As can be seen in Fig.6, the main loop of HypE started with a standard evolutionary algorithm process, then continued with successive application of mating selection, variation, and environmental selection procedures.

Result: P_g of Pareto optimal solutions

Initialize population P by choosing N solutions from X uniform at random

where N : popsize, M : nosamplingpoints;

$g \leftarrow 0$

while $g \leq g_{max}$, where g_{max} is number of generations **do**

$P' \leftarrow \text{matingSelection}(P, R, N, M)$;

$P'' \leftarrow \text{environmentalSelection}(P \cup P', R, N, M)$;

$g \leftarrow g + 1$;

end

Figure 6: HypE Algorithm Main Loop [44]

During the mating selection process, if the number of objectives is equal or smaller than three, the hypervolume values are computed exactly; otherwise these values are estimated based on a hypervolume-based Fitness Value Estimation algorithm. Then, binary tournament selection is realized with several tournaments among a few individuals that randomly selected from the population (See Fig.7). In the variation process, mutation and recombination processes are combined to produce offspring population. Finally, in the environmental selection process, most promising

solutions are chosen from the parent population and offspring. Then, a new population is created for the next generation.

Result: Mating pool Q

where P : population, R : referenceset, N : popsize, M : nosamplingpoints;

if $n < 3$ **then**

 | $\phi \leftarrow \text{computeHypervolume}(P, R, N)$;

else

 | $\phi \leftarrow \text{estimateHypervolume}(P, R, N)$;

end

$Q \leftarrow \emptyset$;

while $|Q| < N$ **do do**

 | choose $(a, v_a), (b, v_b) \in \phi$ uniformly at random;

if $v_a > v_b$ **then**

 | $Q \leftarrow Q \cup \{a\}$;

else

 | $Q \leftarrow Q \cup \{b\}$;

end

end

Figure 7: HypE Mating Selection Algorithm [44]

4. Case Study: The PULSE Project

In order to provide validation for the proposed method, we chose to apply it to a real-world architectural facade design problem.

4.1. Overview

PULSE is the name of the newest addition to the university campus of the Delft University of Technology, an education building that serves as a central place bringing students and lecturers together to make contacts, collaborate, acquire and share knowledge and develop themselves.

The Western facade of the building features a striking large glass area, which is protected by innovative shading elements. The design of said elements has been the focus of an extensive research collaboration between the department of Architectural Engineering and Technology of the Faculty of Architecture of Delft University of Technology and Ector Hoogstad Architects, the architectural firm leading the design of the PULSE building. PULSE being the first energy-neutral building on the TU Delft campus, the demand for an efficient facade that promotes energy conservation and generates a comfortable indoor climate has been high on the agenda. At the same time, it was a requirement for the facade to employ a unique aesthetic that may easily be used to identify the building.

4.2. Daylighting Requirements

The PULSE building includes several indoor areas that are adjacent to the facade in question. Each of these spaces has different requirements with respect to acceptable illuminance ranges. These are presented in figure 8. For each indoor space in question, a grid of measurement points is established in simulation. The grid has a fixed size of 1m. Values from each measurement point are combined in a single objective function by applying the method outlined in section 3.

