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Utilizing Genetic Algorithms and Parametric Design for Efficient Daylighting Performance in Educational Spaces

A thesis Presented in Partial Fulfillment of the Requirements for Master of Science Degree in Architecture Engineering

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<u>Disclaimer</u>

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Abstract

Building simulation tools are used in many domains for the evaluation of various performance criteria. Due to the uprising awareness of more efficient and greener buildings besides, the recent progress in computational techniques, this trend became easier to evolve than ever before. However, design problems cannot be completely explored merely through these tools. They are useful in the analysis and the evaluation of a specific design, or a limited number of alternatives, according to certain criteria. On the other hand, they are not efficient for evaluating a large number of solutions. Hence, the integration of parametric design with genetic algorithms as an optimization tool was investigated as an approach to overcome this problem. A focus of this integration was in conceptual design phase, which returns to the key impacts of decisions taken in this phase.

In chapter one, an emphasis was on performance models and how *"performance"* issues were incorporated in different design models to serve as the driving engine for design exploration. By paying attention to the capabilities of generative models in capturing formal qualities, the integrated approach "generative Performative approach" was highlighted. Moreover, contributions of optimization algorithms in reaching high performance designs were investigated.

In chapter two, the investigated performance criteria was set to be daylighting design. Daylighting is an important building aspect that needs concern from the early beginning of the design process. Still successful daylighting design is a challenging task due to the conflicting requirements to reach the balance between daylighting adequacy and visual comfort. Besides, the fluctuating nature of daylight along the day and year complicates the process. Hence, the significance of integrating optimization algorithms for efficient daylighting design was discussed.

In chapter three, different generative systems were explored for pattern generation, focusing on cellular automata (CA). As a matter of fact, they lack the capability of meeting performance requirements without being guided by performance feedback. Thus, CA was integrated with Genetic Algorithms (GAs) to explore their effectiveness in solar screen formation. The designed solar screen was intended to meet daylighting performance requirements of a south oriented classroom in Cairo. An exhaustive search method was first applied and then was replaced by GAs.

In chapter four, findings of the classroom case study were discussed. All investigated CA rules proved their applicability in reaching satisfactory solutions in terms of the assigned daylighting criteria. In addition, GAs revealed their robustness in finding satisfactory solutions with less computational demands than the exhaustive search method which could be impractical in other cases.

The last chapter introduced the conclusions and recommendations. It elaborated the potentials of parametric design coupled with Genetic Algorithms (GAs) as an optimization tool in reaching highly efficient solutions. A workflow for utilizing generative performative design approach was suggested to meet designers' subjective visual demands and the required performance criteria. At last, future research concerned with optimization studies for building design was suggested.

Acronyms

ASE: Annual Sunlight Exposure

BOP: Building Optimization Problems

BPS: Building Performance Simulation

CA: Cellular Automata

DA: Daylight Availability

DA_{con}: Continous Daylight Availability

DDPM: Dynamic Daylight Performance Metrics

DF: Daylight Factor

GAs: Genetic Algorithms

GUI: Graphical User Interface

IES: Illuminating Engineering Society

LEED: Leadership in Energy and Environmental Design

LS: L-Systems

NSGAII: Non-dominated and crowding sorting genetic algorithm II

NURBS: Non-Uniformal Rational Basis Spline

PSO: Particle Swarm Optimization

SA: Simulated Annealing

sDA: Spatial Daylight Autonomy

SG: Shape Grammars

SQP: Sequential Quadratic Programming

UDI: Useful Daylight Illuminance

WWR: Window to Wall Ratio

Keywords

Daylighting Simulation- Genetic Algorithms- Cellular Automata- Parametric Design- Generative Systems- Solar Screen- Performative Design

Software Used

DIVA: It is a simulation program which interfaces *Radiance and Daysim* engines for the daylighting calculations and *EnergyPlus* engine for thermal analysis. It stands for Design, Iterate, Validate, and Adapt.

Galapagos: It is an evolutionary solver for optimization in Grasshopper which was used to represent Genetic Algorithms.

Grasshopper: It is a graphical algorithm editor as a plug-in Rhino 3-D modelling software for parametric modelling without the need for a prior experience in programming.

Rabbit: it is a plug-in for Grasshopper which can explore pattern formations using Cellular Automata as a generative system.

Rhino: It is 3-D NURBs modelling software used for computer graphics and as computer aided design tool.

Speed-Sim: It is a parallel simulation tool used for DIVA in Grasshopper. It exploits the number of cores in the computer to speed the simulation time.

Other Software

BEopt (Building Energy Optimization): It is an optimization software that can evaluate residential building designs which uses EnergyPlus for simulation analysis.

DOE-2: It is a building program for energy analysis which can perform hourly simulation to predict energy use and cost.

GenOpt®: it is an optimization tool for multi-dimensional problems which can be coupled with simulation programs like EnergyPlus *(a whole energy simulation program).*

ParaGen: It is a tool that explore design alternatives combining parametric modeling, performance simulation software and genetic algorithms.

TRNSYS: It is an energy simulation software package.

GENE-ARCH: It is design tool that combines DOE-2 for the simulation analysis with Genetic Algorithms as the search engine.

Important Definitions

Algorithm: It is a number of steps to find a solution for a definite problem.

Cellular Automata: It is a well-known generative system that imparts a sense of visual quality and guides form generation**.**

Black count: It is the number of solid cells in the first row of the screen array. It controls the openness factor of the solar screen.

Circadian System: It is acting as a biological clock in the human beings affecting sleep patterns and alertness level and it is regulated by daylight.

Deterministic algorithms: They take predictable exact values as an input for the design variables thus, they do not accept the possibility of chance or probability

Exhaustive enumeration method: An optimization method where all possible solutions are evaluated. They are most probably not practical due to computational time.

Generative Design: It is a rule-based design process through which design forms are generated.

Generative Performative Design: An integrated design approach that combines Performative design and generative systems.

Genetic Algorithms (GAs): They are an evolutionary algorithm that are used widely in building optimization. They work on replacing a population of solution with another fitter population by simulating the genetic operators of reproduction, mutation and crossover.

Heuristic methods: They are problem solving techniques that enable searching and discovering the design space.

Optimization: To make something perfect, functional or effective as possible which could be by finding the maximum or minimum of a function.

Parametric Design: It is a design process in which numerous design alternatives of building models can be generated through the identification of a set of relationships between the geometric entities. Interdependencies are governed by mathematical function(s).

Pareto optimal/optimization: It is referred to multi-optimization problems where no objective can be better unless the other is negatively affected.

Performative design: It is a design approach that combines form generation and performance, considering both through optimization algorithm and simulation techniques.

Solar Screens: shading element that was used to be applied in the Middle East for privacy and shading intents.

Solution space: It refers to all possible alternatives for problem solving which is formed by cross-referencing all design variables.

Stochastic algorithms: are randomly determined algorithms where random variables are added to the optimization problem. Otherwise, randomness is introduced in the search process as in Genetic Algorithms.

List of Contents

List of Figures

List of Tables

INTRODUCTION

- OVERVIEW
- PROBLEM DEFINITION
- HYPOTHESIS
- RESEARCH OBJECTIVE
- RESEARCH METHODOLOGY
- RESEARCH STRUCTURE

Overview

Building construction is from the largest and most important industries in the world. Its rapid increase has imposed the adoption of new approaches for building design. The approach towards simulation-based optimization has been widely utilized from the early beginning of the design process. Optimization techniques have been developed to cope with the rising demand for more efficient buildings. In spite of its challenges and limitations that hinder the replacement of conventional design methods, it is believed that it will become the norm in the near future.

Many different optimization strategies and methods have been developed trying to confront the various optimization problems related to building performance. The selection of the appropriate optimization algorithm is not a straight forward method that could be applied through a generic rule. Instead, a number of considerations should be taken into account. Searching through the various types of algorithms and the extent to which it could be appropriate for optimizing daylighting performance, genetic algorithm was chosen.

It is claimed that most of our time is spent in the indoor environment. Thus, that urges the realization of indoor spaces that comply with a high performance standards and the user satisfaction. Daylighting design is a challenging process that could be so rewarding from that perspective. There are many approaches for achieving successful daylight, implementing different strategies that consider both quality & quantity. This can be more attainable if it is thought about from the early beginning of the design. Taking this in to consideration, the transition phase from the urban context to the architectural scale is the critical phase to concern about. Any further treatments in the later stages won't recompense the value of the early adjustments in the conceptual design. Hence, the need of integrating parametric design with optimization algorithm comes in the conceptual design phase.

This study discusses the contributions of optimization algorithms in the field of the building design problems. The focus is on the combination of Genetic Algorithm (GAs) with parametric modeling and its potential to determine the set of best possible building geometry that fulfill a daylighting performance criterion.

Problem Definition

Daylighting is a critical element that is most probably neglected in the conceptual design phase or in best cases is casually considered. Daylighting design is a difficult process due to its variations throughout the day and year, besides the possibility of accompanying excessive heat gain. In general, the traditional design process is a complicated and a tedious process when it faces a large number of parameters. Considering simultaneously different aspects of conflicting objectives - aspiring to reach the optimal solution- would lead to a lot of trials and errors.

The question is: what is the approach that could impact the form generation in a way that meet both designers' aspiration and the intended performance criteria? Besides, on what basis could be the selection of the optimization algorithm to be integrated with the parametric modeling? Then, how its effectiveness can be explored for this particular daylighting study?

Hypothesis

Adopting generative performative design is an approach that could be so rewarding from the daylighting point of view. The conceptual design phase, where form generation is settled, impacts the success of the design solution. Coupling Genetic Algorithms (GAs) with parametric design is the proper selection for approaching daylighting performance problem as optimal solutions can be obtained with a limited number of simulations.

Research Objective

The main objective of this study is identifying the implicit relationship between the geometrical screen patterns and daylighting efficiency through generative performative design.

Secondary objectives

- Identifying the transformation occurred in the architectural design process, and how performance was prioritized.
- Highlighting the capabilities of generative systems in the formation of screen patterns that comply with a predefined criteria.

- Exploring the potentials of Cellular Automata (CA) as a generative tool in screen pattern formations for efficient daylighting performance.
- Exploring the potentials and limitations of Genetic Algorithms (GA) as an optimization tool was intended aiming to reach an efficient daylighting performance for a classroom space.

Research Methodology

The research is divided into a number of sequential stages:

- **Theoretical study**

First, a theoretical study on building optimization algorithms and parametric modelling was carried out to find the their contributions in achieving highly efficient designs. With an emphasis on daylighting performance, an investigation was done on daylighting simulation tools and metrics.

- **Analytical Study**

Analysing the capabilities of generative systems (Cellular Automata in specific) in complying with the daylighting requirements.

- **Simulation/Optimization Analysis**

By focusing on a classroom space as a case study, a generative system (Cellular Automata) and an optimizaion algorithm (Genetic Algorithm) were applied to form and optimize a screen pattern for efficent daylighting performance.

Research Structure

Chapter1: Inception of Performance-based design

It overviews the contributions of optimization algorithms in the building design particularly for daylighting design. It emphasizes the key role of the automation of the simulation process leading to the optimal design solutions, highlighting its potentials in comparison to the limited capabilities of the traditional design approach. Furthermore, it explores and classifies building optimization problems -performance based problems- and optimization algorithms, supporting the proper selection of an optimization algorithm for the daylighting performance criteria.

Chapter 2: Daylighting as a Performance Criteria

It introduces daylighting visual and non-visual aspects. Then, an overview on daylighting simulation programs and metrics is presented. Finally, the significance of integrating optimization for efficient daylighting is highlighted.

Chapter 3: Optimized Facades for Daylighting Performance: Classroom Case Study

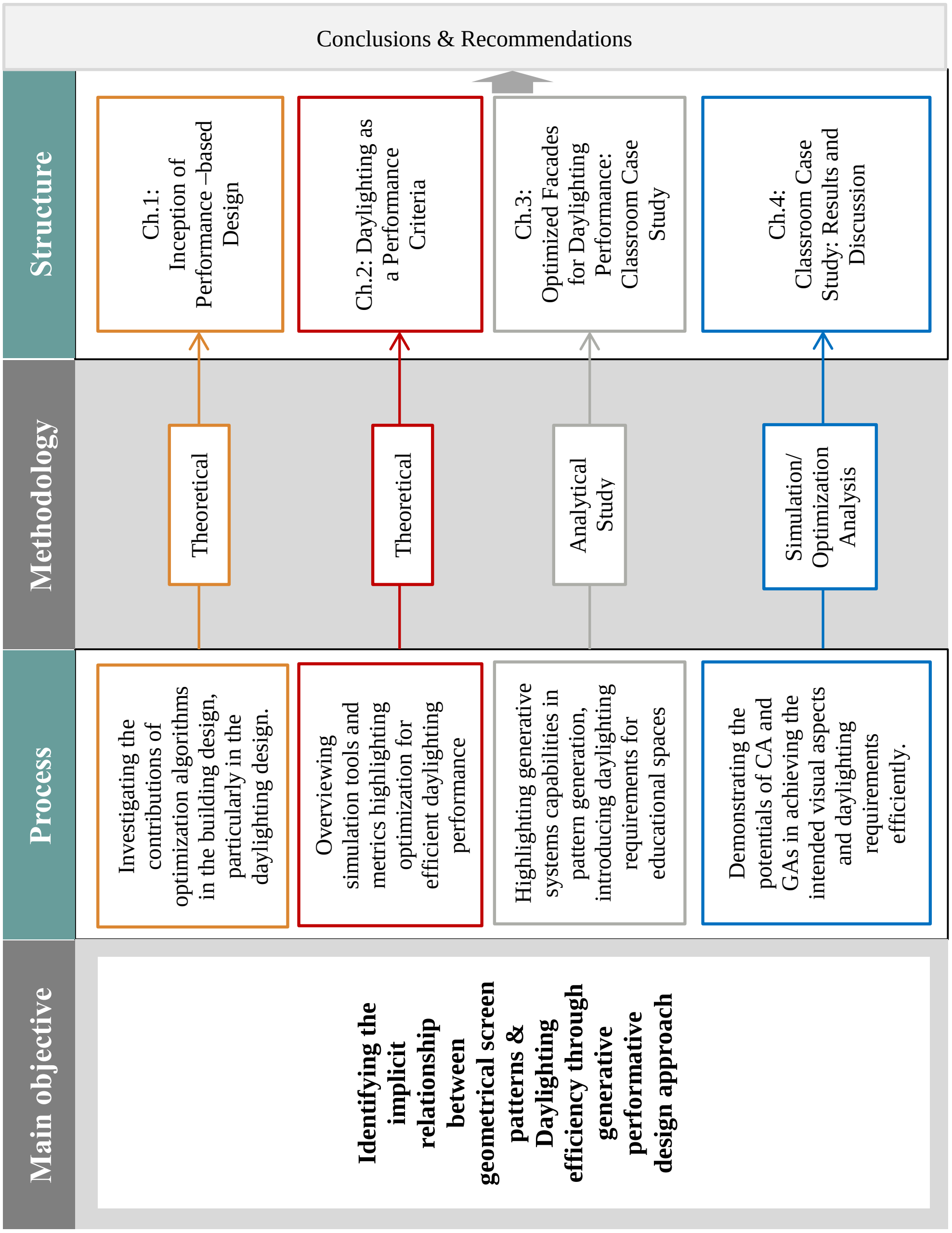
In this Chapter, a brief introduction on façade design treatments was given with an emphasis on solar screens as one of the well-known design treatments. Besides, an overview of different generative design systems was introduced to highlight their capabilities in pattern generation. Cellular Automata (CA) and Genetic Algorithms (GAs) were chosen for generating optimal solar screen design for a classroom space in the hot arid climate of Cairo.

Chapter 4: Classroom Case Study: Results and Discussion

Summing up with findings of the classroom case study, demonstrating the potentials of CA and GA in achieving the intended visual aspects and daylighting requirements efficiently.

Chapter 5: Conclusions and Recommendations

Highlighting the potentials of the adopted research methodology where generative performative approach was utilized, besides outlining the possible outcomes from expanding it to other research work.


Conclusions & Recommendations
Structure
Ch.1: Inception of Performance –based Design
Ch.2: Daylighting as a Performance Criteria
Ch.3: Optimized Facades for Daylighting Performance: Classroom Case Study
Ch.4: Classroom Case Study: Results and Discussion
Methodology
Theoretical
Theoretical
Analytical Study
Simulation/ Optimization Analysis
Process
Investigating the contributions of optimization algorithms in the building design, particularly in the daylighting design.
Overviewing simulation tools and metrics highlighting optimization for efficient daylighting performance
Highlighting generative systems capabilities in pattern generation, introducing daylighting requirements for educational spaces
Demonstrating the potentials of CA and GAs in achieving the intended visual aspects and daylighting requirements efficiently.
Main objective
Identifying the implicit relationship between geometrical screen patterns & Daylighting efficiency through generative performative design approach

CHAPTER 1

INCEPTION OF PERFORMANCE-BASED DESIGN

- DESIGN PROCESS IN THE ARCHITECTURAL PRACTICE
- TRANSFORMATION OF THE CONCEPTUAL DESIGN PHASE
- PARAMETRIC MODELLING
- OPTIMIZATION ALGORITHMS FOR BUILDING DESIN PROBLEMS
- SIMULATION-BASED OPTIMIZATION APPROACH

1.1 Introduction

Recently there has been a drift towards the utilization of building simulation tools for the evaluation of building performance. Different performance criteria have been adopted due to the uprising awareness of more efficient and greener buildings. Besides, the recent progress in computational techniques is making this trend easier to evolve than ever before.

Many different simulation tools that are applied to building performance analysis have arisen. The increasing demand for these tools has imposed the development of more-friendly user interfaces, working on decreasing the computational time, and other issues for the facilitation of their use. Through time and by practice, it was found that the design problem cannot be completely explored through these tools. They could be helpful in the analysis and the evaluation of a specific design alternative, or a limited number of alternatives, according to specified criteria. However, they are not efficient for evaluating a large number of solutions. This is could be an exhaustive process with a lot of trials and errors. Hence, the problem of design exploration comes which is suggested to be overcome by parametric design coupled with genetic algorithms.

This chapter introduces the architectural design process, focusing on the conceptual design phase and its significance for the decision making. It also investigates the transformation occurs in the design thinking starting from the paper-based methods till reaching the digital design age. A classification of digital design methods is presented emphasizing on the performance models and how it is incorporated in different design models to serve as the driving engine for design exploration. Thus, contributions of optimization algorithms in reaching high performance designs was investigated.

1.2 Design Process in the Architectural Practice

The design process is a set of actions that are taken in a hierarchal order aiming to reach an intended final output based on specific design requirements and objectives.[1] This set of actions is constantly changing through time trying to adapt with uprising design needs and respond to the demands of new design approaches.

In conceptual phases of the design process, the paper-based methods have been adopted as the main design media for centuries. It has not been so long since it was still believed

[1] G. Broadbent and A. Ward, 1969. *Design Methods in Architecture*: Lund Humphries London.

that it is more efficient in such early phases where the input data is changing and may be conflicting.[1] According to Schon and Wiggins, architectural practice based on these conventional methods like sketching and physical modelling is referred to as “reflective practice”. They develop the setting of their problem and create their own way towards its solution.[2] As for the evaluation of their own crafted solutions, Schon argued that they could implicitly state their own qualitative judgments, which is a reflection of their own knowledge and experience, but that does not mean that their solutions could be explicitly stated against specific criteria.[3]

However, a new approach has evolved which has changed the way of building design. Instead of depending on the designers' experience and knowledge in making design judgments, it can be made based on performance and generative criteria. This is what called a paradigm shift in design thinking.[4] This has emphasized the significance of decision making in the conceptual phase instead of its delegation to later design phases.

1.2.1 The Nature of the Architectural Design Process

The Design process can be described as an iterative process where a number of dependent or interdependent design tasks are performed in sequence till reaching a desired goal.[5] The effectiveness of this process can be revealed through this loop of action and assessment (activity and reflection) that is highly reliable on the design media. Design tools and techniques used influence the problem representation and how it is perceived. Thus, they affect the designers conceptual thinking to develop ideas and reflect upon the results.[6]

Design process can be described by four ways as shown in Figure 1-1[7]:

1. *Linear sequence*; It is a sequence of activity followed by a decision. It is a systematic way of thinking convenient for typical problems that are seldom used for innovative practice.