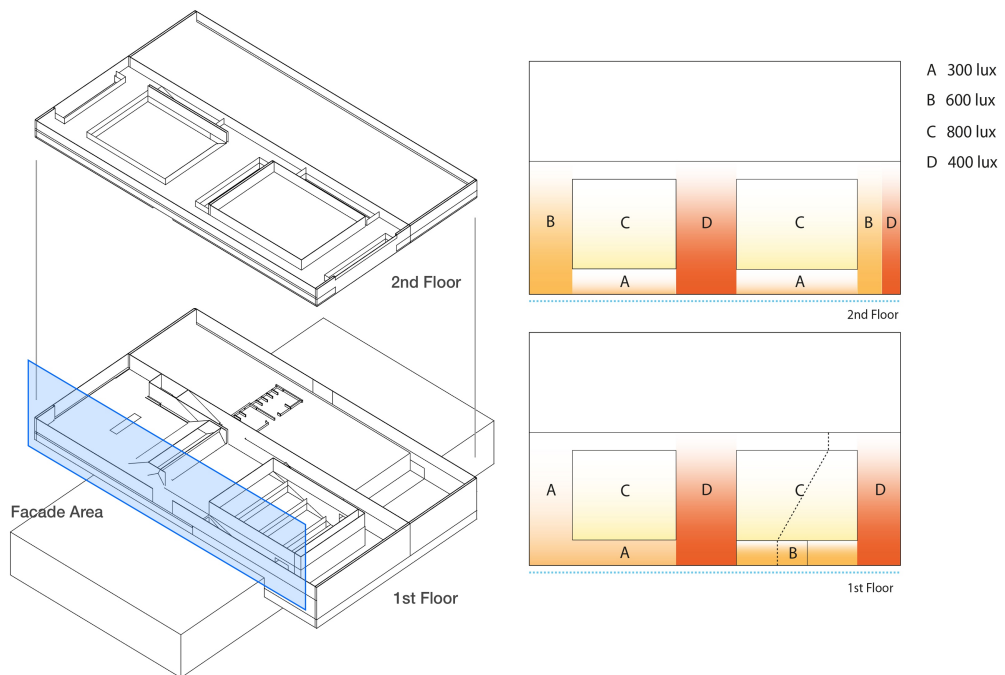


Figure 8: Left: Axonometric view of two of the building floors that are of interest, 1st and 2nd floor, in addition to facade location. Right: Location of interior spaces of interest in relation to the facade (dotted green line), and minimum lighting requirements. Image and design by Ector Hoogstad Architecten & TU Delft

In addition to daylighting, a second objective function aims to minimize material volume of the shading elements. For this case study, material volume is associated with several cost aspects of the project such as direct material costs, shading element fabrication time, total facade weight (and associated structural requirements) and so on. As such, reduction of shading element material has been established as an objective.

4.3. Shading Element Design

The form of the shading element has an abstract wave shape as inspiration. A visual pattern of waves is formed when the elements are in arrangement on the facade. A 3D printed prototype of the element form is visible in figure 9. The main form of the element is constructed by sweeping a profile curve along the curved axis, with different profile curves along various axis points. The profile of the

element is thus wider at the center, where it offers most of the potential for mediating direct sunlight. Each element offers three connection points to neighboring elements: Two on each edge of the “wave”, and one at the center of the element. The connection pattern is edge-to-center, with two elements connecting to a third elements’ center. The elements include hollow paths along their diagonal, which are run through by steel reinforcement cables under tension. The purpose of the cables is to increase the stiffness of the shading device along the surface, so that it is able to better withstand lateral loads (e.g. wind load). The configuration of the elements along with the reinforcement system is available in figure 10.



Figure 9: Physical prototype of a single shading element. Image and design by Ector Hoogstad Architecten & TU Delft

4.4. Rapid Prototyping and Material Technologies

In order to realize the individually varying forms of the shading modules in a cost-efficient way, 3D printing has been decided as the fabrication technology. Individual elements are printed on a large-scale printer as hollow elements with the bulk of the material volume concentrated on the element surface. Therefore, it is possible to accurately approximate material volume by computing the surface of the element and multiplying with a fixed thickness value. With respect to computational performance evaluation, this allows for simplifications to be made that reduce computational burden. In practice, the reduction of material volume is redefined as reduction of the surface area of the facade element. Under these assumptions, the material usage of a shading device design may be defined as follows:

$$u(X) = A_{tot} = \sum_{e \in E} a(g_s(V_e))$$

In the above equation, we introduce a as a function that computes the area of a given surface entity, and g_s as a simplified geometry generation function that generates the shading device geometry given a parameter vector.

4.5. Parametric Definition of Shading Device

The PULSE facade parametric definition has been developed with the aim of testing and optimizing the element parameters of the facade shading device, by application of the method outlined in the previous section. The shading device is a rectangular region that occupies the front of the Western glazed area of the PULSE building. The arrangement of elements is fixed. There are a total of 3800 individual elements arranged in a diamond-shaped grid that measures 76 elements in each row and 50 elements in each column. The angles for each side of the diamond are 45 and 30 degrees accordingly. A schematic view of the shading elements in combination with the supporting wire arrangement is available in figure 11.

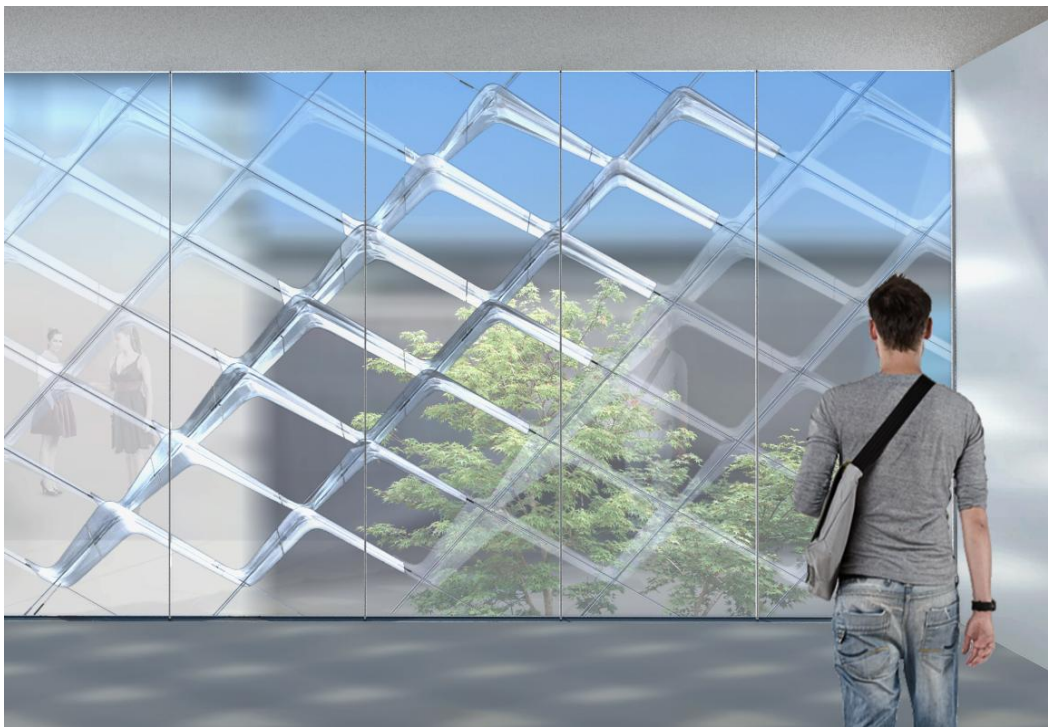


Figure 10: Diagonal arrangement of shading elements on facade. Image and design by Ector Hoogstad Architecten & TU Delft

The form of each individual shading element is controlled by three parameters: Two parameters control the shading element's angle, one along each of the two steel wire directions, and one parameter controls the width along the element centerline. A visualization of the element's parameters is available in figure 11.

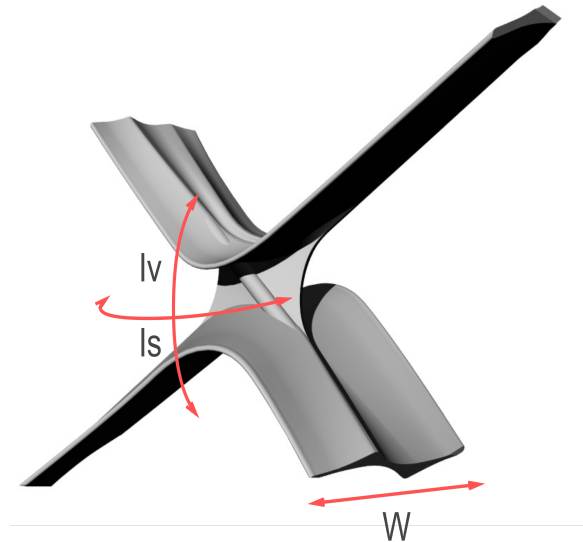


Figure 11: Cross-section of a single facade element, where decision variables effects are demonstrated. Element design by Ector Hoogstad Architecten & TU Delft