[1]I. Basa and B. Şenyapılı, (2005). "The (in) Secure Position of the Design Jury Towards Computer Generated Presentations." *Design Studies* 26, no. 3: 257-270 .
[2] D. A. Schon and G. Wiggins, (1992). "Kinds of Seeing and Their Functions in Designing." *Design studies* 13, no. 2: 135-156.
[3] D. A. Schön, 1983. *The Reflective Practitioner: How Professionals Think in Action*. Vol. 5126: Basic books.
[4] R. Oxman, (2006). "Theory and Design in the First Digital Age." *Design studies* 27, no. 3: 229-265.
[5] Y. E. Kalay, (1999). "Performance-Based Design." *Automation in construction* 8, no. 4: 395-409.
[6]J. Anderson, 2010. *Basics Architecture 03: Architectural Design*. Vol. 3: AVA Publishing.
[7] C. Gänshirt, 2007. *Tools for Ideas: Introduction to Architectural Design*: Walter de Gruyter.

2. *Testing and scanning*; the designer test the initial solution and if it doesn't meet his desired outcome, he returns back to find another one.
3. *Systematic production of alternatives*; in which the designer explores multiple design alternatives before making a decision. This variety of alternatives helps him in making his critical judgment and thus saving time possibly wasted in a lot of trials and errors.
4. *Forming alternatives in a multi-step process*; this differs from the previous in imposing a number of constrains when exploring the alternatives, thus reducing the vast design space into smaller viable one, so that design solutions will be filtered to the most relevant ones.

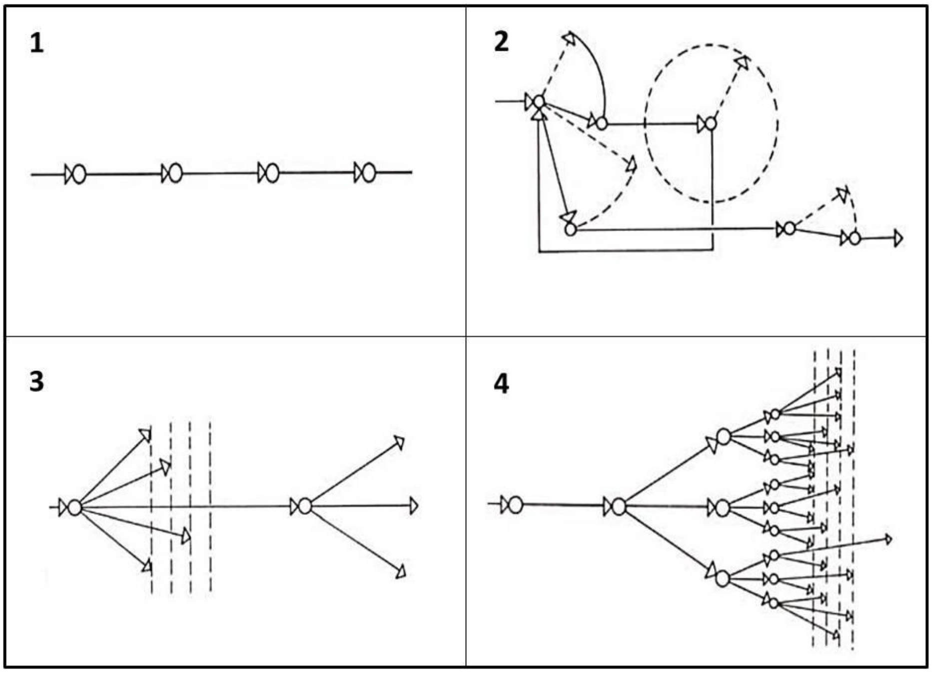


Figure 1-1: Schematic illustrations of four alternatives of the design processes 1) linear sequence 2) testing and scanning 3) systematic production of alternatives 4) Forming alternatives in a multi -step process[1]

Architectural design problems are complex; they vary greatly according to various stimuli/ circumstances affecting them. Various scientific problems are complex problems that seek for one single solution or proving one theory that rejects the others. On the contrary, in architectural design problems, there is no one best solution or one correct

[1] J. Anderson, 2010. *Basics Architecture 03: Architectural Design*. Vol. 3: AVA Publishing.

way to design, the perception of the problem, its representation and its solution are not confined to just one correct answer. Instead, multiple interpretations of each design problem are introduced. An empirical approach is followed for this problem solving.[1]

Normally, no two designers have the same response towards the same problem each have his/her own design process; it differs according to their own perception and understandings of the design problem and thus, their judgments differ. Critical judgment is a way of thinking for making decisions facing the challenge of comparing and choosing from multiple possible solutions.[2] It reflects the designers own knowledge and experience so it's a subjective assessment that's vulnerable to their bias and preferences. From here, new approaches have emerged that is able to quantify the criteria upon which the design is assessed. This emphasizes the significance of decisions made in the conceptual design phase that has a pivotal impact on the later stages.

1.2.2 Conceptual Design Phase

In the conceptual design phase, design objectives are interpreted as different preliminary concepts that need to be analyzed and filtered down to those eligible for further enhancements.[3] In other words, this phase represents two sub phases namely; divergent and convergent phases, where different alternatives are generated in the former, whereas in the latter they are grouped and nominated for selection according to specific criteria. The two steps are repeated sequentially till reaching promising concepts to be further developed in the modulation and the detailed phase.[4]

Decisions in the conceptual phase could be a turning point that transforms the design towards more efficiency in performance. In spite of applying high design standards is possible in further stages, this will not compensate the benefits of taking the right decision from the early beginning.[5] This emphasizes the significance of exploring different design alternatives in this early phase, consequently enhancing decision making.

Traditionally, in the early phases of design, where the design problem is represented, a set of solutions are suggested to meet the design requirements. The designer is constantly going back and forth between these alternatives coping with the uprising changes to best

[1] *Ibid*.
[2] *Ibid*.
[3] G. Pahl et al., 2007. *Engineering Design: A Systematic Approach*. Vol. 157: Springer Science & Business Media.
[4] Y.-C. Liu et al., (2003). "Towards an 'Ideal'approach for Concept Generation." *Design Studies* 24, no. 4: 341-355.
[5] M. Turrin et al., (2011). "Design Explorations of Performance Driven Geometry in Architectural Design Using Parametric Modeling and Genetic Algorithms." *Advanced Engineering Informatics* 25, no. 4: 656-675.

meet all required objectives. This set of actions is traditionally informed by functional and aesthetic aspects that rely on designer expertise and knowledge thus, leaving the performance and environmental issues to post design phases.[1] Paying attention to these shortcomings, a new design approach has been rapidly developed and adopted in the architectural practice today.

1.3 Transformation of the Conceptual Design Phase

The dynamic nature of the design activity and the continuous increase of complexity, besides the need for more sustainable buildings have imposed the development of new approaches. The constantly uprising demands are confronted with these approaches and techniques. A holistic design approach has emerged in which different aspects affecting building performance such as building form, orientation, interior design and structure are considered in the design process from the early beginning. This necessitates collaboration between all stakeholders for efficient decision making especially in the early design phase;[2] it is the necessity that always incites inventions.

Design concepts such as morphogenesis, generative design, and performance-based design have replaced the conventional concepts in the design theory. Through digital design thinking, new venues have been opened for design exploration and creativity, departing from typological and deterministic environment to where formation, generation and performance are the driving design forces.[3] The formation of new form of knowledge, theoretical basis and models of design based on digital design are dominating the current architectural discourse.

Developments in the computational technology have made it possible to support this shift in design thinking. Initially, computational design has been exploited as a complement of the paper-based methods; it has been used in visualization, drafting and documentation. The Computer-aided-design (CAD) models are considered as the first step towards digital design modelling. They have been used since the early 1980’s.[4] First, they have been acting as descriptive models by which different graphical representations

[1] *Ibid*.
[2] Q. Zuo et al., (2010). "Integrating Performance-Based Design in Beginning Interior Design Education: An Interactive Dialog between the Built Environment and Its Context." *Design Studies* 31, no. 3: 268-287.
[3] R. Oxman, (2008). "Digital Architecture as a Challenge for Design Pedagogy: Theory, Knowledge, Models and Medium." *Design Studies* 29, no. 2: 99-120.
[4] R. Ramilo and M. R. B. Embi, (2014). "Critical Analysis of Key Determinants and Barriers to Digital Innovation Adoption among Architectural Organizations." *Frontiers of Architectural Research* 3, no. 4: 431-451.

could be reached through modelling and rendering software.[1] It is described to be an imitation of the conventional paper methods with a different representational environment. By estimating their contributions in the qualitative aspects of the design, relative to the conventional paper based methods, it is found to have a little impact.[2]

Another direction has been evolved in which the use of computational tools is not confined to the representation or the visualization aspects. Instead, it is based on making use of the computational capabilities where simulations and calculations offer other methods and processes for design generation that could be based on performance aspects.[3] Digital design tools have been converted from drafting to be actually acting in the design thinking process. This direction provides designers with the possibility to inform the design evaluation, thus converting the implicit cognitive process in the former direction to be explicit in this one.

The digital design thinking imposes other demands regarding the knowledge of the updated technologies and their capabilities. Designers' role includes acting as a tool maker and this is reflected in their interaction with computational mechanisms, besides the digital representation itself. The centrality of the designer is preserved with a high degree of control over the design media. Thus, facing the challenge of acquiring the needed knowledge to operate and manipulate different design media and being up to date with the technological and media developments is inevitable.[4]

1.3.1 Emergence of Digital Design Models

The digital design process is considered a unique set of actions rather than an alternative for the conventional process that differs in design media.[5] Different digital design models have demonstrated the uniqueness of digital design thinking. Thus, supporting this transformation and emphasizing on its assets. Great implications have resulted from this transition; conventional concepts and principles have been replaced by other design concepts related to performance, generation and other issues.[6] Accordingly, digital design tools have been involved in design thinking rather than merely drafting.

[1] R. Oxman, (2006). "Theory and Design in the First Digital Age." *Design studies* 27, no. 3: 229-265.
[2] Y. E. Kalay, 2004. *Architecture's New Media: Principles, Theories, and Methods of Computer-Aided Design*: MIT Press.
[3] Q. Zuo et al., (2010). "Integrating Performance-Based Design in Beginning Interior Design Education: An Interactive Dialog between the Built Environment and Its Context." *Design Studies* 31, no. 3: 268-287.
[4] *Op. cit.: R. Oxman, (2006).*
[5] *Op. cit.: R. Oxman, (2006).*
[6] R. Oxman, (2008). "Digital Architecture as a Challenge for Design Pedagogy: Theory, Knowledge, Models and Medium." *Design Studies* 29, no. 2: 99-120.

Digital design or computational architecture incorporate mathematical or logical processes for the exploration and manipulation of geometric forms. They are classified according to their underlying concepts into:[1]

- *Topological architecture*; it represents a departure point from the typological Euclidean geometry to topological space where non-Euclidean geometry are represented through a Non-Uniform Rational B-Spline curves and surfaces (NURBS). Relationships between geometries are set by parametric functions.
- *Isomorphic architecture*; another transition comes by isomorphic surfaces (Blobs and Metaballs) where fields of attraction and repulsion are formed. Objects are constantly interacting with each other reacting to any change in location or intensity.
- *Animate architecture*; the role of the animation software is shifted to be the driver of the form generated rather than merely a visualization medium. Forces and motion are considered the incentive behind form generation. The bus terminal in NewYork by Greg Lynn is a well-known example of animate architecture where the movement of pedestrians, buses and cars are the driving force behind generating the roof shape and lighting scheme.
- *Metamorphic architecture*; in this design model, geometrical forms undergo transformations by techniques like Keyshape animation and deformation of the modeling space.
- *Parametric architecture*; forms are defined through parameters and their relationships and interdependencies are governed by mathematical function(s). A complete control on geometrical behavior is acquired through the manipulation of parametric values and equations.
- *Evolutionary architecture*; generative rules are what define and control form generation. Emulating the nature's evolutionary processes, it offers potentials for creativity and generation; unexpected forms are emerged and can be evaluated according to performance criteria. Genetic algorithms are considered to be 'Key concept' in evolutionary architecture. The critical part is not modeling the shape itself but the logic behind its generation.

To clarify more these emerging digital concepts, another classification is represented in more detail where processes of formation, generation, performance are illustrated, highlighting performance as a key concern in the early design stages.

[1] B. Kolarevic, (2000). "Digital Morphogenesis and Computational Architectures." *Construindo n (o) espaço digital, PROURB, Universidade Federal do Rio de Janeiro, Rio de Janeiro*: 98-103.

A framework suggested by Oxman in which she classifies digital design models into five models: CAD models, formation models, generation models, performance models, and integrated compound models.[1]

- *CAD models*; they represent the early transition from paper based media to digital design media. However, it could be considered an imitation of paper based design. They could be described through two subdivisions: descriptive CAD models and Predictive CAD models. In the former, modeling and rendering software provide designers with the graphical environment where interactions with geometric entities can occur. Whereas predictive CAD models enabled analytical evaluation where analysis and synthesis are performed sequentially on geometric models that are already developed.[2]
- *Formation models*; they represent the actual start of the digital architectural design (DAD), which differs from the computer- aided- design (CAD); these models start to be liberated from the static formal representation of CAD models. Not as it was, where the concept of form is the concern, the concept of formation has dominated. New forms of representation have emerged where dynamic concepts can inform the formation process. Topological and non-deterministic processes have dominated over the convention typological and deterministic processes. Giving a high degree of interaction and control, responsive design can be acquired. Parametric design and animation are two subclasses of formation models that have brought in the concepts of topological variation and dynamic design. Animation can be employed as a driving force for form generation; form transformations are based on simulating the field of forces.[3] In parametric design, interdependencies between parameters and the transformational logic of the geometric entities are defined rather than their static shape. Thus, by making use of the associative modeling, a large number of alternatives can be reached.[4] An emphasis on parametric design will be illustrated in the next section.
- *Generative models*; these models explicate the generative processes within the digital environment; formal digital representations are generated by a mechanism. These computational mechanisms, which are derived by a set of rules or relations, define the generative processes by which shapes and forms are generated. This is what differs them from formation models where formal

[1] R. Oxman, (2006). "Theory and Design in the First Digital Age." *Design studies* 27, no. 3: 229-265.
[2] *Ibid*.
[3] *Ibid.*
[4] M. Stavric and O. Marina, (2011). "Parametric Modeling for Advanced Architecture." *International journal of applied mathematics and informatics* 5, no. 1: 9-16.

qualities are not predefined. It allows the designer intervention to guide the selection mechanisms to meet their goals. Not only one can interact with the digital representation but also with its operative part.[1] Shape Grammars, Cellular Automata and Evolutionary Algorithms are well-known examples for generative models. The generative design model is described in Figure 1-2.

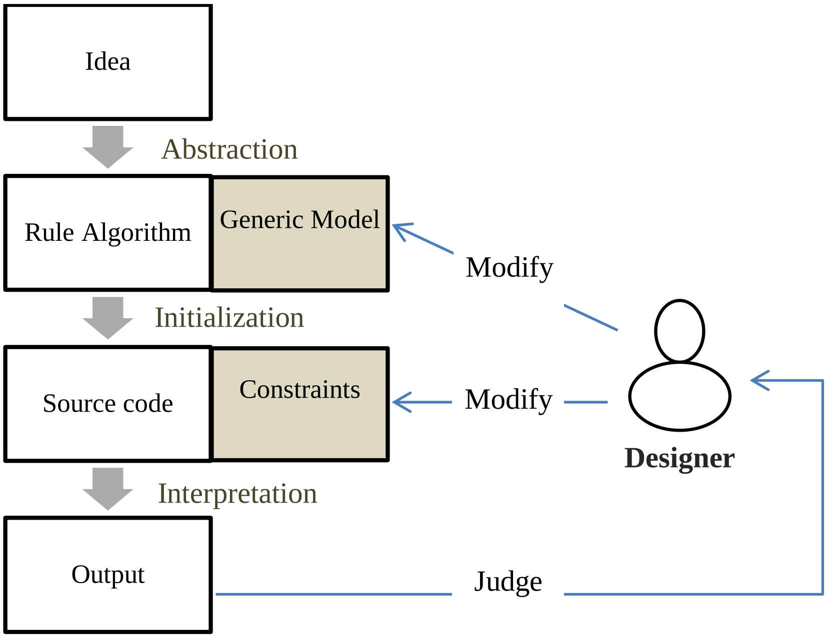


Figure 1-2: Generative Design Model[2]

- *Performance models*; It is agreed that decisions taken in the early design phases of building design has a great impact on the whole design. Mistakes result from wrong decisions in these phases may cause huge penalties especially in large projects. These decisions are influenced by the design media, tools, and techniques being used. In this design model, performance issues are what inform the decision making, instead of leaving the designers taking decisions based on their critical judgment that depends on their own knowledge, understandings and representation of the problem.

[1] R. Oxman, (2006). "Theory and Design in the First Digital Age." *Design studies* 27, no. 3: 229-265.
[2] S. Krish, (2011). "A Practical Generative Design Method." *Computer-Aided Design* 43, no. 1: 88-100.

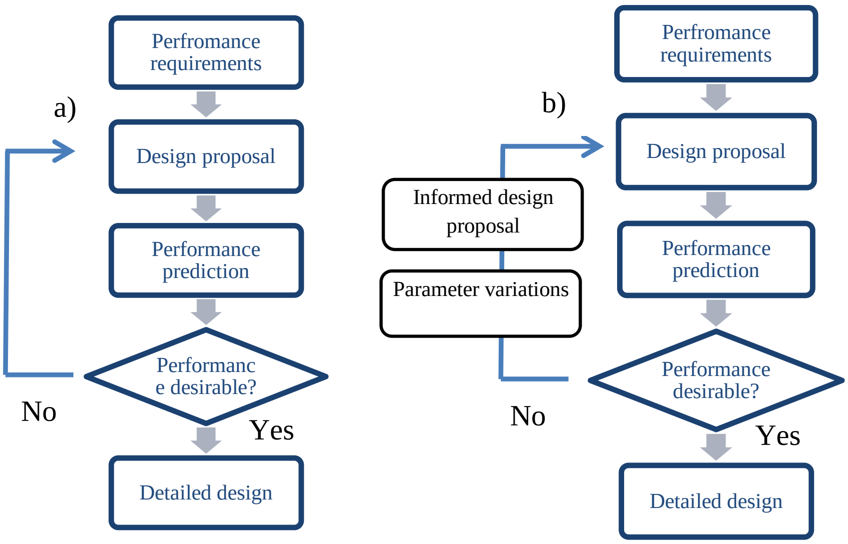


Figure 1-3: a) The workflow in performance-based design, b) the proposed modification on the performance-based design workflow [1]

Trying to support designers for making better decisions, Performance based design as a paradigm is first introduced by Kalay[1]. He described the workflow as in Figure 1-3a the design iteration first starts with defining the performance requirements, and then an initial design is proposed that to be evaluated relative to the performance criteria.[2] Thus, simulation tools are integrated in the workflow for performance evaluation. They act as a guide to decide whether to stop the iterations or not; however, they don't support the designer with active solutions if the criteria is not met.[3] In case of rejected performance, the critical part is in identifying the required modification to meet a certain criterion without affecting another one negatively which has been already satisfied. This is a common act with inexperienced designers especially when facing novel situations. Accordingly, a large number of iterations is needed until reaching a satisfactory solution; that may lead to an endless loop of trials and errors. A modification on this work flow is suggested by Petersen and Svendsen[4] to mitigate these limitations. A subtask is added within the work flow called "parameter variation" as shown in Figure 1-3b. This added the value of knowing the effect of varying different design parameters on the required performance. Thus, it facilitates the decision making process and reduces the number of design iterations. Parameter variations could be performed on one parameter at a time, so

[1] Y. E. Kalay, (1999). "Performance-Based Design." *Automation in construction* 8, no. 4: 395-409.
[2] *Ibid.*
[3] S. Petersen and S. Svendsen, (2010). "Method and Simulation Program Informed Decisions in the Early Stages of Building Design." *Energy and Buildings* 42, no. 7: 1113-1119.
[4] *Ibid.*

it acts as differential sensitivity analysis; knowing how much the effect of each parameter on the performance prior taking any design action. However, it ignores the interaction between parameters; hence in other cases the effect of a combination of parameters can be explored.[1] This method has proved its superiority upon the previous performance-based design workflow. A survey have been conducted and found that the average number of design iterations is 2.8, which is definitely not enough number to reach the optimal solution due to the complexity of the design problems. This is the case because it is time consuming process, besides they tend to validate a certain design solution rather than exploring a number of alternatives.[2] Hence an effective approach that directly automates this iterative process searching for the optimal desirable solutions has appeared. Another class of performance models differs from performance-based design which is the performance-driven design. This difference is discussed by Shi; the main difference is the incorporation of optimization technique in the workflow, as shown in Figure 1-4, to act as the driving engine for form generation.[3]

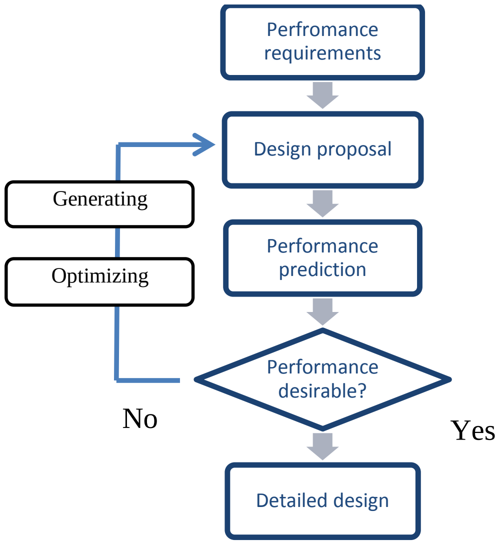


Figure 1-4: The workflow in performance-driven design[4- 5]

[1] *Ibid.*
[2] F. Flager et al., (2009). "Multidisciplinary Process Integration and Design Optimization of a Classroom Building." *Journal of Information Technology in Construction* 14: 595-612.
[3] X. Shi, (2010). "Performance-Based and Performance-Driven Architectural Design and Optimization." *Frontiers of Architecture and Civil Engineering in China* 4, no. 4: 512-518.
[4] S. Petersen and S. Svendsen, (2010). "Method and Simulation Program Informed Decisions in the Early Stages of Building Design." *Energy and Buildings* 42, no. 7: 1113-1119.
[5] *Op. cit.: X. Shi, (2010).*

In short, performance based models transform the implicit interrelation between the designer and the performative requirements to be explicated within the framework of the design process. They are driven either by analytical or generative simulations accordingly, they are categorized into *performance-based formation* models and *performance-based generation* models. In the former, performance acts as a formation technique in which analytical simulations of the desired performance drives the formation process. While in the latter, generative processes are driven by performance; simulations for synthesis and generation replace the conventional analytical simulations. The generative processes directly modify the form to meet the required design goals.[1]

Pointing out that processes of formation, generation, and performance could be integrated within the digital design media,[2] other approaches have been emerged.