As the parametric model is only used for evaluating the quality of daylight and optimizing shading element arrangement, the geometry of the shading device is a simplified version of the geometry outlined previously. In particular, each shading element consists of a single swept surface that passes through five guiding lines. The central line is the one that determines the width of the element. The middle three lines, together with the central one, determine the angle of the element along the two directions of the supporting steel wires.

A regularly located grid of 21 control nodes cover the surface of the shading device in order to control the shading elements configuration. The control nodes utilize a biased inverse-distance-proportional control aggregation function with constant falloff, like the one outlined in section 3. A separate problem instance that included variable falloff modifiers as decision variables has been tested, however, it was deemed that it did not offer advantages that would justify the increase in search space complexity. There are seven control nodes in each row of the control grid, and three in each column. Each control node controls separately the three parameters that correspond to a single element's configuration. This corresponds with a search space of 63 dimensions in total. It is interesting to note that had each shading element have had its own parameters as decision variables in the problem definition, the dimensionality of the search space would be 11250, which would render exploration of search space extremely costly. The configuration of control nodes is available in figure 12.

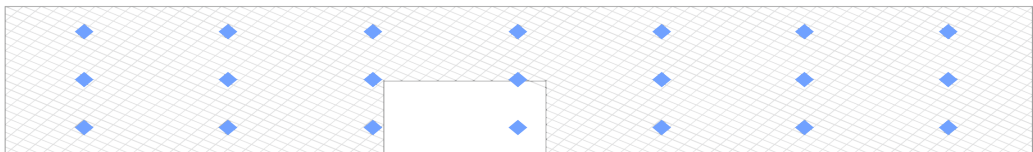


Figure 12: Location of control nodes for the PULSE facade

The geometry of the facade at the end of the parametric composition process consists of a number of surfaces corresponding to the shading elements in their current configuration. This geometry is converted to a mesh and is output to the daylight computation software RADIANCE via the Diva plugin. In addition to the shading device, the entirety of the building geometry is also input to the daylight simulation, in the correct orientation and with appropriate material properties for each of the surfaces. Finally, for each space that is in contact with the facade, relevant measurement points are defined and input to the daylight simulation. The output of the simulation consists of a structured representation of values that correspond to the fraction of time that each of the measurement point is within the defined illuminance thresholds. These values are combined to form an aggregate performance figure that is used as an objective function.

Finally, the material usage for each panel is approximated by summing up the computed surface area of each panel individually.

4.6. Problem Definition

Under the assumptions outlined above, we formulate a real-coded, bi-objective unconstrained optimization problem, which we aim to address using evolutionary computation and in particular the HypE algorithm outlined in section 3.4. The decision variables together with their indexing and variable bounds are available in table 1. The optimization problem definition is as follows:

$$\underset{x}{\text{minimize}} \quad 1 - \text{sUDI}(S, R, g(X)) \\ u(X)$$

As shown in the above formula, in order to obtain a minimization problem, it is required to convert maximization of sUDI to minimization. In order to obtain an understandable relation between the two quantities, the remainder of the daylight compliance is used. $u(X)$ above denotes the material use of the shading element.

Experimental Set-up

The experimental setup consisted of a parallel computing cluster that is coordinated by a remote master running the optimization algorithm and relevant task synchronization algorithms. A communication protocol based on HTTP was designed to convey the decision variables and receive the objective values from each of the clients. The values were encoded in a dictionary in Javascript Object Notation (JSON) format, a popular hierarchical data encoding format. The computing cluster used for optimization trials resulted from the use of a highly heterogeneous mix of project partners' existing computing infrastructure. The machines in question varied highly in the following aspects:

- Technical specifications
- Robustness of network connections
- Machine availability throughout the daily schedule

The above variations introduced unexpected delays in objective function evaluations. As such, computation time became the most significant constraining factor in the optimization trials. It was eventually identified that an optimization run of 50 generations with a population of 100 individuals could be completed within a single weekend on the available computing cluster, and as such these values were chosen. In particular and in both trials, the required simulation computations were performed in a heterogeneous cluster of machines using the parallel computation scheme outlined in section 3.3. The cluster comprised 25 machines of varying processing power and availability that was mainly during weekends. To maintain project schedule, it was decided that each trial would be

carried out within one weekend – allowing for two additional weekends prior to trials in order to perform test runs. The running time for each simulation was near five minutes, as such an optimization run of 50 generations of 100 individuals would have a minimum duration of 18 hours. However due to unexpected phenomena such as machine shutdowns and data loss over the remote connection, the actual duration was slightly more than 24 hours, allowing a time window enough for a single run per weekend

Table 1. Decision Variable types and properties

Name	Symbol	Type	Range	Count
Vertical Inclination	I_V	Real	[-1, 1]	21
Sideways Inclination	I_S	Real	[-1, 1]	21
Width	W	Real	[0, 1]	21

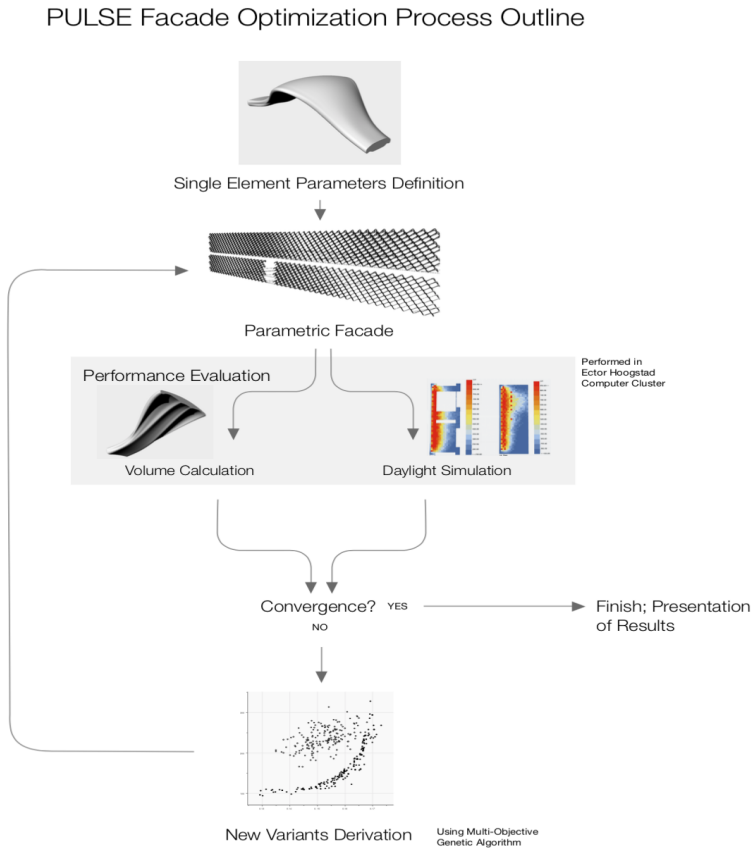


Figure 13: Overview of the performance optimization process as applied in the PULSE case study

4.7. Results and Discussion

Figure 13 presents an overview of the performance optimization method as applied in the PULSE case. Two extended trials using the proposed method were performed during the course of the PULSE project. The first was performed at an intermediate design point, where the precise constraints related to manufacturing and structural aspects were not fully known by project partners. The second trial was performed at the end of the preliminary design stage, where such aspects were known to a detailed degree.