1.3.2 Generative Performative Design

Based on the previously mentioned design models an integrated approach called "Generative Performative Design" has emerged.[3] Performative design alone is an approach derived from performance models. It amalgamates form generation and performance, considering both through optimization algorithm and simulation techniques. No longer are simulation tools utilized for analysis only, but they are used for both performing analysis and synthesis simultaneously; form is driven by generative processes guided by analytical simulation techniques that automatically modify the model. The concept of *form making* shifted to be *form finding*.[4] Geometric models are needed to be formulated in a way that reacting to the stimulus of the evaluation process and complying with the modifications of the generative process can be in a consistent manner. Hence, parametric modeling is essential to support the generative process informed by the performance evaluation.[5] In short, perfromative design as an important design paradigm in architecture intended mainly to meet building performance requirements. It needs three consecutive processes:

- Parametric Modelling
- Optimization Algorithm

[1] R. Oxman, (2006). "Theory and Design in the First Digital Age." *Design studies* 27, no. 3: 229-265.
[2] *Ibid.*
[3] E. Fasoulaki, "Integrated Design: A Generative Multi-Performative Design Approach" (Massachusetts Institute of Technology, 2008.(
[4] R. Oxman, (2009). "Performative Design: A Performance-Based Model of Digital Architectural Design." *Environment and planning. B, Planning & design* 36, no. 6: 1026.
[5] R. Oxman, (2008). "Performance-Based Design: Current Practices and Research Issues." *International journal of architectural computing* 6, no. 1: 1-17.

- Simulation Technique

On the other hand, generative design captures the aesthetics qualities of the design through a rule-based process that inform the generation of large range of solutions. Combining both models in one approach gives the advantage of reaching the aesthetic quality aspired while respecting the performance criteria needed. This would be through:

- Parametric Modelling
- Generative System
- Optimization Algorithm
- Simulation Technique

1.4 Parametric Modelling

Parametric modelling/design is a process in which numerous design alternatives of building models can be generated through the identification of a set of relationships between the geometric entities. Those entities are represented through variables and function(s) that relate them together. Thus, it offers the designer with the ability to change the variables values for creating a number of alternatives, avoiding the exhaustive traditional process.[1] In the latter, the process requires repeating the design from scratch for every change. On the other hand, in parametric modelling, the original design is defined by a number of predefined variables from which a whole set of alternatives can evolve. The critical part in setting a parametric model lies in defining the design constraints and the logic that controls parameters' modification.

Parametric modelling gives the chance to generate different solutions of different attributes, but the problem appears when the search space is big, this arouses the issue of how this amount of alternatives could be evaluated and selected according to performance criteria. This is a cumbersome process that could last for a long time without reaching a satisfactory solution, therefore there is a need to assign an algorithm that aims to optimize the performance criteria. It is working on finding the link between geometric attributes and performance, accordingly it is aimed to minimize or maximize a given objective function to reach an optimal or near optimal solutions.[2]

[1] M. Turrin et al., (2011). "Design Explorations of Performance Driven Geometry in Architectural Design Using Parametric Modeling and Genetic Algorithms." *Advanced Engineering Informatics* 25, no. 4: 656-675.
[2] *Ibid.*

There are large numbers of different optimization algorithms that are used in building performance design. A quick overview of these optimization methods with the most appropriate for approaching the daylighting problem will be held in the next section.

1.4.1 Potentials and Limitations of Parametric Modelling

A number of reasons have made parametric modeling adopted in large scale in the last few decades. They could be summarized as follows[1]:

- The ability to generate a large set of alternatives that could be analyzed and evaluated based on predefined criteria.
- Parameters manipulation allow the exploration of different, may be unexpected, configurations, hence, opening avenues for creativity and innovation.
- The interaction of the designer have increased and facilitated, allowing him to visualize prompt variations on the 3D model. Thus, provides him a quick evaluation based on either predefined performance or aesthetic criteria or even a relative comparison between instances.
- Another important benefit appears in interdisciplinary and decomposing complexity; based on the parameterization process itself in which the model structure is defined, it is accepted for different disciplines to share in the setup of the design strategies and subtasks. This setup explicates the hierarchical associations between geometries.

Besides the potentials that contribute in this wide spread, there are a number of limitations. Sometimes limitations are faced when the need for high level of computation. This could imply decreasing the number of parameters forming a partial model (partial representation of geometric entities) by which the computation level can be overcome.[2]

Another important problem appears when exploring large solution spaces. In this case, the complete success of the parameterization process depends on the selection of the appropriate range of solutions accordingly, depends on the search mechanism that satisfy the performance criteria.[3]

1.4.2 Problem of Design Exploration

Design exploration requires the study of the different parameters affecting performance, this is through parametric analysis that basically relies on building simulation tools, but

[1] *Ibid.*
[2] *Ibid.*
[3] *Ibid.*

at the same time this will not guarantee an optimization. Hence, optimization techniques are needed for exploring the solution space more efficiently and effectively.[1]

The problem of exploration is interrelated with evaluation; constantly the feedback from the evaluation process supports the exploration process. It could be impossible to evaluate every possible solution; they are numerous so they will be time consuming and need a high computation level. On the other hand, if it is left to the designer's intuition or experience to choose the range of solution to be evaluated, it may work, but probably the results will be questionable. From here comes the need for a more digital support.

The support of an optimization algorithm in the design process could be inevitable in some cases. The question here is when it should be coupled with parametric modeling, what could be appropriate for building performance analysis in general and what is more suitable for daylighting performance in particular.

Mainly, optimization techniques play the role of a search mechanism to find the optimal or near the optimal values of parameters based on particular criteria.[2] A number of factors affect the extent of the optimization technique fitness to a certain problem. Generally, an important issue is the range of solutions generated. According to Turrin et al. in design problems a range of solutions is needed for optimization instead of just one for avoiding the problem of discarding suboptimal solutions.[3] Hence, a focus on the population based optimization algorithms are illustrated further on.

1.5 Optimization Algorithms for Building Design Problems

Building design is not a straight forward process that could be the same for all buildings even of the same type. Each has its own circumstances that could differ greatly depending on the purpose, the site, client, target group, etc. The different parameters affecting their creation and their large range of possibilities have contributed in the complexity of the process. The selection of the best possible solution among a large solution space is a tedious task without applying an optimization algorithm.

To optimize something means to make it perfect, functional or effective as possible. In mathematics and other sciences, optimization is a process in which the best possible

[1] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.
[2] M. Turrin et al., (2011). "Design Explorations of Performance Driven Geometry in Architectural Design Using Parametric Modeling and Genetic Algorithms." *Advanced Engineering Informatics* 25, no. 4: 656-675.
[3] *Ibid.*

solution is sought; by determining the maximum or minimum values of a specified function that is subjected to a set of constraints.[1] In building design problems it is not necessarily to find the optimum but it could be a solution near the optimum.[2]

In building design, complex problems could be faced which need unconventional techniques to handle them. At that point, heuristic techniques could be vital. They are problem solving techniques that enable searching and discovering the design space. They can be used for optimization where reaching the optimum solution cannot be ensured, but they are promising methods for finding the near optimal. Evolutionary algorithms are the mostly used, they are stochastic population-based algorithms that mimic the principles of natural evolution, for each time step new solutions are generated and the poorest ones are eliminated. There are other methods that could be used instead of evolutionary algorithms; one popular method is the direct search methods. Direct search methods such as pattern search and linear and non-linear programming can be used, but their main limitation is getting stuck in a local optima.[3]

Application areas of optimization algorithms in building design problems are constantly evolving.[4] The challenge is in selecting the most suitable optimization methodology for a specific design aspect. Thus, there is a need for classifying Building Optimization Problems (BOP) and optimization algorithms to be the base in selecting the appropriate optimization algorithm for a certain building design problem. Besides, it can help in creating new strategies for approaching building optimization problems.[5]

1.5.1 Classification of Building Optimization Problems (BOP)

Areas of application related to building design and control that could make use of optimization techniques are vast; they include:[6] daylighting performance, automated solar shading control, building layout and form, natural ventilation strategies, façade design, thermal comfort, geometry position, density of fenestration, energy use, heating, ventilating and air conditioning (HVAC) systems sizing. In addition, more than one

[1] The dictionary, http://www.thefreedictionary.com/OPTIMIZE, last accessed: 10-10-2014
[2] A.-T. Nguyen et al., (2014). "A Review on Simulation-Based Optimization Methods Applied to Building Performance Analysis." *Applied Energy* 113: 1043-1058.
[3] R. Evins, (2013). "A Review of Computational Optimisation Methods Applied to Sustainable Building Design." *Renewable and Sustainable Energy Reviews* 22: 230-245.
[4] S. Attia et al., (2013). "Assessing Gaps and Needs for Integrating Building Performance Optimization Tools in Net Zero Energy Buildings Design." *Energy and Buildings* 60: 110-124.
[5] A.-T. Nguyen et al., (2014). "A Review on Simulation-Based Optimization Methods Applied to Building Performance Analysis." *Applied Energy* 113: 1043-1058.
[6] *Op. cit.: S. Attia, (2013).*

objective can be optimized simultaneously, e.g. simultaneous optimization of building envelope and HVAC elements.

Building optimization problems can be classified as follows: number, nature and type of design variables, number and nature of objective functions, presence of constraints and their nature, and the problem domain. Most of BOP are constrained, these set of constraints define the solution space. If more than one domain is considered in the optimization, then it is a multidisciplinary optimization and it is much more complex than the single domain optimization. In general, BOP can be classified according to their variables (number, nature, and type) and their objective function (number and nature)[1] as shown in Figure 1-5. If more than one variable exist then it is multi-dimensional optimization. The assigned variables could be independent or associated with each other with relationship to be in that case mutually dependent. They also can accept only discrete values or any real number (continuous values).

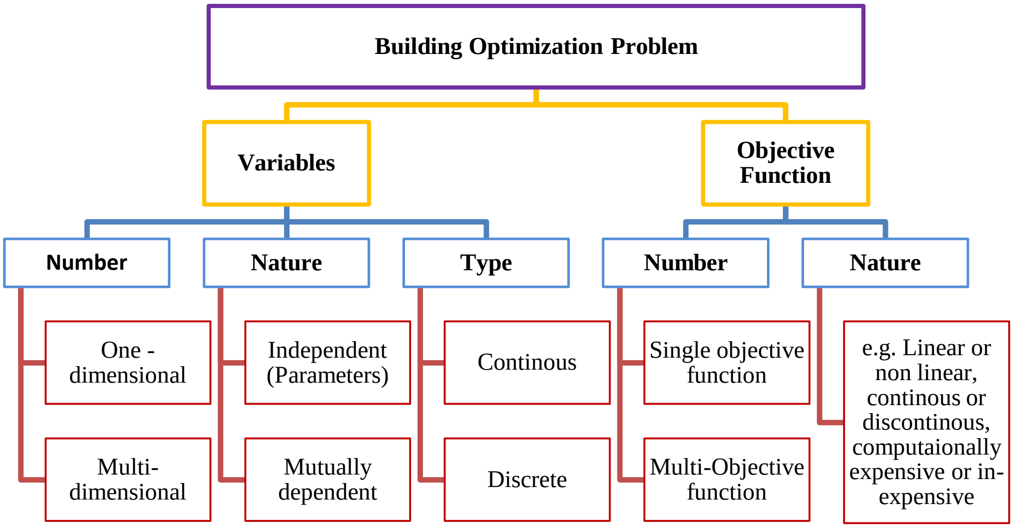


Figure 1-5: Classification of building optimization problems

Any optimization problem is represented by an objective function. In case there is more than one objective function then this problem needs a multi-objective optimization. There are two ways for approaching this type of problems: weighted sum function and pareto

[1] A.-T. Nguyen et al., (2014). "A Review on Simulation-Based Optimization Methods Applied to Building Performance Analysis." *Applied Energy* 113: 1043-1058.

optimal.[1] However, More than half the number of the building optimization studies is single objective according to Evins.[2]

- *Weighted- sum function*

For each objective a weight factor is assigned then integrated to form a single objective function. It is an efficient and easier way to implement, but it doesn't provide any information about how different objectives affect each other. Besides, there is a difficulty in assigning those weight factors due to the differences in their objectives, significance, and metrics; it requires prior knowledge for setting the right weight factors. Another drawback is giving only one solution, however; to get through this, different factors can be assigned for getting different solutions.[3]

- *Pareto Optimal*

A solution is called Pareto optimal or is referred to Pareto optimization when a compromise between objectives is set in response to their contradictions. It is referred to multi-optimization problems where no objective can be better unless the other is worse. The diverse solutions formed are called Pareto frontier showing the trade-off between the objectives. In case of two objectives, the so-called "Pareto frontier" is represented by a curve as shown in Figure 1-6. The advantage of the Pareto solution is exploiting a diversity of solutions unlike the weighted sum. Due to the complexity of building optimization problems, most studies uses only two objective function. The critical part is the selection of the best solution from the Pareto front.

[1] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.
[2] R. Evins, (2013). "A Review of Computational Optimisation Methods Applied to Sustainable Building Design." *Renewable and Sustainable Energy Reviews* 22: 230-245.
[3] Ibid

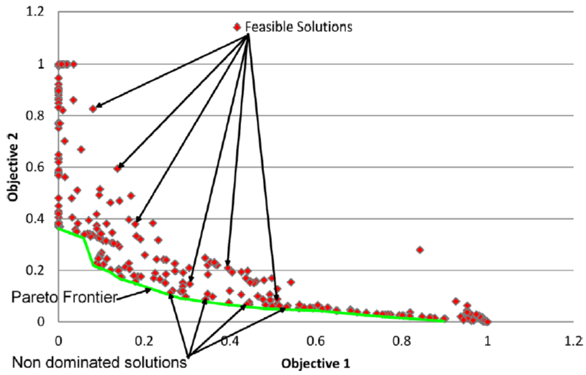


Figure 1-6: A Prototype of a Pareto Optimal Problem Having Two Objectives[1]

1.5.2 Classification of Optimization Algorithms

The design problem itself is what affects the performance of the optimization method used; for each specific problem there should be a thorough selection for the appropriate optimization method. In case the optimization method is coupled with a building simulation program, the main problem faced is the computation time; simulations last from a few seconds to several hours or even days depending on several parameters.[2] This is just for a single evaluation and the optimization method may require hundreds or even thousands number of evaluations and still cannot guarantee finding the optimal solution. Hence, there is a need for presenting the reasoning behind the optimization problem addressed and the corresponding optimization technique selected.

In general, optimization algorithms used in building design problems can be classified into:[3]

- Enumerative
- Deterministic
- Stochastic

In the exhaustive enumeration methods, all possible solutions are evaluated thus, they are most probably not practical due to computational time. However, parallel computing can

[1] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.
[2] *Ibid.*
[3] S. Attia et al., (2013). "Assessing Gaps and Needs for Integrating Building Performance Optimization Tools in Net Zero Energy Buildings Design." *Energy and Buildings* 60: 110-124.

mitigate this problem. In a previous study, the exhaustive search method was utilized to find the true optimum among 1600 alternatives formed by all combinations of variables. It was a daylighting study where the huge computational time was overcome by a parallel simulation tool[1] developed to enable the calculation engine-which was Radiance- to conduct multiple simulation runs at the same time. The potential of this method lies in showing the influence of each variable and their interaction on the overall performance. It can also be used to benchmark other possible methods that do not guarantee finding the optimal.[2]

Deterministic algorithms take predictable exact values as an input for the design variables thus, they do not accept the possibility of chance or probability (e.g. direct search and sequential quadratic programming algorithms). These particular requirements may not be met in design performance problems with high constrains or multi objective functions. However, stochastic algorithms overcome these previously mentioned problems as they do not have mathematical restrictions and can deal with highly constrained problems.[3]

In stochastic algorithms, which means randomly determined algorithms, random variables are added to the optimization problem. Otherwise, randomness is introduced in the search process as in Genetic Algorithms.[4] Nguyen, Anh-Tuan et al.[5] have estimated the use of various optimization algorithms in more than 200 building optimization studies and found that stochastic population-based algorithms are the mostly used. These algorithms cannot ensure the true optimal solution; however, they have high probability of obtaining good solutions. [6]

A well-known stochastic population based algorithm is the evolutionary algorithms. These algorithms can handle nonlinear problems without being stuck in local minima (where it is thought to be the best solution). Genetic Algorithms (GAs) is an evolutionary algorithm that is used widely in building optimization. It imitates the principles of natural evolution where populations of solutions are created through the processes of reproduction, crossover and mutation that work on the survival of the fittest.[7] The first

[1] A. Wagdy, "Speedsim for Diva" http://www.aymanwagdy.com/#!speedsim/cjg9 (accessed 21-12-2015).
[2] A. Wagdy and F. Fathy, (2015). "A Parametric Approach for Achieving Optimum Daylighting Performance through Solar Screens in Desert Climates." *Journal of Building Engineering* 3: 155-170.
[3] S. Attia et al., (2013). "Assessing Gaps and Needs for Integrating Building Performance Optimization Tools in Net Zero Energy Buildings Design." *Energy and Buildings* 60: 110-124.
[4] *Ibid.*
[5] A.-T. Nguyen et al., (2014). "A Review on Simulation-Based Optimization Methods Applied to Building Performance Analysis." *Applied Energy* 113: 1043-1058.
[6] *Ibid.*
[7] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.

population (generation) is randomly selected, then new solutions are created aiming to enhance their fitness against the specified objective criteria thus, forming new population better than the previous and so on.

Other stochastic algorithms exist like Particle Swarm Optimization (PSO), and Simulated Annealing (SA) which are called heuristic, but their low contributions in building design problems, relative to Genetic Algorithms (GAs), is seemed to be. In cases their contributions in building design are found, daylighting was not considered in their application. PSO, the most common relative to others, was used by Rapone and Saro[1] to optimize curtain wall facades for office buildings.

These algorithms could be combined forming hybrid algorithms thus exploiting the potentials of both algorithms. An optimization study was carried out making use of hybrid algorithms (Particle swarm optimization (PSO) coupled with Generalized pattern search algorithm) to investigate energy performance of solar screen configurations. It was conducted through a generic optimization program called GenOpt. Results have shown the significance of the horizontal louvers depth on energy savings that could reach up to 30.7%.[2] Another study made use of another hybrid algorithms (Simulated Annealing (SA) with Sequential Quadratic Programming (SQP)) for layout design optimization. This method helps in finding a range of design alternatives and many local optima.[3]

1.5.3 Genetic Algorithms for Building Performance Optimization

Genetic Algorithms have been used in various fields within the building design problems, but the focus will be in its applications for environmental performance especially daylighting issues. The efficiency of using Genetic Algorithms for environmental performance aspects has been demonstrated through a verified methodology done by Caldas and Norford.[4] The study combined Genetic Algorithm as a search engine with a simulation software DOE2.1E, searching for the optimal window sizes that best meet the thermal and lighting performance criteria required.

[1] G. Rapone and O. Saro, (2012). "Optimisation of Curtain Wall Facades for Office Buildings by Means of Pso Algorithm." *Energy and Buildings* 45: 189-196.
[2] R. Arafa et al. (2013). Energy Efficient Configuration of Non-Conventional Solar Screens Using Hybrid Optimization Algorithm Optimizing Screen Depth, Perforation and Aspect Ratio. Proceedings: BESS-SB13, Building Enclosure Sustainability Symposium Sustainable Buildings Conference, Advancing Toward Net Zero.
[3] J. Michalek et al., (2002). "Architectural Layout Design Optimization." *Engineering optimization* 34, no. 5: 461-484.
[4] L. G. Caldas and L. K. Norford, (2002). "A Design Optimization Tool Based on a Genetic Algorithm." *Automation in construction* 11, no. 2: 173-184.

Rakha and Nassar[1] have used Genetic Algorithms to optimize the ceiling geometry for maximizing daylighting uniformity. An optimization method was demonstrated using a text programming language for finding a range of solutions that best meet daylighting criteria. Turrin et al.[2] have combined parametric modeling and genetic algorithm with performance simulation software to explore various design solutions using ParaGen tool. A methodology was presented for designers and was more illustrated through two case studies; one of them is concerned with solar heat and daylighting transmission for a large span roof. He emphasized the importance of adopting this approach from the early beginning.

Modifications can be done on Genetic Algorithms to suit multi-objective building problems for, not just used it its simplest form e.g. Non-dominated and crowding sorting genetic algorithm II (NSGAII), which was developed by Deb[3] and a tool for its implementation was developed by Chan- trelle et al.[4] In general, multi-objective GAs were used for environmental performance of buildings. A study by Caldas has presented seven applications of a generative design tool called GENE_ARCH which utilizes Genetic Algorithms as a search engine and DOE2.1E software for energy calculation. One application made use of Pareto GAs where a frontier with the best trade-offs between initial cost of materials and energy performance of building was provided. In another application the two conflicting objectives were daylighting use and thermal performance.[5]

1.5.4 Potentials and Limitations of Genetic Algorithms for Building Optimization Problems

The selection of the appropriate optimization algorithm for a specific design problem is a crucial step that affects the whole process. Finding this match is not based on a direct rule to be followed instead analyzing and classifying building optimization problems (BOP) and optimization algorithms is needed besides reviewing the previous works.

In one study the needs of building performance optimization for net zero energy buildings were sought; 165 building optimization publications were reviewed and 28 international

[1] T. Rakha and K. Nassar, (2011). "Genetic Algorithms for Ceiling Form Optimization in Response to Daylight Levels." *Renewable Energy* 36, no. 9: 2348-2356.
[2] M. Turrin et al., (2011). "Design Explorations of Performance Driven Geometry in Architectural Design Using Parametric Modeling and Genetic Algorithms." *Advanced Engineering Informatics* 25, no. 4: 656-675.
[3] K. Deb, 2001. *Multi-Objective Optimization Using Evolutionary Algorithms*. Vol. 16: John Wiley & Sons.
[4] F. P. Chantrelle et al., (2011). "Development of a Multicriteria Tool for Optimizing the Renovation of Buildings." *Applied Energy* 88, no. 4: 1386-1394.
[5] L. Caldas, (2008). "Generation of Energy-Efficient Architecture Solutions Applying Gene_Arch: An Evolution-Based Generative Design System." *Advanced Engineering Informatics* 22, no. 1: 59-70.

optimization experts were interviewed. It is concluded that evolutionary algorithms prevailed among others in solving highly constrained design and operation problems with an emphasis on genetic algorithms.[1] It is obvious that GAs are the most commonly used and the most popular evolutionary algorithms. This returns to a number of reasons:[2] handling both types of variables; discrete and continuous, having parallel processing ability that helps in reducing computational time, handling both single and multi-objective optimization problems. Besides, avoiding sticking in local optima; Wetter and Wright [3] have compared GAs with Hooke and Jeeves algorithm used for optimization building energy consumption and found the latter trapped in local optima unlike GAs. They have also compared 8 types of algorithms including GAs with the aim of reducing the number of cost function evaluation, and it is found that GAs got close to the best minimum.[4]

An important factor for selecting GAs, which is also found in other evolutionary algorithms, is that defected solutions resulted from errors will not impede the optimization process as it works on eliminating failed solutions from the population showing high robustness to simulation failures.[5] Tuhus Dubrow and Krariti have verified the superiority of Genetic Algorithms (GAs) upon particle swarm optimization (PSO) and sequential method in case there are more than ten parameters and GAs were the best in the computational time; it requires half the number of iterations needed by others to find the optimal solution.[6] In the recent years, an increasing interest in GAs have been noticed; which can be considered the most efficient stochastic algorithm in many cases related to building design problems.[7]

For a population based algorithm like GAs, stochastic operators are applied on a population of solutions; this doesn’t guarantee obtaining a good result. However, this could be overcome by adding predefined solutions to the initial population, the critical

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[1] S. Attia et al., (2013). "Assessing Gaps and Needs for Integrating Building Performance Optimization Tools in Net Zero Energy Buildings Design." *Energy and Buildings* 60: 110-124.
[2] A.-T. Nguyen et al., (2014). "A Review on Simulation-Based Optimization Methods Applied to Building Performance Analysis." *Applied Energy* 113: 1043-1058.
[3] M. Wetter and J. Wright (2003). Comparison of a Generalized Pattern Search and a Genetic Algorithm Optimization Method. Proceedings of the 8th International IBPSA Conference, Eindhoven, Netherlands.
[4] M. Wetter and J. Wright, (2004). "A Comparison of Deterministic and Probabilistic Optimization Algorithms for Nonsmooth Simulation-Based Optimization." *Building and Environment* 39, no. 8: 989-999.
[5] S. Attia et al. (2013). Computational Optimisation for Zero Energy Buildings Design: Interviews Results with Twenty Eight International Experts. Proceedings of the 13th Internationcal Conference of the IBPSA.
[6] D. Tuhus-Dubrow and M. Krarti, (2010). "Genetic-Algorithm Based Approach to Optimize Building Envelope Design for Residential Buildings." *Building and environment* 45, no. 7: 1574-1581.
[7] S. Attia et al., (2013). "Assessing Gaps and Needs for Integrating Building Performance Optimization Tools in Net Zero Energy Buildings Design." *Energy and Buildings* 60: 110-124.

part is choosing these solutions that are based mainly on the designers experience and still cannot ensure finding the optimal solution. For more refining, a local optimizer can be applied before the global searching of the Genetic Algorithms. They require the designers' interference to determine the initial solutions or otherwise it could be applied after the global search.[1]

1.5.5 Optimization Tools

Design optimization tools could be described as creativity support tools that make use of optimization algorithms integrated with performance simulation and parametric modeling software for generating, exploring, evaluating and modifying design solutions. Not only do these tools automate design generation, but also do enable the experimentation of the design space and explore the solution space. Thus, they provide more creative unexpected ideas.[2]

Optimization tools are categorized according to Machairas, Vasileios et al. into:

- Custom programmed algorithms
- General optimization packages
- Special tools for building design.

The first category has high flexibility but it requires programming skills using C+, Java or Visual Studio, etc. The second category includes effective optimization algorithms and post processing capabilities. It is characterized by having graphical user interface (GUI). MatLab and GenOpt are examples of this category.[3] The former is mentioned by its additional features that designers can make use of like, data analysis, link to excel. GenOpt is a generic optimization tool used in the field of building optimization problems. Simulation programs like Energy Plus, Radiance and DOE.2 can be coupled with them. Besides, it is provided with a number of algorithms like, PSO, GA, Hooke and Jeeves and others, moreover; it gives the possibility to add more to the library.[4]

The last category, special tools for building design, mainly use GA as the optimization algorithm coupled with a simulation program. Turrin et al. discussed the optimization of

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[1] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.
[2] E. Bradner et al. (2014). Parameters Tell the Design Story: Ideation and Abstraction in Design Optimization. Proceedings of the Symposium on Simulation for Architecture & Urban Design, Society for Computer Simulation International.
[3] *Op. cit.: V. Machairas, (2014).*
[4] M. Hamdy et al. (2009). Combination of Optimisation Algorithms for a Multi-Objective Building Design Problem. IBPSA: 11th International Building Performance Simulation Association Conference, Glasgow-UK.

a large span roof structurally and environmentally using ParaGen tool, combining GA with parametric modeling and simulation software.[1] BeOpt software[2] uses sequential search method as the optimization algorithm and DOE-2 or EnergyPlus as the simulation engine; it is an easy to use tool with a graphical user interface supported with a number of training tutorials. Chantrelle FP et al. presented MultiOpt tool that uses NSGA II algorithm with TRNSYS as the simulation program.[3] Caldas have applied GENE-ARCH which uses DOE-2 coupled with micro GA and Pareto GA.[4]

It can be deduced that the first two categories are not user-friendly. Although the fast processing and the open source code provided by the coding language used in the first category, architects are not familiar with such codes to manipulate with. As for the second category, it included commercially optimization programs that are argued to have limited modeling capabilities. On the other hand, the third category uses geometric modeling programs as a platform. It provides powerful modeling capabilities with a high level of visualization and more familiar interface from the perspective of an architect.[5]

The essential characteristics of an optimization tool can be summarized in its high level of performance, the provision of a graphical user interface (GUI), provision of multiple solutions and a parallel processing ability. Besides, their allowance for the designer to direct the search in the right way in order to minimize the search space thus, decreasing the computational time.[6]

1.6 Simulation-based Optimization Approach

Seeking towards optimal solutions needs the integration of the appropriate optimization tool with parametric modelling. Then, the implementation of the analytical simulation tools comes to fulfill this goal.

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[1] M. Turrin et al., (2011). "Design Explorations of Performance Driven Geometry in Architectural Design Using Parametric Modeling and Genetic Algorithms." *Advanced Engineering Informatics* 25, no. 4: 656-675.
[2] C. Christensen et al., 2006. *Beopt Software for Building Energy Optimization: Features and Capabilities*: National Renewable Energy Laboratory.
[3] F. P. Chantrelle et al., (2011). "Development of a Multicriteria Tool for Optimizing the Renovation of Buildings." *Applied Energy* 88, no. 4: 1386-1394.
[4] L. Caldas, (2008). "Generation of Energy-Efficient Architecture Solutions Applying Gene_Arch: An Evolution-Based Generative Design System." *Advanced Engineering Informatics* 22, no. 1: 59-70.
[5] X. Shi and W. Yang, (2013). "Performance-Driven Architectural Design and Optimization Technique from a Perspective of Architects." *Automation in Construction* 32: 125-135.
[6] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.

Approaching a building design problem through "Parametric Simulation Method" was known to be beneficial for improving performance. Traditionally, a set of variables are varied one by one to see the effect of each on the outcome while keeping the others unchanged. Repeating this step iteratively for each variable is time consuming in addition, it ignores the interaction between variables. So, in best cases a partial improvement is achieved.[1] Instead, "Simulation-based Optimization" can be adopted seeking for an optimal performance.

What differs this approach is that it combines an optimization algorithm in the framework of the process by which an optimal or near optimal solution can be reached. This approach represents a shift from analytical simulations, where modifications on the design model are done after analyzing the performance of the design. Instead, algorithms and generative processes take the feedback from the simulation results to automatically generate and modify designs according to a certain performance criteria. This synergy between generative processes and performance is a significant distinction from the traditional simulation method. The operation sequence clarifies the difference between the two approaches as shown in Figure 1-7. In the conventional, the design model is formed first to be analyzed by the simulation program then it is evaluated according to a predefined criteria. In contrast, in the simulation –based optimization, the simulation results feedback the optimization algorithm to manipulate the design variables forming the design model.

Most building research studies concerned with this approach have appeared since the late 2000s[2]. As in Figure 1-8, it is easy to notice the increasing tendency towards optimization studies and the sharp increase since 2005. Increasing the research and development throughout the last decade have increased awareness and have highlighted the potentials of using such techniques. Even that building codes are more likely to be adjusted to suit this approach.[3] In addition, high points given by the building rating systems, like LEED, have encouraged designers to use optimization techniques whether in their design or their researches. This approach has contributed powerfully in enhancing building performance.

[1] A.-T. Nguyen et al., (2014). "A Review on Simulation-Based Optimization Methods Applied to Building Performance Analysis." *Applied Energy* 113: 1043-1058.
[2] *Ibid.*
[3] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.

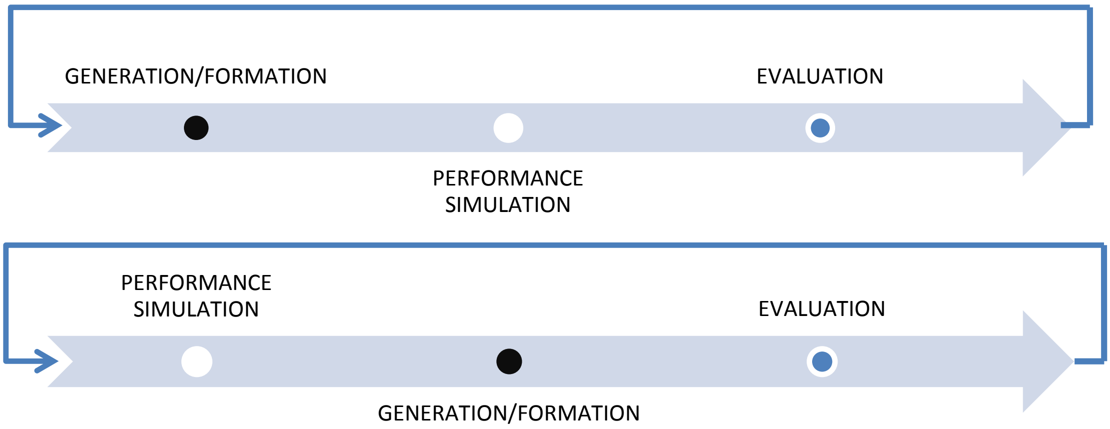

Figure 1-7: Sequence of processes: (upper part) in conventional analytical simulation, (lower part) in the simulation based optimization approach,
Source: adapted from Oxman (2008)

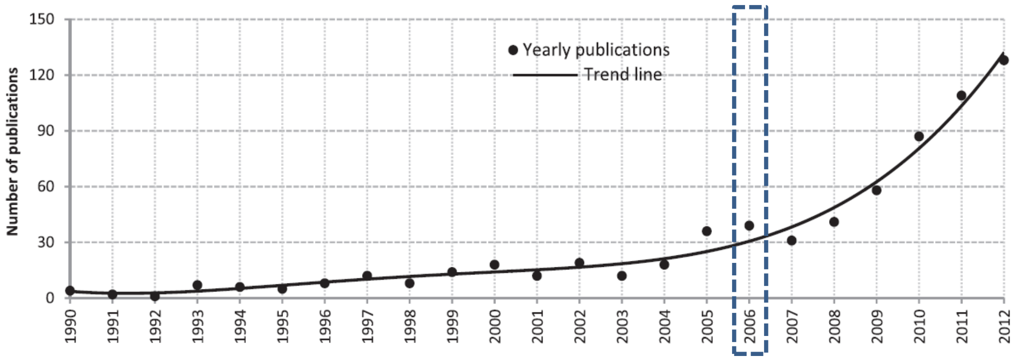

Figure 1-8: Yearly Publication of Optimization Studies, shows the increasing trend in the last decade[1]

1.6.1 Main Phases for a Simulation-based Optimization Study

Phase's division in simulation based optimization studies differs from one to another; Nguyen, A.-T. et al. subdivided the process into three main phases: preprocessing, optimization phase and post processing.[2]

[1] *Ibid.*
[2] A.-T. Nguyen et al., (2014). "A Review on Simulation-Based Optimization Methods Applied to Building Performance Analysis." *Applied Energy* 113: 1043-1058.

1. *Preprocessing phase*; the inception of a process is the first indicator of its success and here lies the significance of this phase. The critical part in this phase lies in the formulation of the optimization problem; describing the mathematical definition of the design problem. This implies abstracting the design problem in a quantifiable form regarding design objectives, setting up the design variables and parameters; understanding the logic that relates them together, adjusting their range or discrete values and their constraints, building up the model; deciding on the simulation program and the optimization algorithm with the consideration the platform that could combine them.[1]

In abstracting the design problem, neither the low precision nor high one is good for the quality and quantity of solution space. Instead, a balance is needed to avoid poor solution space or a plethora of solutions that impede finding the best solutions. Understanding and predicting the interaction of different variables and their impact on the design performance is difficult even for skilled designer; this form as a challenge to understand the statistical correlation between them.[2]

After identifying the parameters affecting the design problem, they will be confined to the most effective ones, thus avoiding insignificant ones. Their number depends on: the complexity of the problem and the selected optimization algorithm, but still there is no defined criteria for determining the appropriate number of parameters.[3] In real world, building optimization problems (BOP) can have both continuous and discrete variables. Nguyen, Anh-Tuan et al. made a statistical study from ten arbitrary studies showing the number and type of variables used; more than half the studies were dealing with both types of variables. As for the number of variables, in average there were about 15 variables with maximum of 24 and minimum of 8 variables. However, there is still no agreement on the recommended number of the variables. [4]

In addition, sensitivity analysis could be conducted to reduce the size of the search space, hence, increasing the efficiency of the process.[5] Eisenhower et al. pointed out to the importance of sensitivity and uncertainty analysis for the reduction of computational time

[1] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.
[2] E. Bradner et al. (2014). Parameters Tell the Design Story: Ideation and Abstraction in Design Optimization. Proceedings of the Symposium on Simulation for Architecture & Urban Design, Society for Computer Simulation International.
[3] A.-T. Nguyen et al., (2014). "A Review on Simulation-Based Optimization Methods Applied to Building Performance Analysis." *Applied Energy* 113: 1043-1058.
[4] *Ibid.*
[5] *Ibid.*

as it works on reducing the search space size to include only the most effective parameters. They have proposed an approach to exclude ineffective, time consuming parameters in the optimization process.[1]

2. *Optimization phase*; monitoring the process and detecting errors is what this phase is about. Estimating the computational time of the optimization algorithm to reach a satisfactory solution is not addressed in most studies. However, Wright and Ajlami have tried to compare different settings of GA and their effect on the speed of convergence[2]. They have tried three different population sizes: 5, 15, and 30 individuals per population and found that the least population size was the best in terms of speed and cost.[3]
3. *Post Processing Phase;* This phase is concerned with analyzing the output data and extracting valuable information from the optimization process with the aid of tables, charts, or diagrams. Visualization and data plots are two ways that describe the solution space. They aid designers to analyze the impact of their design decision on different performance aspects. Pareto plots are example of data plots are used in multi-objective optimization; they provide the designer with information about the tradeoff between different objectives. [4]

Some useful methods can be used to verify results, such as sensitivity analysis that were used in a study by Tuhus-Dubrow and Krarti; they altered some design variables (weather files, utility rates and the operation strategies) to see their effect on the final output.[5] It is useful to ensure the reliability of the results in this final phase.

1.6.2 Building Simulation Tools

In the last decade the use of building simulation tools have been widely used among designers. There is a time lag between its utilization in the architectural practice and between their existences, this returns to a number of reasons like its complexity to be used by non-experts, cost, long computation time and uncertainty in their results.