The objective function space of the algorithm population pertaining to generations 1 and 50 of the first trial is presented in figure 14. As may be observed in this figure, the final population comprises mostly non-dominated solutions, however it seems that the algorithm did not fully converge and convergence may be achieved if the algorithm is allowed to run further. Still, looking at the results at hand it is possible to see that the optimized designs offer significant material savings (up to 67% for the one end of the Pareto front) and overall better compliance to the daylight requirements of roughly 2% on average.

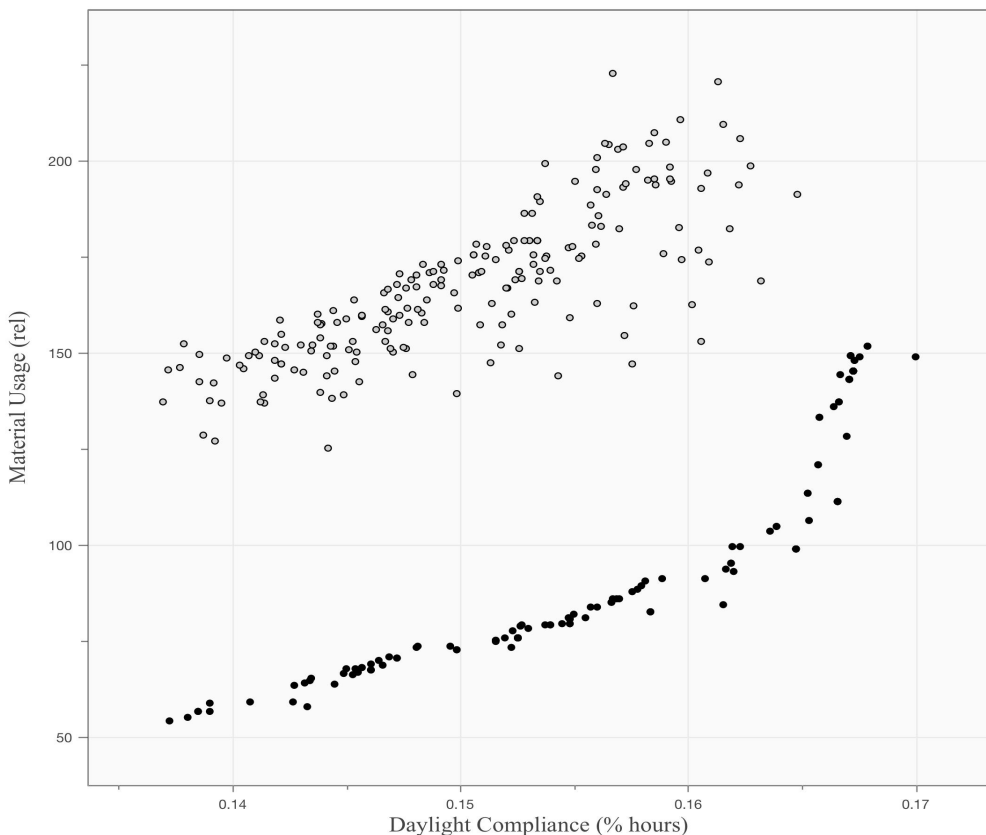


Figure 14: Objective function space visualization for individuals in the first generation (grey) and the final generation (black), first trial.

The second trial utilized a geometry generation model that was much more constrained in terms of the formal variation that could be achieved by the shading element. This is due to structural requirements that dictated much of the shading element shape, apart from a narrow region close to its middle. In particular, it was decided that pretensioned steel cables would run the two diagonals the elements were organized on, in order to improve the stiffness of the facade. As a result, the second optimization trial demonstrated modest improvement in comparison to the first trial.

Objective function charts pertaining to generations 1 and 50 of the second trial are available in figure 15. As in the first trial, the 50th generation is not fully converged and further generations may be able to improve optimality. As seen in the figure, there is a 5% improvement on average in use of material in comparison to the initial population, and a 1% improvement in terms of daylight requirements compliance. Figure 16 presents six Pareto optimal designs corresponding to the coloured points in figure 15. As can be observed, areas of the facade where less daylight is required overall are more dense on solutions with more material use. The opposite is also true, areas with more daylight requirements are generally less occluded by the shading device. Solutions that demonstrate minimal material use do not show significant variations in occlusion, however the orientation of the shading elements is still affected to either allow or block daylight as required.

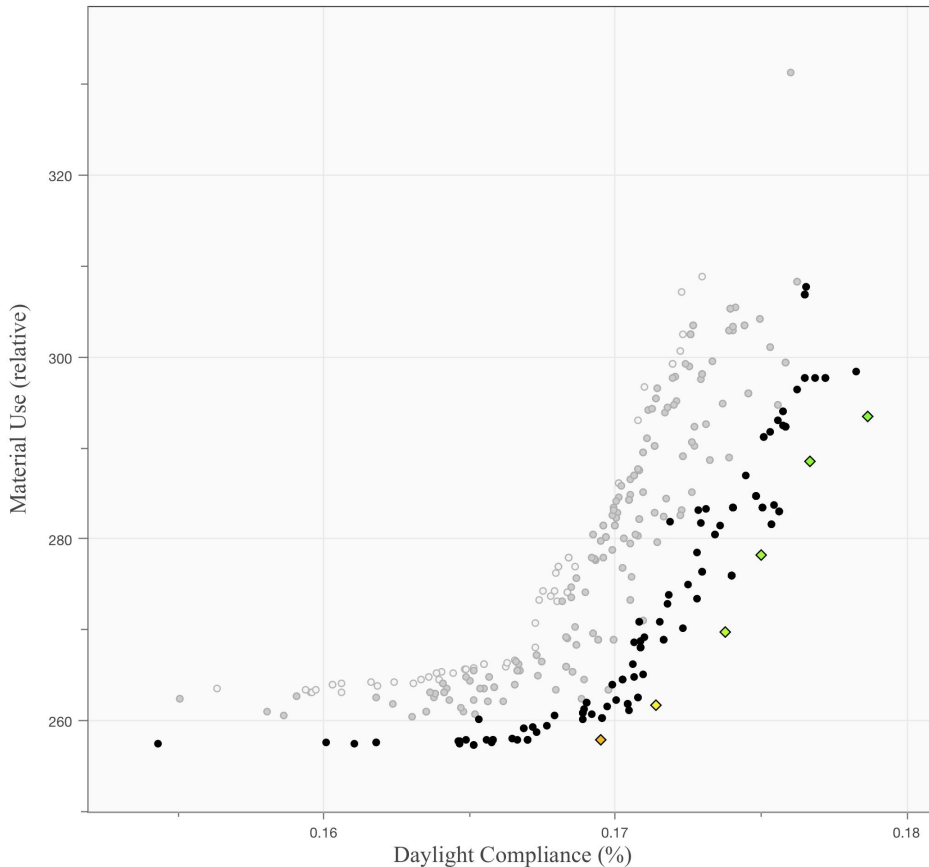


Figure 15: Objective function space visualization for individuals in the first generation (grey) and the final generation (black), final trial.