[1] B. Eisenhower et al. (2012). Uncertainty-Weighted Meta-Model Optimization in Building Energy Models. IBPSA-England 1st Conference on Building Simulation and Optimization (BSO12).
[2] Convergence term indicates that the final solution reached by the algorithm.
[3] J. Wright and A. Alajmi (2005). The Robustness of Genetic Algorithms in Solving Unconstrained Building Optimization Problems. Proceedings of the 7th IBPSA Conference: Building Simulation, Montréal, Canada August.
[4] E. Bradner et al. (2014). Parameters Tell the Design Story: Ideation and Abstraction in Design Optimization. Proceedings of the Symposium on Simulation for Architecture & Urban Design, Society for Computer Simulation International.
[5] D. Tuhus-Dubrow and M. Krarti, (2010). "Genetic-Algorithm Based Approach to Optimize Building Envelope Design for Residential Buildings." *Building and environment* 45, no. 7: 1574-1581.

Nowadays, these limitations are overcome by continuous development of such tools; they are now available with user-friendly interfaces and training materials that facilities their use by designers, besides the advancement in the technicalities for more reliable results with much less amount of computation time.[1]

There are three approaches that could be adopted for the building performance evaluation:

- Simplified analytical models
- Building performance surrogate models
- Detailed building simulation models

The first approach is applicable only for simple problems, the advantage of this approach is its instantaneous need of time for computing, thus it facilitates reaching the true optimal through searching the whole solution space by a specific algorithm or by using brute force technique. The second approach, the surrogate models or Meta models are statistical models which are based on machine learning; like artificial neural network and genetic programming. It is an effective approach for problems with large number of variables or large solution space and many local optima. The problem with these models is that they require an expert knowledge in the field of artificial intelligence; hence it is not commonly used for building design problems.[2]

Detailed building simulation models represent the third approach; they imply simulation tools specifically designed for the evaluation of certain design issues. Machairas et al. have reviewed the methods and tools used in building design and it is noticed that the most commonly used simulation programs are TRNSYS, DOE-2, EnergyPlus, Ecotect, Radiance, and computational fluid dynamics (CFD) tools. These tools do the calculations taking: climatic data, building geometry, materials, occupancy, schedules, HVAC description and operation as the input data. Results are generated whether they are thermal analysis, energy consumption, daylighting utilization or any other measurement.[3]

1.6.3 Barriers against the Integration of Optimization Methods with Building Simulation Tools

The urging need of highly efficient buildings helps in the integration of optimization techniques with simulation programs. Not all of these techniques are flexible enough to

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[1] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.
[2] *Ibid.*
[3] *Ibid.*

be coupled with building performance simulation (BPS). According to Attia, S. et.al, less than 5% of the BPS tools presented in DOE website in 2012 allow optimization.[1] Barriers that limit their spread in conventional building design practice could be summarized in: [2]

- Coupling interfaces between BPS tools and optimization packages
- The inevitable tradeoff between the required features in the optimization methods; flexibility versus visualization, efficiency versus time or cost.
- The restriction of the computational speed.
- Lack of government policies that urges high performance buildings.
- The complexity of building optimization techniques; they encompass many fields for their development: mathematics, computer science, environmental science, engineering, etc.

1.6.4 Steps for an Optimization Study

To wrap up, there are a set of steps to be identified for the optimization of any design problem:

- Defining the problem to be solved; this implies identifying the objective of the optimization and the factors affecting its achievement are set.
- Selecting the simulation engine; it is responsible for the evaluation process.
- Identifying variables and parameters; they should be set in a mathematical form to outline the objective function.
- Constructing the geometrical model; making it ready for the last step which is
- Selecting the optimization algorithm.

The objective of this optimization study revolves around the environmental impact, particularly daylighting performance and solar control. The defined parameters should represent the geometrical entities affecting performance, forming the objective function which could be more than one and in this case a multi objective optimization is sought for. Influential parameters could be: the orientation, building shape, openings, window to wall ratio (WWR), depth to height ratio, glazing type, materials. Computational time consumed varies depending on: the simulation engine, adjustment settings, the optimization algorithm selected, and the complexity of the model that affects the size of

[1] S. Attia et al., (2013). "Assessing Gaps and Needs for Integrating Building Performance Optimization Tools in Net Zero Energy Buildings Design." *Energy and Buildings* 60: 110-124.
[2] A.-T. Nguyen et al., (2014). "A Review on Simulation-Based Optimization Methods Applied to Building Performance Analysis." *Applied Energy* 113: 1043-1058.

the solution space. Typically it needs hundreds to thousands of simulation runs to reach a satisfactory solution.[1]

The design process have changed dramatically owing to increasing environmental awareness and the advancement in the digital design tools. Simulation programs have been incorporated in the decision making process in the conceptual design phase. Besides, the continuous development of these tools has given the chance to incorporate optimization techniques as well.

1.7 Summary

The conceptual design is a critical phase where decisions made could transform the success of the design based on the methodology adopted. It is a key factor that influences the decision making in the whole design process.

Changes occur constantly in the early phases of the design process. In conventional design work flow, sketching and physical models are the main elements through which design ideas are explored. Nowadays, digital technologies have invaded the design practice where ideas are represented in the digital media for visualization and drafting until a final solution is reached, then it is yielded to another layer of refinement for a precise documentation. However, the problem is the disengagement of digital tools from the design thinking from the early beginning, thus a no-full use of the capabilities of digital technologies is confronted.

The urging need of more efficient buildings imposes the investigation of new approaches and frameworks that make best use of the capabilities of these technologies. With the aid of the emerging digital design tools and techniques, unexpected unique forms and concepts have emerged. This is considered an important asset for the development of the digital design process.

The implications of this paradigm shift: 1) the need of parametric modeling where a large number of design solutions can be automatically generated through representing geometric entities and their relationships by a number of parameters and functions. Thus, it offers the designer the possibility of numeric evaluations. The visualization of the form and its correlation with performance facilitate the designer interaction, thus enhancing the design process. 2) The selection of the appropriate optimization algorithm, which is

[1] V. Machairas et al., (2014). "Algorithms for Optimization of Building Design: A Review." *Renewable and Sustainable Energy Reviews* 31: 101-112.

critical for ensuring a satisfactory performance, was recommended to be genetic algorithms. However, to ensure its robustness for this study, an exhaustive search was first applied. 3) The implementation of analytical tools is required for supporting performance evaluation. In this regard, a paradigm shift is experienced in which the new digital design process has evolved calling for a performative design. 4) The possibility to integrate generative systems to satisfy the designers' visual aspiration, thus balancing between both performance and visual aspects through generative performative design approach

In this study, a daylighting design problem was under investigation through this developed schematic diagram shown in Figure 1-9.

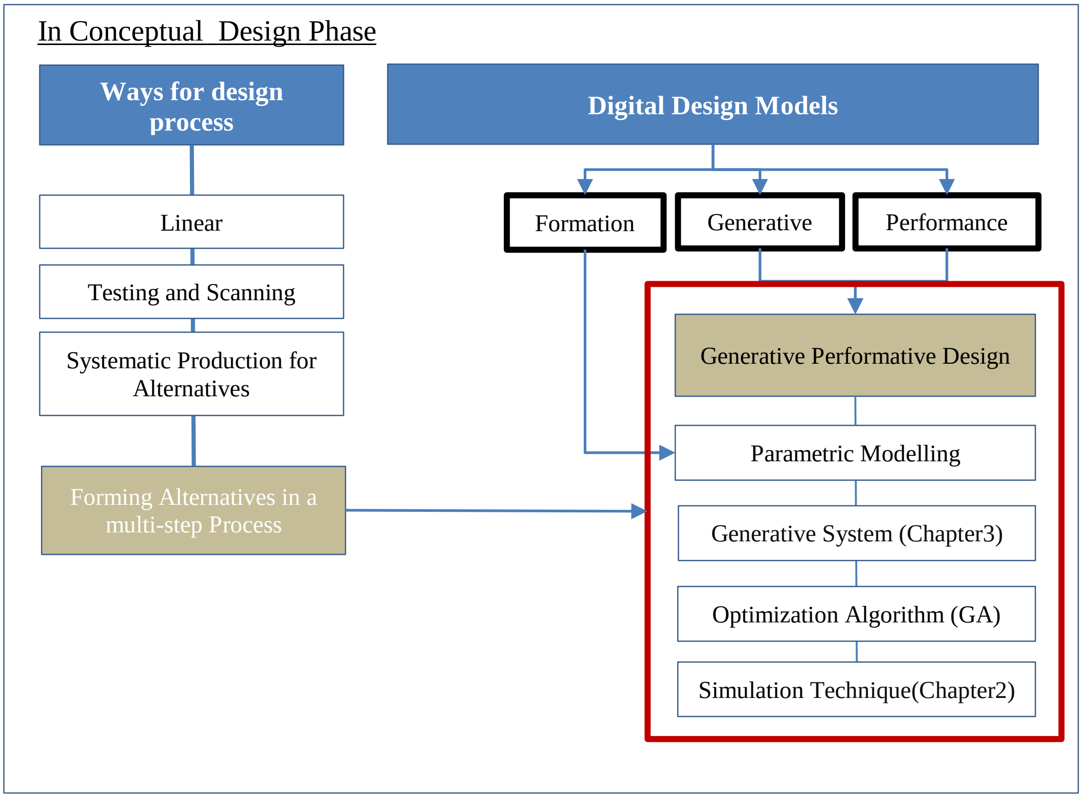

Figure 1-9: Schematic diagram suggested for approaching the daylighting simulation problem in the conceptual design phase, highlighting the adopted approach

CHAPTER 2

DAYLIGHTING AS A PERFORMANCE CRITERIA

- DAYLIGHTING PERFROMANCE ASPECTS
- DAYLIGHTING CALCULATIONS METHODS
- DAYLIGHTING PERFROMANCE METRICS
- INTEGRATING DAYLIGHITNG SIMULATION PROGRAMS WITH OPTIMIZATION ALGORITHMS

2.1 Introduction

The paradigm shift occurs in the design thinking imposes the use of analytical tools for performance evaluation. In this chapter daylighting adequacy was set to be the performance criteria under investigation. Daylighting is an important building aspect that needs concern from the early beginning of the design process. It is about the manipulation of natural light entering the space and controlling it according to the intended performance objective. [1] Its significant impact on occupants has been constantly emphasized in different studies; its impact on human health, productivity, and delight was discussed. Daylighting endows a remarkable ambience that effects our perception of the space. Actually, everyone has his own perception and attitude towards daylight so it is subjective to identify what is a “well daylit space”.

Many studies were conducted to ensure providing adequate daylight in the indoor environment while avoiding direct sunlight. Still successful daylighting design is a challenging task due to the conflicting requirements to reach the balance between daylighting adequacy and visual comfort. Besides, the fluctuating nature of daylight along the day and year complicates the process.

Daylighting performance assessment was concerned with different calculation methods and tools. Over the years, different metrics and tools have evolved and are still being developed. The aim of these emerging metrics was to better represent daylighting performance. Besides, incorporating them within simulation tools to be easily integrated within the design workflow was intended. Increasing the accuracy of these tools was targeted for getting more reliable results that can inform the design process not only for daylighting requirements but also for energy savings.

This chapter introduces daylighting visual aspects as well as the non-visual effects. In addition, an overview on daylighting simulation programs and metrics are presented. Finally, the significance of integrating optimization for efficient daylighting is highlighted.

2.2 Daylighting Performance Aspects

The prime concern in daylighting performance regards its adequacy for the intended visual task. Different indicators were developed for benchmarking daylighting

[1] C. Reinhart, 2013. "Daylighting Handbook-Volume I."

performance inside the space. Static metrics appeared for evaluating daylighting performance. Paying attention to their drawbacks, dynamic daylight performance metrics (DDPM) have emerged to overcome the limitations of the former.[1] However, daylighting performance is not confined to visual aspects, where it is concerned with other dimensions like energy savings, and indoor environmental quality. Thus, balancing all aspects that are possibly contradicting is a challenging problem to tackle.

First, a definite set of objectives is needed to be defined for approaching the daylighting design. However, what is perceived "good lighting" by someone is not the same by the other, it is a subjective issue that cannot be definitely set.[2] In an attempt to define daylighting as shown in Table 2-1, no specific definition was set, where different professions showed how it was differently conceived and handled to meet with various performance requirements. This study concerns with daylighting from the perspective of architectural definition.

Table 2-1: Daylighting Definitions from different perspectives[3]

Architectural	*"The interplay of natural light and building form to provide a visually stimulating, healthful, and productive interior environment."*
Lighting Energy Savings	*"The replacement of indoor electric illumination needs by daylight, resulting in reduced annual energy consumption for lighting."*
Building Energy Consumption	*"The use of fenestration systems and responsive electric lighting controls to reduce overall building energy requirements (heating, cooling, lighting)."*

[1] C. F. Reinhart et al., (2006). "Dynamic Daylight Performance Metrics for Sustainable Building Design." *Leukos* 3, no. 1: 7-31.
[2] C. Reinhart, 2013. "Daylighting Handbook-Volume I."
[3] C. Reinhart and A. Galasiu, (2006). "Results of an Online Survey of the Role of Daylighting in Sustainable Design." *NRC-IRC Report* 3, no. 1: 1-25.

Load Management	*"Dynamic control of fenestration and lighting to manage and control building peak electric demand and load shape."*
Cost	*"The use of daylighting strategies to minimize operating costs and maximize output, sales, or productivity."*

2.2.1 Visual Daylighting Aspects

Traditionally, visual aspects like illumination, daylighting uniformity, glare, and luminance are the main indicators used for the assessment of daylighting performance. These indicators are concerned with daylighting quantity and quality to ensure that the recommended thresholds are met and visual comfort is attained. These aspects are interpreted into daylight metrics to be used in simulation programs for design evaluation.

2.2.2 Non-Visual Daylighting Aspects

In addition to visual aspects, efforts have been deployed to find out non-visual and perceptual aspects which complement the assessment of daylighting strategies. These aspects can have beneficial psychological and health effects that ranges from enhancing alertness, mood, and productivity to helping in a faster recovery of patients. A study has correlated a higher alertness level and better performance of occupants in an office space when exposed to daylight rather than electric ones.[1] Other studies have promoted the provision of natural light in educational spaces for its positive impact on both students and staff members. It was proven to decrease the rate of absence, increase their productivity and their level of satisfaction with their learning environment.[2]-[3] Being aware of these beneficial effects, a need for considering these aspects to support daylighting design exists.

An attempt to incorporate the non-visual aspects in the design process was introduced by Andersen, M., et al.[4] Apart from conventional visual aspects, this study presented a dynamic light-response model to predict health aspects within a framework for the

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[1] M. Münch et al., (2012). "Effects of Prior Light Exposure on Early Evening Performance, Subjective Sleepiness, and Hormonal Secretion." *Behavioral neuroscience* 126, no. 1: 196.
[2] L. Edwards and P. A. Torcellini, 2002. *A Literature Review of the Effects of Natural Light on Building Occupants*: National Renewable Energy Laboratory Golden, CO.
[3] G. Heath and M. J. Mendell (2002). Do Indoor Environments in Schools Influence Student Performance? A Review of the Literature. Proceedings of the 9th International Conference on Indoor Air Quality and Climate, Indoor Air 2002.
[4] M. Andersen et al. (2013). Beyond Illumination: An Interactive Simulation Framework for Non-Visual and Perceptual Aspects of Daylighting Performance. BS2013-13th International Conference of the International Building Performance Simulation Association.

Lightsolve simulation program. Besides, design intent-driven metrics were suggested for indicating the perceptual aspect of contrast and delight to act as a design factor.[1]

Another study has suggested daylighting dashboard to help in the decision making process in the conceptual design phase. It is considered the first integrative approach to include 'circadian stimulus' as a design goal for daylighting design. The significance of circadian stimulus lies in its effect on physiological and biological processes -acting as a biological clock- in the human beings which is regulated by daylight. A twenty-four points scoring system is used to represent how much daylight is sufficient for circadian stimulation that accordingly affects sleep patterns and alertness level.[2]

2.3 Daylighting Calculation Methods

Measurements of visual aspects can be conducted using either physical scale models or mathematical formulas which were incorporated within simulation tools.[3] About two decades ago, daylighting simulation programs notably started to replace the traditional techniques. These programs gained popularity due to its fast and efficient performance. It is easier and more flexible to integrate daylighting within the whole design process rather than using actual physical mock ups. In addition, their wide spread usage returned also to the familiarity of computer applications in architectural and engineering education.[4] Many studies have contributed in the developments of these simulation programs and their adoption from the early beginning of the design process [5]-[6]-[7]. They were integrated within the design workflow to support the decision making concerned with daylighting strategies from the early beginning.

2.3.1 Daylighting Simulation Algorithms

Simulation needs a set of instructions that can effectively inform the calculation process for predicting actual conditions. These instructions are called simulation algorithms. In

[1] *Ibid.*
[2] R. Leslie et al., (2012). "Conceptual Design Metrics for Daylighting." *Lighting Research and Technology* 44, no. 3: 277-290.
[3] S. Kota and J. S. Haberl, (2009). "Historical Survey of Daylighting Calculations Methods and Their Use in Energy Performance Simulations."
[4] C. E. Ochoa et al., (2012). "State of the Art in Lighting Simulation for Building Science: A Literature Review." *Journal of Building Performance Simulation* 5, no. 4: 209-233.
[5] C. F. Reinhart and J. Wienold, (2011). "The Daylighting Dashboard–a Simulation-Based Design Analysis for Daylit Spaces." *Building and environment* 46, no. 2: 386-396.
[6] K. Lagios et al., (2010). "Animated Building Performance Simulation (Abps)-Linking Rhinoceros/Grasshopper with Radiance/Daysim." *Proceedings of SimBuild*.
[7] J. A. Jakubiec and C. F. Reinhart (2011). Diva 2.0: Integrating Daylight and Thermal Simulations Using Rhinoceros 3d, Daysim and Energyplus. 12th Conference of International Building Performance Simulation Association, Sydney.

general they can be classified into: view-dependent algorithms, and scene- dependent algorithms as shown in Figure 2-1. For daylighting simulation, the most well-known algorithms are ray-tracing and radiosity. [1] They were incorporated within many simulation tools like Radiance, Dialux, and spot.

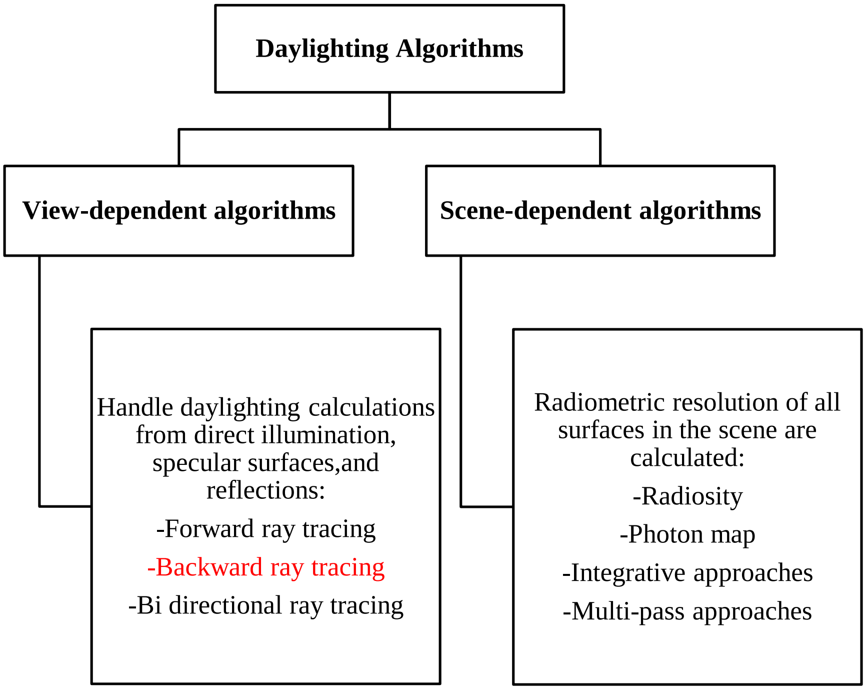

Figure 2-1: Classification of daylighting algorithms

2.3.2 Radiance Simulation Program

Radiance is a well-known lighting simulation engine that was developed in the 1990's.[2] It is based on the backward ray tracing algorithm for daylighting calculations. Radiance has proven its efficiency in daylighting calculations and was validated in several studies

[1] C. E. Ochoa et al., (2012). "State of the Art in Lighting Simulation for Building Science: A Literature Review." *Journal of Building Performance Simulation* 5, no. 4: 209-233.
[2] G. Ward and R. Shakespeare, (1998). "Rendering with Radiance." *Waltham: Morgan Kaufmann Publishers*.