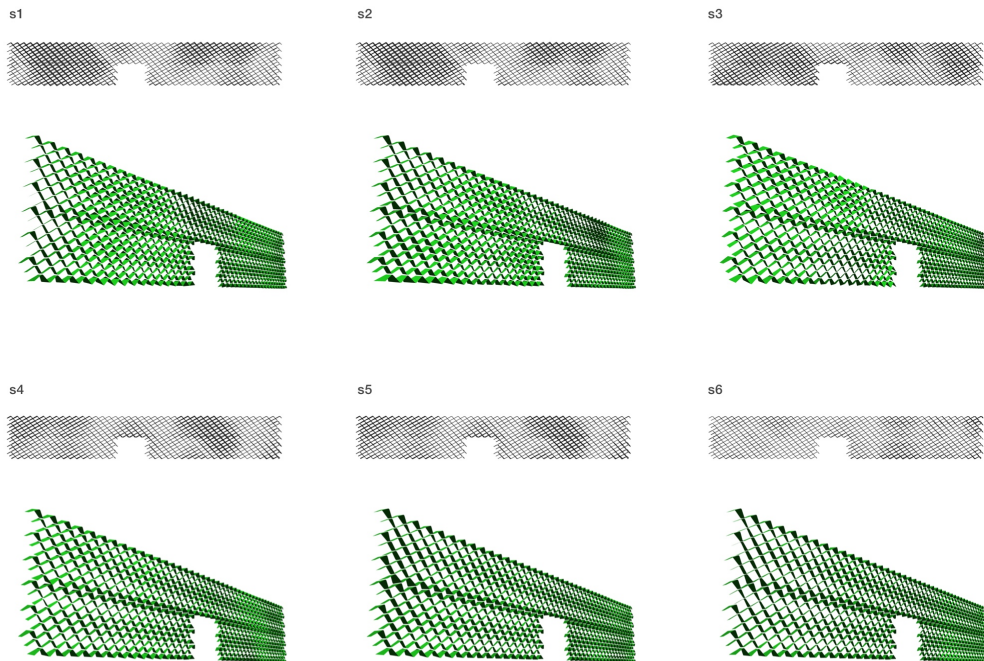


Figure 16: Visualization of facade configurations post optimization, samples according to the distribution in figure 15.

The proposed optimization approach results in a set of Pareto-optimal solutions to the multi-objective facade design problem, which has been also the case in the PULSE application. Following optimization, the process of identifying the most suitable out of the presented solution has taken place. Selection among Pareto-optimal solutions may happen either on the basis of considering the tradeoff between objectives, or considering additional preferences that have not been explicitly treated in the course of optimization. In the case of PULSE decision makers went through an iterative process to examine each of the resulting solutions and decide on the most suitable one, where both tradeoffs between objectives as well as preferences with respect to the formal properties of the design were considered. More specifically, some of the designs that had better daylighting performance were also preferred due to the variation they presented in terms of element transitions. However, the same designs were generally on the higher end of the range of total facade material cost. It is noted here that while this is one approach to post-optimality decision making, other approaches that consider soft objectives and preferences also exist. Addressing soft objectives in the context of computational decision support is a challenging task that has been extensively researched and comprises diverse strategies, such as those presented in [49], [50] and [3], [51]. One future direction for the present work is to research potential methods for augmenting cognitive decision support during the post-optimality phase, so as to better address preferences and satisfy soft objectives beyond those specified before optimization.



Figure 17: Project stakeholders visually inspecting solutions post optimization for selection

5. Conclusions and Recommendations

This study presented a novel approach in computational decision support focusing on supporting the design of complex component-based facades and shading devices where components are dissimilar and individually manufactured. Such problems present high-dimensional decision spaces that are challenging to manage. The proposed method comprises a complexity reduction step that redefines and simplifies the facade or shading device parameter space, combined with a stochastic population-based optimization algorithm that optimized the simplified parameter space according to multiple functions. In addition, a novel definition of a composite objective function for computing compliance to daylight requirements that can handle complex multi-space buildings and complexes, as well as individual daylighting requirements, complements the approach. The second part of the paper presents a real-world case study where the proposed method is tested. The study concerns the design of a large-scale shading device for a new university building in the campus of the Delft University of Technology. Results indicate that the proposed method is able to offer well-performing design results in a design environment that would be difficult to manage and make decisions in.

Even though the proposed method does offer an approach to tackling complex, high-dimensional facade and shading device problems, this is done purely from a performance perspective, and considerations regarding soft design aspects are not explicitly treated. This observation is not necessarily a shortcoming of the method in itself, however it presents a promising opportunity for future research, which can lead to soft aspects such as aesthetics or other tacit preferences to be incorporated in the decision making process in a well-formulated and consistent manner. Incorporation and augmentation of the proposed method through such approaches offers a promising direction for future research.

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