[1]-[2]-[3]. It is argued to be the most flexible in comparison to other daylighting simulation tools.[4] A survey was conducted by Reinhart and Fitz on “the use of daylight simulation in building design” and found that more than 50% of the used programs that employ Radiance as the simulation engine.[5] It is considered the most prominent in the daylight simulation community and this may return to a number of reasons:[6]

- Being validated in several studies.
- Giving accurate daylighting representations not just for image rendering.
- Having flexibility in dealing with reflection and transmittance materials with complex geometry besides the ability to simulate specular surfaces.
- Being an open source program allowed a broad range of usage for various purposes.

Many simulation programs employ Radiance as the simulation engine for their daylighting calculations. Daysim was among these Radiance-based daylighting programs.[7] It was first introduced in a study by Reinhart and Herkel and proved its superiority upon other Radiance-based methods regarding simulation time and accuracy.[8] It calculates the annual daylight illuminance levels by combining the ray tracing algorithm of Radiance with the daylight coefficient method[9] and Perez sky model[10]. A flow diagram describing the Daysim simulation method was introduced by Reinhart and Anderson as shown in Figure 2-2.

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[1] C. F. Reinhart and O. Walkenhorst, (2001). "Validation of Dynamic Radiance-Based Daylight Simulations for a Test Office with External Blinds." *Energy and Buildings* 33, no. 7: 683-697.
[2] C. F. Reinhart and M. Andersen, (2006). "Development and Validation of a Radiance Model for a Translucent Panel." *Energy and Buildings* 38, no. 7: 890-904.
[3] J. Mardaljevic, (1995). "Validation of a Lighting Simulation Program under Real Sky Conditions." *Lighting research and Technology* 27, no. 4: 181-188.
[4] R. Guglielmetti et al. (2010). On the Use of Integrated Daylighting and Energy Simulations to Drive the Design of a Large Net-Zero Energy Office Building. Proc. Fourth National Conference of IBPSA-USA, New York, NY.
[5] C. Reinhart and A. Fitz, (2006). "Findings from a Survey on the Current Use of Daylight Simulations in Building Design." *Energy and Buildings* 38, no. 7: 824-835.
[6] C. E. Ochoa et al., (2012). "State of the Art in Lighting Simulation for Building Science: A Literature Review." *Journal of Building Performance Simulation* 5, no. 4: 209-233.
[7] C. F. Reinhart et al., (2006). "Dynamic Daylight Performance Metrics for Sustainable Building Design." *Leukos* 3, no. 1: 7-31.
[8] C. F. Reinhart and S. Herkel, (2000). "The Simulation of Annual Daylight Illuminance Distributions—a State-of-the-Art Comparison of Six Radiance-Based Methods." *Energy and Buildings* 32, no. 2: 167-187.
[9] P. Tregenza and I. Waters, (1983). "Daylight Coefficients." *Lighting Research and Technology* 15, no. 2: 65-71.
[10] R. Perez et al., (1993). "All-Weather Model for Sky Luminance Distribution—Preliminary Configuration and Validation." *Solar energy* 50, no. 3: 235-245.

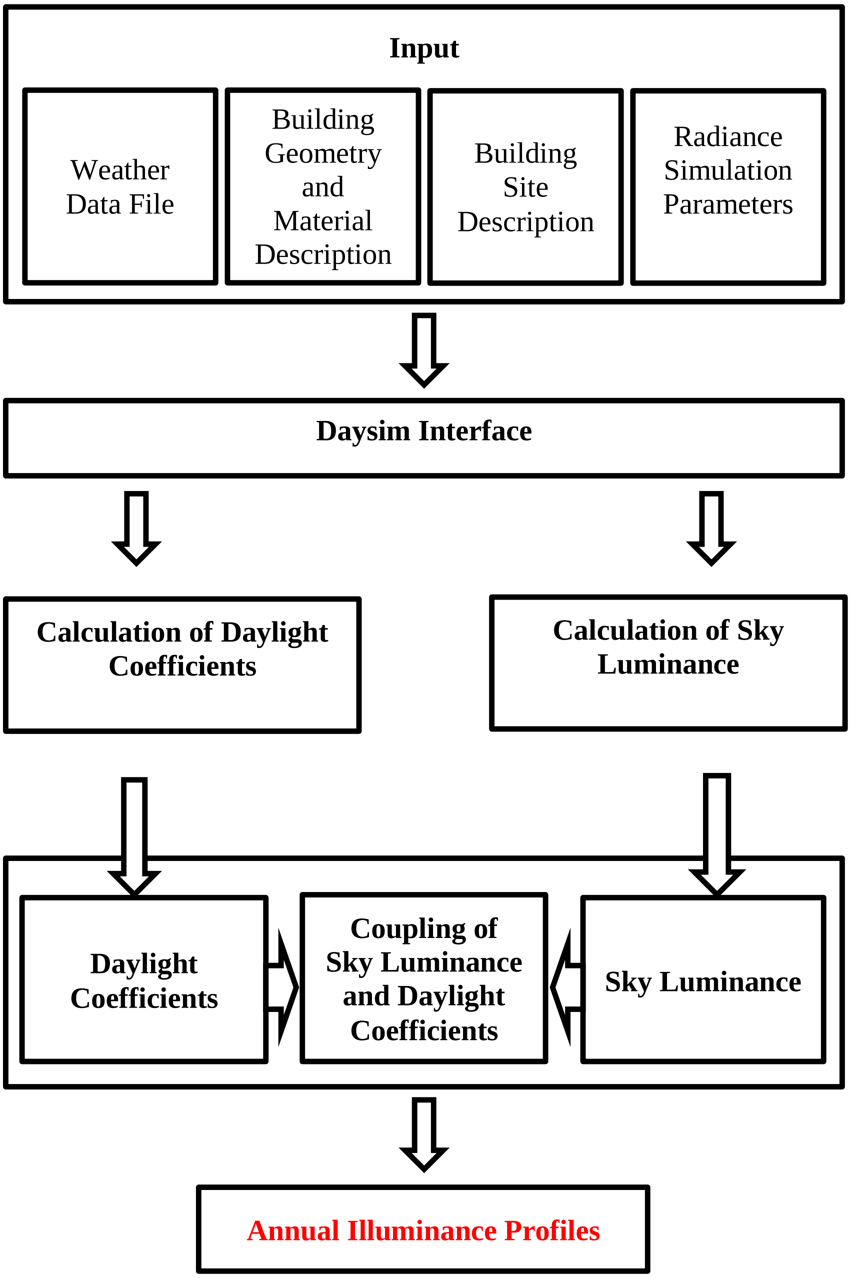

Figure 2-2 Flow diagram of Daysim method[1]

[1] C. F. Reinhart and M. Andersen, (2006). "Development and Validation of a Radiance Model for a Translucent Panel." *Energy and Buildings* 38, no. 7: 890-904.

The concept of daylight coefficient was first introduced by Tregenza to overcome the limitation of static daylight measurement. It is based on dividing the sky into a number of patches each contributes to the illuminance levels at each sensor point considering the dynamic nature of daylight along the day and year. Diffuse, ground, and direct daylight coefficients are calculated then coupled with sky luminance calculated by the all-weather Perez sky model.[1] This sky model is among the widely used sky luminance distribution models besides CIE clear and overcast sky models. It takes direct and diffuse irradiance data to provide luminous distribution of different locations.

2.4 Daylighting Performance Metrics

For assessing the previous visual aspects using Radiance-based simulation, daylighting performance metrics come to act as ‘quality measures’. They are used for benchmarking building design performance relative to a predefined thresholds. They are also useful for giving an indication for the best design in evaluating and comparing different alternatives. These metrics can be classified into static and dynamic as shown in Figure 2-3.

Dynamic Daylight Performance Metrics (DDPM) have replaced static metrics which only account for a single sky condition. Daylight Factor (DF) was the most widely used static metric for measuring daylighting performance. However, it is rather an indicator for the minimum lighting requirement than an indicator for good daylighting. It follows the approach of "the more is better" without taking into account the building location, orientation, sky condition, time of day and season. Thus, problems of glare, energy consumption, and excessive heat gain can occur. First, a combined approach was proposed to mitigate some of these limitations in which daylight factor is compromised with direct sunlight avoidance. Still neither the climatic condition nor the building type is considered.[2]

On the other hand, DDPM consider the annual climatic conditions, and the occupancy patterns with the varying sky conditions. This replacement has been facilitated through:[3]

- The increase of computing capabilities of computers which are accessible to architectural firms and students;

[1] *Ibid.*
[2] C. F. Reinhart et al., (2006). "Dynamic Daylight Performance Metrics for Sustainable Building Design." *Leukos* 3, no. 1: 7-31.
[3] *Ibid.*

- The common interest in the use of computer applications;
- The friendly user interfaces that facilitate building the 3D model and the daylight simulation model required for performing DDPM.

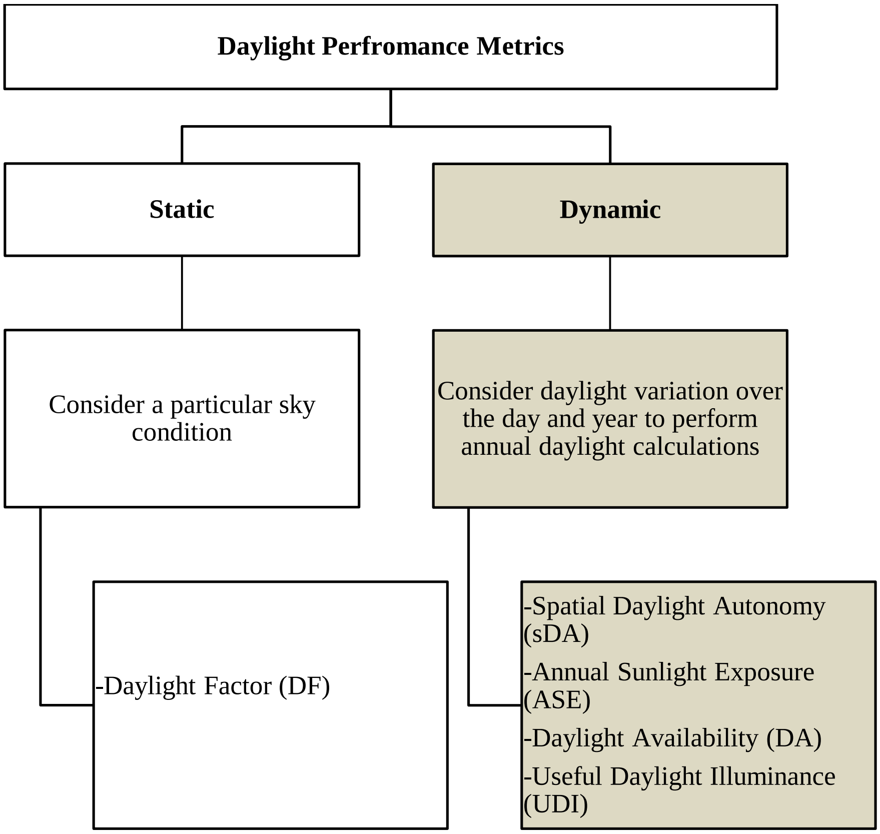

Figure 2-3: Daylight Performance Metrics

Steps for developing a dynamic daylight performance analysis for a defined space encompasses the same input of Daysim method:[1]

- Building the three-dimensional model with the assigned surface materials
- Identifying the number and location of sensor points (typically, they form a grid of points located at the height of work plane)
- Describing the site (modeling external obstruction if existed)
- Importing the weather file data of its location

[1] *Ibid.*

- Determining the time range which is based on occupancy patterns or the daylit hours of the year.
- Identifying a daylight criteria for the assessment of daylighting adequacy.

As for the last step, it is concerned with the selection of the daylighting metrics for evaluating the design performance. Several dynamic metrics, which are also referred to as climate based metric, were developed. They are based mainly on illuminance and luminous profiles for example:

1) *Daylight Autonomy;* which represents measuring the illuminance levels at the work plane, gives a percentage of the occupied hours of the year that exceeds a minimum illuminance threshold. It indicates if there is sufficient daylight to rely on for the assigned task in the space without the need of supplementary lighting sources.[1]
2) *Continuous Daylight Autonomy (DAcon);* it is a modified metric of the Daylight Autonomy where the difference lies in giving a partial count to the illuminances values that lies below the minimum threshold.[2]
3) *Maximum Daylight Autonomy*; it represent the percentage of occupied hours when illuminance levels exceeds a maximum threshold; it is suggested to be ten times the recommended minimum.[3]
4) *Daylight Availability*; it is a metric introduced by Reinhart and Wienold. [4] It have the same minimum threshold of the Daylight Autonomy besides adding a maximum threshold which is ten times the minimum. The space area is represented by three zones; ‘partially daylit’ where the minimum threshold (300lux) is received less than 50% of the occupied times; the ‘overlit’; where the maximum threshold is exceeded for more than 5% of the occupied times; and the ‘daylit’ area. This last area, which is intended to be maximized, denotes the area receiving illuminance level between 300 and 3000 lux for 50% of the time.
5) *Useful Daylight Illuminance (UDI);* it implies from its name a range of useful illuminance that is proposed to be from 100lux to 2000lux. So, it can be defined as the percentage of the occupied hours that lies in this range. What lies below the minimum threshold represent too dark area and signifies an increase in

[1] *Ibid.*
[2] Z. Rogers, (2006). "Daylighting Metric Development Using Daylight Autonomy Calculations in the Sensor Placement Optimization Tool." *Boulder, Colorado, USA: Architectural Energy Corporation: http://www. archenergy. com/SPOT/SPOT_Daylight% 20Autonomy% 20Report. pdf*.
[3] *Ibid.*
[4] C. F. Reinhart and J. Wienold, (2011). "The Daylighting Dashboard–a Simulation-Based Design Analysis for Daylit Spaces." *Building and environment* 46, no. 2: 386-396.

electric energy consumption, while that above 2000lux signifies occupant discomfort.[1]

The approved Illuminating Engineering Society (IES) method has provided two metrics mentioned in their report number LM-83-12.[2] They are Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE) giving an absolute benchmark levels for the pass or fail criteria. The first metric ($sDA_{300/50\%}$) gives an indication about daylighting adequacy inside the space where a minimum illuminance of 300lux is meant to be reached 50% of the occupied hours across at least 55% of the space area. However, it is preferred to reach at least 75% of space area according to the IES report. As for $ASE_{1000/250hr}$, it indicates excessive sunlight exposure when receiving direct sunlight of 1000lux for more than 250 hours. It should not exceed 10% of the space area. However, it is preferred to reach a maximum value of 3% ASE to avoid possible visual discomfort due to sun penetration.

Applying the aforementioned metrics give a clear picture about the daylighting performance for each specific case. However, the problem comes when evaluating a large number of alternatives in order to reach the optimal solution. Thus, a need for an optimization algorithm is inevitable.

2.5 Integrating Daylighting Simulation programs with Optimization Algorithms

Evaluating the potential of various daylight design strategies in achieving the required optimal or near optimal performance may be a cumbersome process. This is normally the case when there is a large number of parameters and thus a lot of trial and errors to reach the required performance. Sometimes environmental concerns are considered, but with a lack of knowledge and techniques. In this sense, form is driven by the designer's own experience and sensibility, making it vulnerable to his prejudice. This lead to a questionable design from that perspective.

Instead of using conceptual unquantifiable techniques or delegating daylighting issues to post design, optimization from the early beginning can be considered in the workflow. Optimization influences the design in a way that cannot be effectively compensated in the later design stages. Changes occur in later stages may cause penalties regarding cost

[1] A. Nabil and J. Mardaljevic, (2005). "Useful Daylight Illuminance: A New Paradigm for Assessing Daylight in Buildings." *Lighting Research and Technology* 37, no. 1: 41-57.
[2] I. IESNA, (2012). "Lm-83-12." *IES Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE). New York, NY, USA, IESNA Lighting Measurement*.

or performance. Integrating parametric modeling with daylighting simulation tools and optimization algorithms have opened new venues for creativity and efficiency, besides generating new unexpected forms that comply with the required needs and imposed constraints. Incorporating an optimization algorithm in the design workflow is what distinguishes performative design, and hence allowing the direct generation of form based on daylighting performance requirements as shown in Figure 2-4.

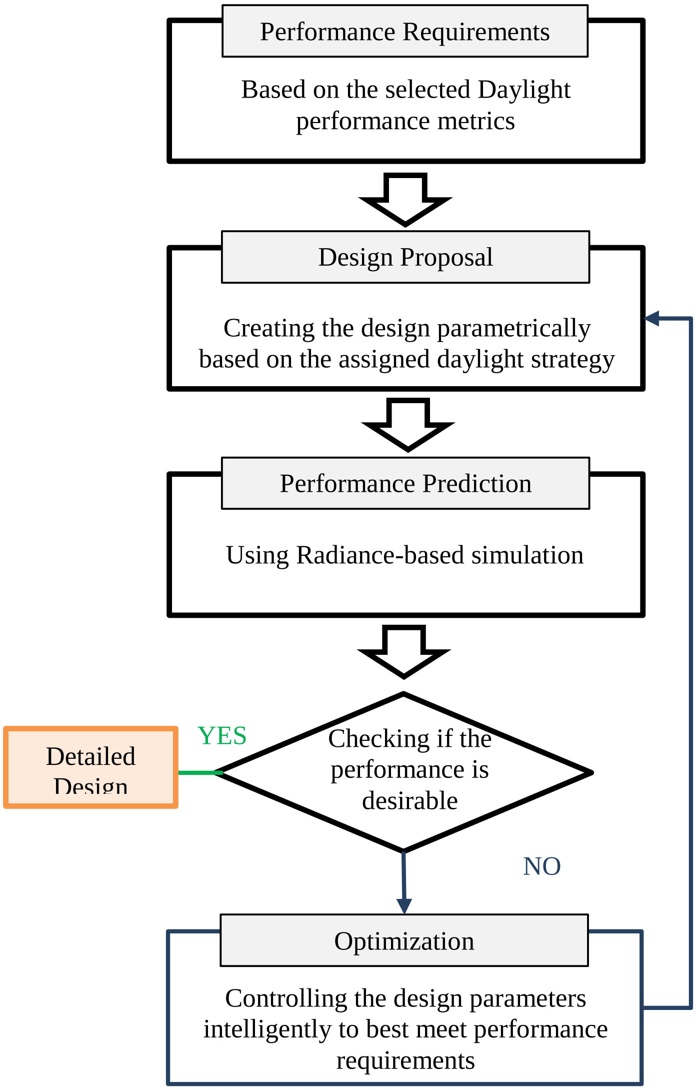

Figure 2-4 Performance-driven approach for daylighting design

2.6 Summary

Daylighting performance has two different aspects: visual and non-visual aspects. Focusing on visual ones regarding illuminance levels, a number of daylight metrics were proposed to evaluate these aspects. Aiming to find the balance between adequate illuminance levels and visual comfort, the approved method of IES has introduced two complementary metrics: 1) spatial daylight autonomy (sDA) and 2) annual sunlight exposure (ASE). The first aims to ensure reaching a minimum of 75% of the space area to illuminance value of 300lux for at least 50% of the time. As high illuminance levels could mean excessive penetration of direct sunlight, the second metric comes to ensure its avoidance. Annual sunlight exposure (ASE) benchmarks the allowable direct sunlight penetration by 3% as a maximum percentage of the space that reach 1000lux for more than 250 hours. Meeting both criteria ensure daylighting adequacy without excessive sunlight exposure.

These two metrics form the basis of evaluating the daylighting strategy adopted in the next chapter. As for the program used for daylighting calculations, Radiance-based simulation was found to be the most prominent daylighting simulation method. It was extensively validated and used in many studies[1] thus, Radiance as a simulation engine was identified for daylighting performance prediction. However, still the problem of evaluation comes when a large number of alternatives is needed. Hence, an optimization algorithm was needed to be incorporated within the workflow to support the search process for a successful daylighting design strategy that meet the intended daylighting performance.

[1] C. F. Reinhart and M. Andersen, (2006). "Development and Validation of a Radiance Model for a Translucent Panel." *Energy and Buildings* 38, no. 7: 890-904.

CHAPTER 3

Optimized Facades for Daylighting Performance: Classroom Case Study

- FAÇADE TREATMENTS FOR DAYLIGHTING DESIGN
- GENERATIVE SYSTEMS FOR FAÇADE OPTIMIZATION
- CELLULAR AUTOMATA FOR OPTIMIZED SCREEN PATTERNS: CLASSROOM CASE STUDY
- CLASSROOM CONFIGURATIONS FOR DAYLIGHTING DESIGN

3.1 Introduction

Adopting a holistic design approach that takes environmental concerns into consideration from the early beginning is intended. Apart from the conventional design that only emphasizes the aesthetics or the functional aspects, generative performative design is sought. This approach was applied on a classroom space to explore the design capabilities of Cellular Automata (CA) in maintaining its visual/formal qualities while complying with daylighting performance requirements.

In this chapter, a brief introduction on façade design treatments was given with an emphasis on solar screens as one of the well-known design treatments. Besides, an overview of different generative design systems was introduced to highlight their capabilities in pattern generation. Hence, they could be useful in solar screen formation in a way that meet daylighting performance requirements when integrated with optimization. Cellular Automata (CA) was chosen to be applied in designing solar screen for a classroom space in the hot arid climate of Cairo. As for the optimization technique used, the study was divided into three phases where exhaustive search and Genetic Algorithms (GAs) were applied.

3.2 Façade Treatments for Daylighting Design

Building facades mediate between the outside and the inside environment. They protect the indoor environment from the external harsh conditions; like excessive solar radiations, and high or low temperatures. Different techniques can be applied to façade design aiming to enhance its role in enhancing the indoor environment. Focusing on improving the daylighting performance, designers used to employ static and kinetic façade treatments endowing solar shading while still providing natural light. Solar screens, louvers, and light shelves were among the widely used techniques, besides other strategies concerned with massing, orientation and openings to control daylight provision. An overview of some of these techniques was followed by the contribution of solar screens in enhancing daylighting performance.

3.2.1 Conventional Facade Treatments

Traditionally, various daylighting techniques are being employed in the treatment of the façade design. In a clear sky condition, direct sunlight is a serious problem and shading devices need consideration. Different shading elements can be deployed for diffusing daylight inside the space. In the simplest way providing an appropriate glazing area with a single shading element can control the amount of daylight. Louvers and blinds have also been widely used for this reason especially for direct sunlight and glare protection. However, they may not be efficient as they contribute in decreasing the illuminance levels inside the space. [1] Other daylighting techniques can resolve the conflict between providing a proper shading and maintaining adequate illuminance levels. Among these techniques which are sown in Figure 3-1 are: [2]

1. *Light shelves:* they consist of a horizontal overhang with a high reflective surface mounted on the upper part of the window dividing the window into two parts and still providing view to the outside. They are mainly used for providing light deep into the space and thus contributing in a more uniform distribution of the light.
2. *Prismatic panels:* they are sawtooth acrylic panels that can be fixed on façade opening to redirect or refract direct sunlight and diffuse light. Considerations in the profile section should be taken for avoiding glare problems.
3. *Light-guiding shades:* they are external fixed shades consisting of a glass aperture and two reflectors of high reflective materials to direct light rays into the ceiling of the space. They protect the space from direct sunlight and at the same time increase the illumination levels relative to conventional shades.
4. *Anidolic blinds:* they are innovative solar blinds aiming to transmit low sun angles while preventing high solar altitude rays those of summer days. They form an array of parabolic concentrators that reflect light rays and thus controlling undesirable sunlight and glare.

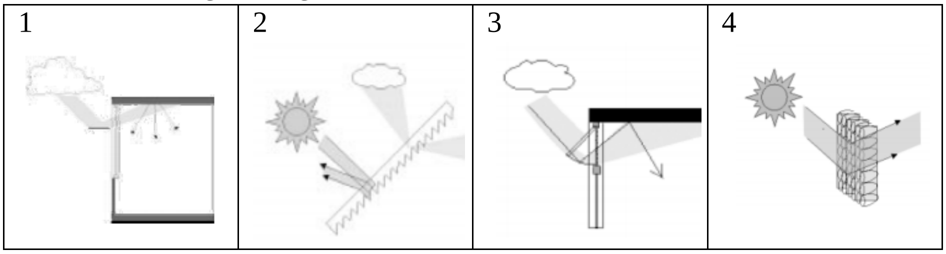

Figure 3-1: Illustration figures for Light shelve, Prismatic panel, Lighting-guiding shades, and Anidolic blinds[3]

3.2.2 Solar Screens for Facade Treatments

Another important shading element that was used to be applied in the Middle East for privacy and shading intents is the solar screen which is known as ‘Mashrabia’. A trend of their utilization in contemporary buildings has started to evolve. Trying to shift the

[1] K. J. a. R. Watkins, *Daylight in Buildings* (United Kingdom: AECOM Ltd on behalf of the international Energy Agency, 2010).
[2] *Ibid.*
[3] *Ibid.*

emphasis from their aesthetic role to focus on its environmental impact, a study has investigated different perforation ratios on both energy saving and daylighting autonomy through an experimental simulation. It is found that perforations range between 30%, and 50% are the best for reaching a good compromise between thermal and daylighting requirements. [1] In another study, an emphasis was on the impact of perforation percentages on daylighting adequacy. The space was divided into three zones; near, mid-length and far, where the minimum perforation percentage for each zone at different point in time was recommended.[2]

Besides perforation percentage, the rotation angle and the aspect ratio are two other effective screen parameters on the daylighting performance and solar radiation transmittance and they were investigated by Sherif et al.[3] The study was conducted in three consecutive phases. Acceptable cases that meet the criteria of the three phases; daylight availability, annual daylight glare probability, and annual solar energy transmittance, were elected. In another study, the problem of daylight non-uniformity and heat gain was addressed for similar climatic and spatial conditions. The effectiveness of solar screens was investigated through different design configurations. Recommendations were given for each orientation regarding adding light shelves, changing rotation angle, changing screen height and aspect ratio.[4]

According to the above literature fixed solar screen parameters were recommended to be used for hot arid climates. Also, dynamic solar screens were suggested. Understanding the possible limitation of static systems, a kinetic system inspired by the traditional mashrabiya was introduced in another study. A solar responsive system called ‘shape variable mashrabiya’ was proposed for maximizing daylight and view to the outside while minimizing solar gains. A logic for its operation was set with the objective of transforming direct sunlight into diffuse light for natural light provision while preventing

[1] A. Batool and I. M.K. Elzeyadi (2014 of Conference). From Romance to Performance: Assessing the Impacts of Jali Screens on Energy Savings and Daylighting Quality of Office Buildings in Lahore, Pakistan. 30th international PLEA conference, Ahmedabad, India.
[2] A. Sherif et al., (2012). "External Perforated Solar Screens for Daylighting in Residential Desert Buildings: Identification of Minimum Perforation Percentages." *Solar Energy* 86, no. 6: 1929-1940.
[3] A. Sherif et al., (2012). "The Impact of Changing Solar Screen Rotation Angle and Its Opening Aspect Ratios on Daylight Availability in Residential Desert Buildings." *Solar Energy* 86, no. 11: 3353-3363.
[4] H. Sabry et al., (2012). "Utilization of Combined Daylighting Techniques for Enhancement of Natural Lighting Distribution in Clear-Sky Residential Desert Buildings." 4, no. 5.20: 3.00.

solar gains. Results proved its effectiveness in achieving daylighting adequacy and uniform distribution thus proving its superiority over typical venetian blinds.[1]

Besides all the previous contributions, more unrevealed geometric attributes and their effectiveness on the intended criteria can be explored resulting in a more innovative solutions. This was suggested by adding other dimensions for performance and relating them to the capabilities of generative systems. The above mentioned treatments have proven their effectiveness in enhancing daylight provision, but there was a need for integrating the subjective visual aspects without violating the performance. Hence, incorporating generative systems was suggested.

3.3 Generative Systems for Façade Optimization

The spread of computation and mathematical frameworks in many design aspects has led to a shift in notions and concepts that used to be standard. This shift has offered the designer with the power of applying generative systems in architectural design. In façade designs, the use of generative systems can support design exploration in a way that form generation can be more performance oriented. This approach was introduced as 'Generative Performative Design' where both form and performance requirements drive the generation process.[2]

3.3.1 Generative Design Systems for Patterns Formation

The concept of generative design implies the use of codes and rules often merged with parametric modelling tools. It is a rule-based design process through which design forms are generated. Geometric representations are manipulated through an algorithmic procedure that is controlling a number of parameters or variables in predefined ways -according to a specified rules- so that they can behave in a certain pattern forming a range of design possibilities. Thus, they have the power to generate forms ranging from the simplest to the most complex. This could be through component-based software where no need of programming or scripting experience is required.[3]

[1] B. Karamata (2014 of Conference). Concept, Design and Performance of a Shape Variable Mashrabiya as a Shading and Daylighting System for Arid Climates. 30th international PLEA conference, Ahmedabad, India.
[2] E. Fasoulaki, "Integrated Design: A Generative Multi-Performative Design Approach".
[3] S. Milena and M. Ognen (2010). Application of Generative Algorithms in Architectural Design. Proceedings of the 12th WSEAS international conference on Mathematical and computational methods in science and engineering, World Scientific and Engineering Academy and Society (WSEAS).

Generative design systems were borrowed from other disciplines to explore their capabilities in form generation and exploration. Among the well-known generative systems that have a significant impact on architectural design are: Genetic Algorithms (GAs), Cellular Automata (CA), L-systems, Shape Grammars (SG), and Voronoi diagram. In this section a brief overview on these generative systems was given.

Genetic Algorithms (GAs): It was introduced previously in chapter one concentrating on its optimization role; however, it is also considered a form generation tool. Based on Darwinian principle of reproduction, which states that the survival for the fittest, GA works on replacing a population of solution with another fitter population by simulating the genetic operators of reproduction, mutation and crossover.[1]

Cellular Automata (CA): It was first introduced by John Von Neumann in the 1940s as an abstract self-reproduction model. It was borrowed from biology to be used in the architecture practice. CA is an array of cells each has a state of two possible states (on or off) and this depends on its initial condition besides the state of its neighbor cells. For each time step (time=t), the state of the cells is updated according to its neighbors and its own previous state (time=t-1) and this is governed by a certain rule.[2] A number of studies have integrated cellular automata (CA) as generative system to devise fenestration design strategies that comply with daylighting requirements.[3-4-5] In these examples, daylighting as a performance criterion was the driving engine behind the formulation of shading systems for building facades, aided by the enhanced design exploration possibilities of CA. In Figure 3-2, different CA patterns were shown wrapped around a building.[6]

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[1] D. E. Golberg, (1989). "Genetic Algorithms in Search, Optimization, and Machine Learning." *Addion wesley* 1989.
[2] S. Wolfram, 2002. *A New Kind of Science*. Vol. 5: Wolfram media Champaign.
[3] J. Kim, (2013). "Adaptive Façade Design for the Daylighting Performance in an Office Building: The Investigation of an Opening Design Strategy with Cellular Automata." *International Journal of Low-Carbon Technologies*: ctt015.
[4] M. Zawidzki, (2009). "Implementing Cellular Automata for Dynamically Shading a Building Facade." *Complex Systems* 18, no. 3: 287.
[5] M. Zawidzki, 2010. *A Cellular Automaton Controlled Shading for a Building Facade*. Translated by. Vol. vols. ed., Edited by.: Springer. Reprint.
[6] K. Terzidis, 2006. *Algorithmic Architecture*: Routledge.

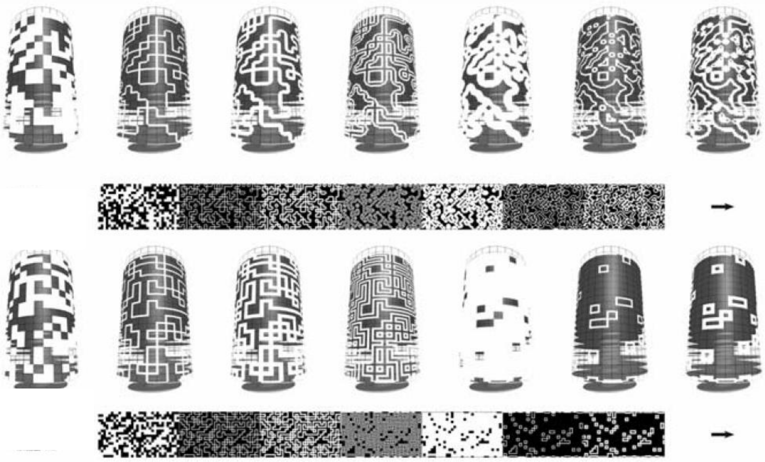


Figure 3-2: CA patterns wrapped on a building[1]

L-systems: They were first developed as a method to simulate the growth of plants and was named after its developer Lindenmayer. First, their geometric aspects were concerned for plant modelling. Then, their potential in generating unexpected patterns allowed their application in architectural design. The essence of this system lies in defining geometric elements through rewriting mechanism. The components of a rewriting system are a number of variables, initial string, and production rules. Starting with an initial string at t=0, the variables forming this string are changing iteratively based on the production rules that control this transformation, thus forming a new expanded string. Lindenmayer's L-system for modelling a plant growth can be exemplified where strings are built of two letters A and B (variables). The string starts with A (initial string) and is transformed through each time step according to the following two rules: A → AB, B → A (production rules) which produces at:

t = 0: A

t = 1: AB

t = 2: ABA

t = 3: ABAAB

t = 4: ABAABABA

[1] *Ibid.*

These letters are interpreted to geometric features in a way that reflects an emerging geometric pattern based on different possible variables, strings and rules. Examples of the possible generated patterns are shown in Figure 3-.[1]

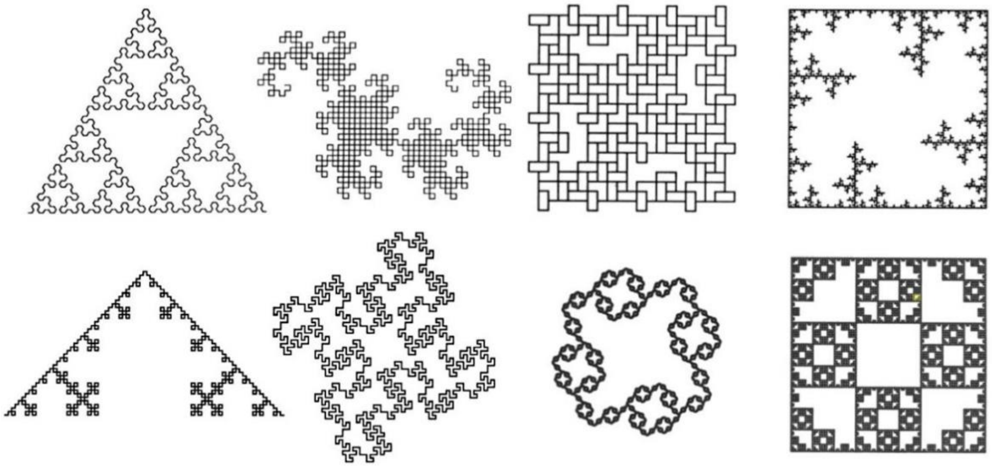


Figure 3-3 Patterns generated by L-system[2]

Shape Grammars (SG): It is the first design-oriented generative system and was introduced by Stiny and Gips in the early 1970's.[3] It is a rule-based method by which various forms (design languages) can be generated through initial shapes (shape vocabulary) and a set of rules that control shape transformation (spatial relations). The rules articulate the designer's ideas in a more explicit communicative way. Besides, it allows a plethora of design alternatives to be explored and evaluated. From the simplest shapes, complexity can arrive.[4] Shape grammars were used to understand and analyze geometric patterns and to generate various designs having the same language. A study made use of this characteristic aiming to generate different Islamic patterns having the same geometric compositions using a shape grammar model. Two geometric templates were generated starting with the same initial shape and similar rule schema as shown in Figure 3-4.[5]

[1] P. Prusinkiewicz and A. Lindenmayer, 2012. *The Algorithmic Beauty of Plants*: Springer Science & Business Media.
[2] *Ibid.*
[3] G. Stiny and J. Gips (1971). Shape Grammars and the Generative Specification of Painting and Sculpture. IFIP Congress (2).
[4] G. Stiny, (1980). "Kindergarten Grammars: Designing with Froebel's Building Gifts." *Environment and planning B* 7, no. 4: 409-462.
[5] U. Ebru (2009 of Conference). A Shape Grammar Model to Generate Islamic Geometric Pattern. 12th generative Art Conference.

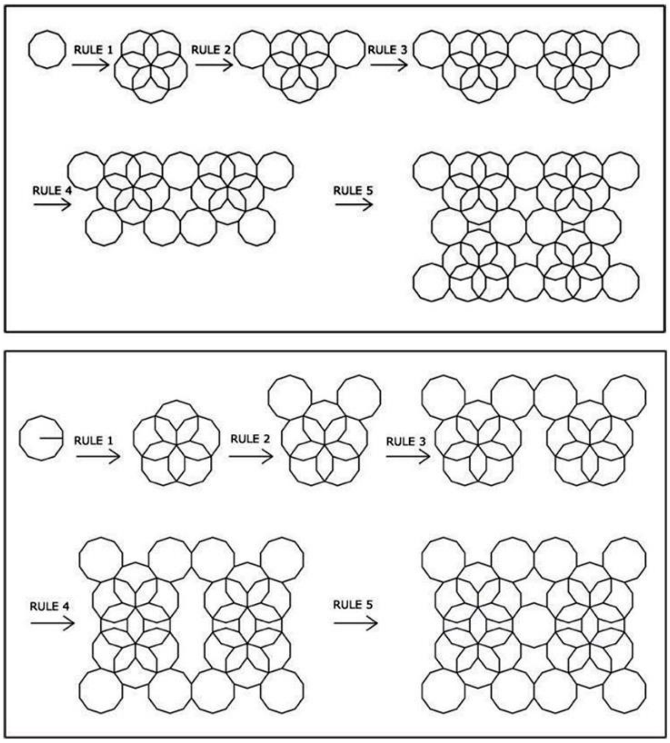


Figure 3-4: Two design templates of Islamic Patterns having similar rule schema in a Shape Grammar Approach[1]

Voronoi diagrams: As a generative tool in architecture, it is characterized by its non-repetitiveness and modular patterns which endows its uniqueness. An example of a parametric design using Voronoi is shown in Figure 3-5. Unexpected interesting patterns and geometries can be generated thus making it tempting to designers for form finding. It is characterized by its inherent spatial relationships and neighborhoods that can be parametrically modeled.

The emergent voronoi structure has the potential to produce a structure order. For instance, it was used for structural optimization as a computational means to explore more complex and adaptive geometries. Edges of the voronoi acted as structural members of a static system. Then, optimizing the cell structure was assessed regarding its structural properties; stability and deformation using simulation software.[2] Another study combined the structural and environmental potentials of voronoi diagram in designing

[1] *Ibid.*
[2] E. Friedrich, "The Voronoi Diagram in Structural Optimisation" (UCL (University College London), 2008).

double skin façade for mid-rise towers. Genetic Algorithms was utilized for optimization searching a diverse range of solutions that meet design requirements.[1]

Figure 3-5: Prototype of a Voronoi Structure

Generative system are not confined to the aforementioned systems. For instance, a study has addressed applying leaf venation algorithm as a generative system for façade design. In this algorithmic approach, leaf venation patterns were informed by a performance criteria where the analysis data controlled veins distribution and their densities as shown in Figure 3-6.[2]

[1] O. O. Torghabehi and P. von Buelow (2014). Performance Oriented Generative Design of Structural Double Skin Facades Inspired by Cell Morphologies. Proceedings of the IASS-SLTE 2014 Symposium "Shells, Membranes and Spatial Structures: Footprints", Brasilia, Brazil.

[2] S. Gokmen (2013). A Morphogenetic Approach for Performative Building Envelope Systems Using Leaf Venetian Patterns. eCAADe 2013: Computation and Performance–Proceedings of the 31st International Conference on Education and research in Computer Aided Architectural Design in Europe, Delft, The Netherlands, Faculty of Architecture, Delft University of Technology; eCAADe

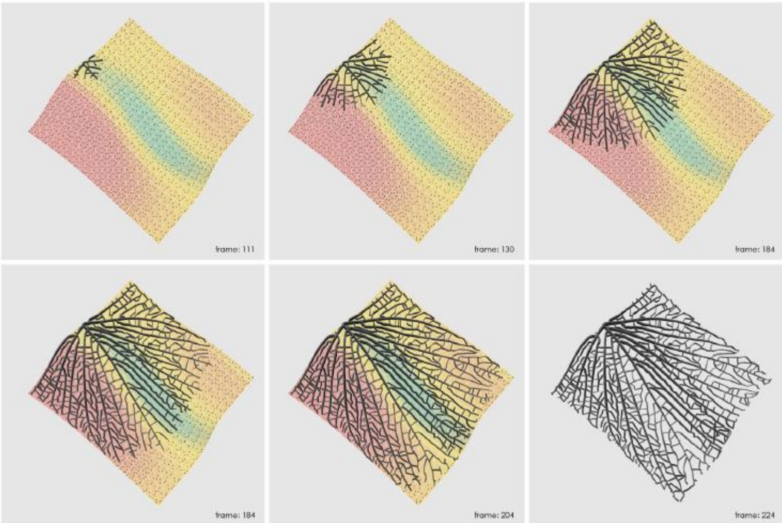


Figure 3-6: Leaf venation pattern based on performance analysis showing its effect on changing veins distribution[1]

Generative systems applications in façade design return to their significance in providing many possibilities of design patterns that can meet both designer's intentions and the intended performance criteria. However, there is a need for optimization algorithm to make this process more efficient.

3.3.2 Integrating Optimization with Generative Systems for Daylighting Design

Both form and performance should be emphasized without the bias of one on the other. They are rather two complementary design principles by considering form not merely a geometric representation but a group of components having effects and behaviors.[2] From here comes the need of 'generative performative design' approach to be adopted for generating building facades in a way that performance act as the driving engine behind the development of the generative technique. For instance, a study aimed to maintain the visual aspects while capturing the performative constraints of daylighting requirements through a responsive model. This model is represented by a matrix of square grid mounted on the south oriented elevation of a prototype house. It applied the rules of a

[1] *Ibid.*
[2] E. Fasoulaki, "Integrated Design: A Generative Multi-Performative Design Approach".

shape grammar in a way that generative electrochromic façade patterns can comply with visual and daylighting illuminance needs.[1]

Daylighting is an important building aspect that needs concern from the early beginning of the design process. The intended design performance when considered from the early beginning acquires a guiding rule that inform geometric elements how to be represented. For this reason, façade optimization was applied in a number of daylight studies. A study by Gadelhak M. investigated the integration of optimization algorithm with a simulation technique for static optimized facades[2]. Another studies were conducted for the development of kinetic façade design[3]-[4], and smart façade optimization[5]. In this sense, simulation techniques that are responsible for performance assessment feed the search method with the guiding information to best meet the required performance. In addition, exploiting the computational capabilities and integrating them with optimization algorithms have opened new venues in solar screen pattern designs.[6]

This study intended to achieve adequate daylighting illuminance levels inside a classroom space in Cairo while preventing excessive sun exposure. Cellular automata (CA) was chosen to be explored in depth for its emergent behavior in generating various screen patterns.

3.4 Cellular Automata for Optimized Screen Patterns: Classroom Case Study

Cellular Automata is a well-known generative system that imparts a sense of visual quality and guides form generation.[7] In this study, both designers' subjective visual requirements and daylighting performance criteria govern the CA pattern generation. The

[1] S. D. Kotsopoulos et al. (2012). A Visual-Performative Language of Façade Patterns for the Connected Sustainable Home. Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design, Society for Computer Simulation International.
[2] M. Gadelhak (2013). Integrating Computational and Building Performance Simulation Techniques for Optimized Facade Designs. eCAADe 2013: Computation and Performance–Proceedings of the 31st International Conference on Education and research in Computer Aided Architectural Design in Europe.
[3] K. Sharaidin et al. (2012). Integration of Digital Simulation Tools with Parametric Designs to Evaluate Kinetic Façades for Daylight Performance. Digital Physicality-Proceedings of the 30th eCAADe Conference.
[4] M. El Sheikh and D. Gerber (2011). Building Skin Intelligence. Proceedings of ACADIA.
[5] C.-S. Park et al. (2003). Daylighting Optimization in Smart Facade Systems. Proceedings of the Eighth International IBPSA Conference.
[6] F. Fathy et al. (2015). Cellular Automata for Efficient Daylighting Performance: Optimized Façade Treatment. roceedings of BS2015: 14th Conference of International Building Performance Simulation Association, Hyderabad, India, Dec. 7-9, 2015.
[7] S. Wolfram, 2002. *A New Kind of Science*. Vol. 5: Wolfram media Champaign.

form generation process complied with daylighting performance criteria using three main modules: *a generative model, a simulation program, and an optimization algorithm*. One-dimensional Cellular Automata (CA) was used to generate screen patterns for the façade of a classroom space, then a simulation was conducted to evaluate all possible generated forms through an exhaustive search method[1]. The first phase was concerned with exploring 18 CA rules under the repetitive class patterns exhaustively, which have the same potential in shading purposes. Then, only one rule (rule 210) was evaluated in more depth so that the efficiency of Genetic Algorithms (GAs) as an evolutionary search method can be explored in reaching optimal or near optimal solutions. This workflow was illustrated in Figure 3-7.

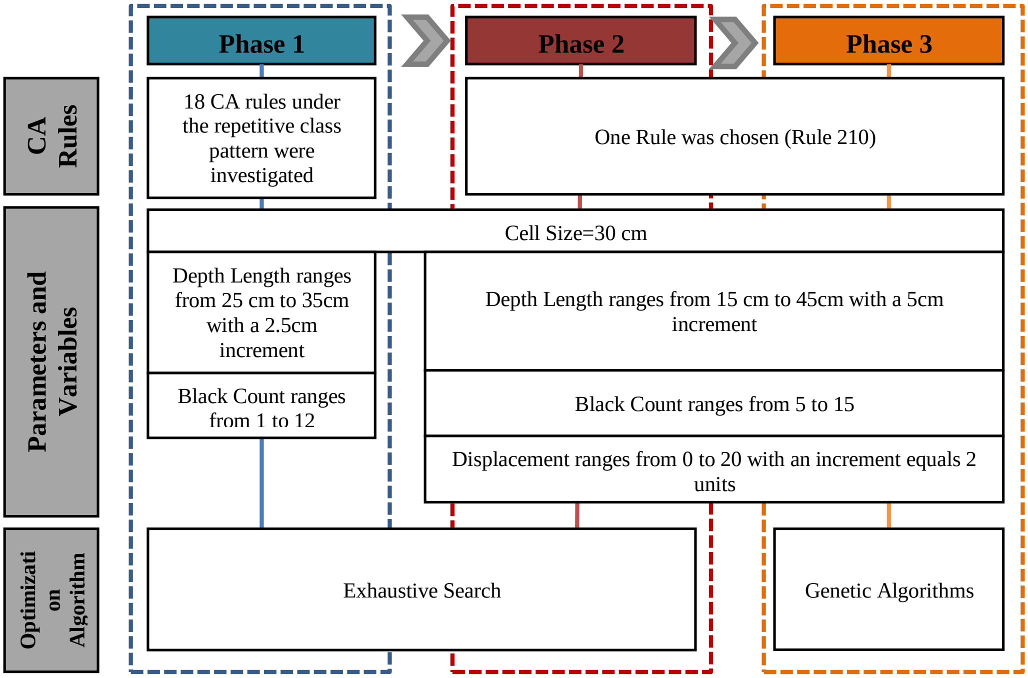


Figure 3-7: Phases applied in the classroom case study

For all phases, the width and height of the repetitive modular unit forming the screen (cell size) was fixed at 30cm as shown in **Error! Reference source not found.**, which was selected as a suitable dimension for visual perception of screen pattern. Whereas, cell depth was varied. According to a previous study[2], the convergence of solutions was found starting at 1:1 depth ratio (depth length divided by cell height). Hence, depth length was

[1] J. Daintith and E. Wright, (2008). "A Dictionary of Computing."

[2] A. Wagdy and F. Fathy, (2015). "A Parametric Approach for Achieving Optimum Daylighting Performance through Solar Screens in Desert Climates." *Journal of Building Engineering* 3: 155-170.

varied within a range of average value 30cm. This range was enlarged with a larger increment at phase 1 and 2 because the main objective was to explore the performance of GAs in finding solutions and detecting successful range of variables. Thus, the range was intended to cover varied alternatives rather than confining them to the deduced successful limit. Similarly, the black count range–which is the number of solid cells in the first row of the array and this denote and control the ratio of solid to void area– differed to cover a range of hypothetically unsuccessful alternatives so that GAs can be evaluated more objectively. In addition, one other variable –which is displacement effect– was added to increase the solution space and detect its influence on daylighting performance.

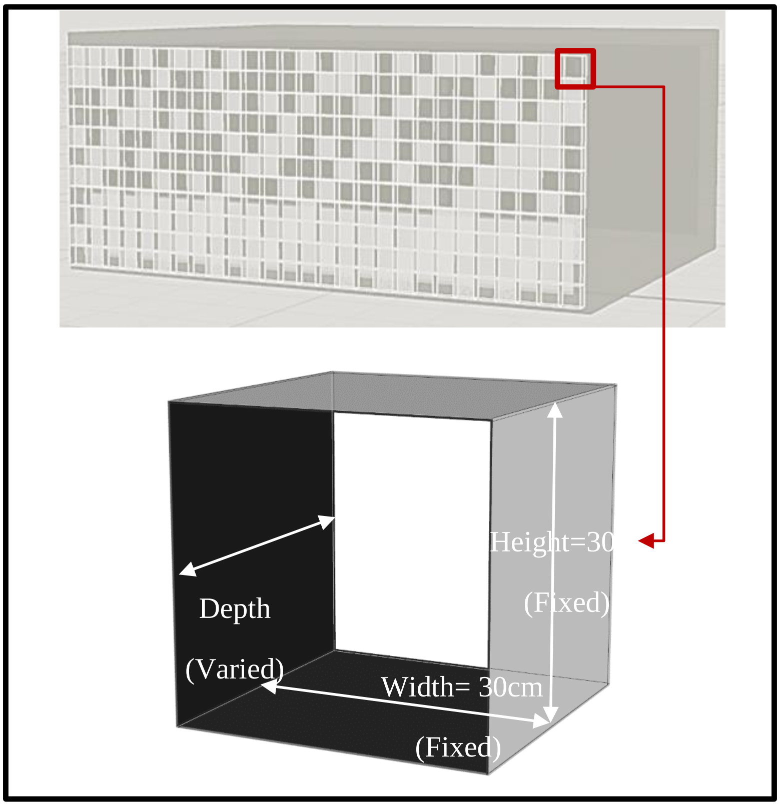


Figure 3-8: Modular Cell Configuration of the solar screen

Rhinoceros 3D modelling software and its graphical algorithm editor Grasshopper[1] were used as a common platform for CA pattern generation, daylighting simulation analysis, and optimization.

[1] D. Rutten, "Grasshopper-Algorithmic Modeling for Rhino Software Version 0.9077" (accessed 10-10 2014).

3.4.1 Naming Logic of CA Rules

Cellular Automata was formed by an array of modular cells, where each has two possible states (0 or 1). In one-dimensional CA, the state of each cell depends on its previous state and its two adjacent cells in the previous time step. Hence, for the subsequent time step, the cell becomes 'off' or 'on' based on $2^3 = 8$ possible reference states, as shown in Figure 3-9. The total possible arrangement of the cell states relative to the eight references is $2^8 =$ 256 cases or rules, ranging from rule 0 when all eight states are off, and rule 255 when all cell states are on. The naming logic of each rule returns to this arrangement. For instance, in rule 210 this was demonstrated where each 'alive' cell had a corresponding value that was added to form the rule name as shown in Figure 3-9.

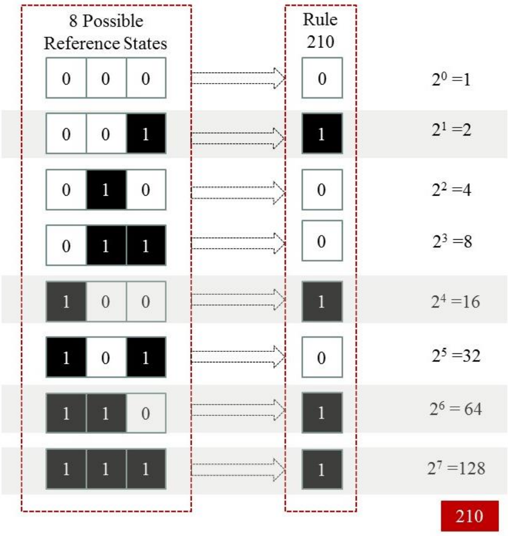


Figure 3-9: The naming Logic of rule 210

3.4.2 Rule Selection

According to Zawidzki[1] eighteen one-dimensional CA rules were classified under the repetitive class, justifying their suitability for shading applications. In this set of rules as shown in Figure 3-10, the opacity level of the whole CA array is proportional to that of the initial row condition. This was controlled by assigning the number of solid cells to the void ones. For instance in Figure 3-11, the initial black count, which was randomly set for rule 210, controls the opacity of the whole array. All of the eighteen generated patterns may have the same potential for diffusing daylight. Hence, they were all explored

[1] M. Zawidzki, (2009). "Implementing Cellular Automata for Dynamically Shading a Building Facade." *Complex Systems* 18, no. 3: 287.

in the first phase to explore their pattern efficiency on a south oriented façade in such a clear sky of Cairo. However, in the second phase, only one rule (210) was examined. This rule was chosen based on a subjective visual intention, which was aimed to be prioritized without breaching the required performance criteria.

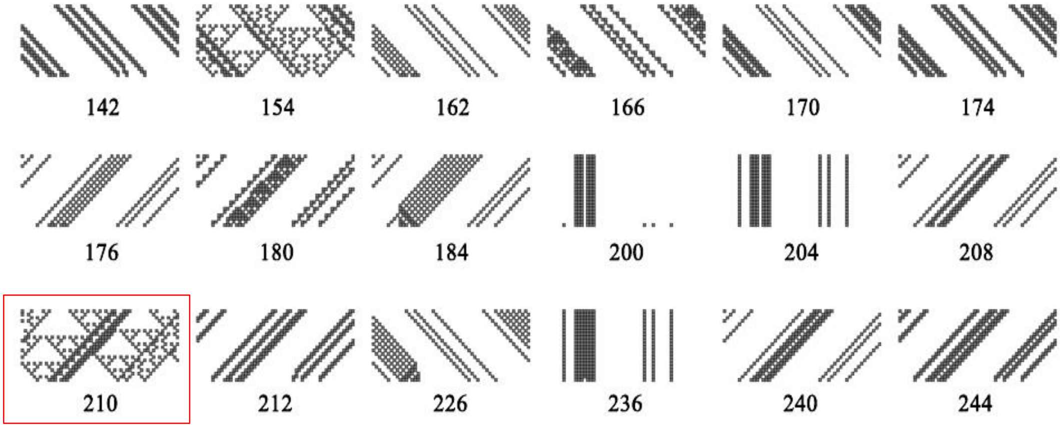


Figure 3-10: The eighteen CA rules under the repetitive class[1]

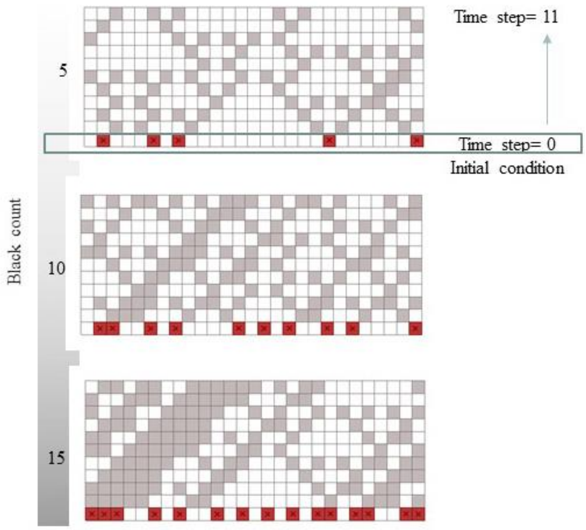


Figure 3-11: Pattern of rule 210 showing direct relation of screen openness factor with initial black count

[1] *Ibid.*

3.4.3 Screen Modelling

Rabbit plug-in for Grasshopper was used to simulate the emergent behavior of cellular automata in the process of generating the screen patterns. CA was applied on a regular square grid. Each row represents a state of a time step forming an array of cells that shows the history of generations, as shown in Figure 3-11. For each CA rule, a number of parameters were identified to explore their variations on daylighting performance. In the first phase, cell size was fixed to 30 cm while, two parameters were varied across the 18 rules:

1. *Cell depth;* it ranges from 25 to 35 cm with a 2.5cm increment.

2. *Black count;* it ranges from 1 to 12 black cells, which indicates openness factor that ranges from 4% to 48%.

In previous studies concerned with solar screens -which were formed by merely horizontal and vertical intersecting louvers-, the results indicated the possibility of finding solutions with no black count.[1] However, the limit was set high till 12 to create more visual interest and discover whether it could be applicable from the daylighting performance perspective.

In the second and third phase (for rule 210), three parameters were varied, which are:

1. *Cell depth;* it ranges from 15 to 45 cm with a 5cm increment.
2. *Black count;* it ranges from 5 to 15 black cells, which indicates openness factor that ranges from 20% to 60%.
3. *Displacement value;* which indicates the pattern shift in the X direction. The displacement ranges from 0 to 20 with an increment equal to 2 cell units. This variable could give an indication about the randomness effect of black count and whether the sequential order of black count –input in the first row– has an influence on daylighting performance or not. This range limits was set to cover the window width (8m) with varied patterns besides, the increment was set by 2 unit cells so that variation could be recognized as shown in Figure 3-12.

[1] A. Sherif et al., (2012). "External Perforated Solar Screens for Daylighting in Residential Desert Buildings: Identification of Minimum Perforation Percentages." *Solar Energy* 86, no. 6: 1929-1940.

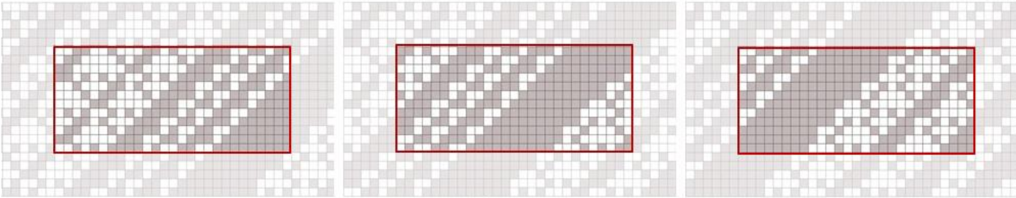


Figure 3-12: Displacement effect

3.4.4 Daylighting Evaluation Criteria

Daylighting simulation analysis was conducted using Diva-for-Rhino; a plug-in for Rhino which acts as an interface for Radiance and Daysim for daylighting calculations. This study complied with the approved IES method (IES report number LM-83-12).[1] This method introduced two metrics, which are Spatial Daylight Autonomy ($sDA_{300/50\%}$) and Annual Sunlight Exposure ($ASE_{1000/250hr}$), giving absolute benchmark levels for the pass or fail criteria.

The first metric ($sDA_{300/50\%}$) gives an indication of daylighting adequacy inside the space, where a minimum illuminance of 300lux is meant to be reached at 50% of the occupied hours across at least 55% of the space area. The second metric ($ASE_{1000/250hr}$) indicates excessive sunlight exposure when receiving direct sunlight of 1000lux for more than 250 hours. This should not exceed 10% of the space area. For this study, optimal cases have to reach at least 75% sDA and a maximum value of 3% ASE to avoid possible visual discomfort due to sun penetration.[2]

It is attempted to apply DIVA approach for the evaluation module which is an evidence-based approach mentioned by Reinhart in his daylighting handbook[3]; which stands for, design, iterate, validate, and adapt. The four main steps in this approach are: 1) formulating design objectives (Performance requirements); 2) generating a number of alternatives as suggestions (Design exploration); 3) evaluating and assessing design ideas through a verified simulation program for achieving valid and reliable results (Performance prediction); 4) adapting the final solution to meet up with the predefined performance objectives (Optimization). These steps were interpreted in the form of a workflow as shown in Figure 3-13 showing the tools and methods used.

[1] I. IESNA, (2012). "Lm-83-12." *IES Spatial Daylight Autonomy (sDA) and Annual Sunlight Exposure (ASE). New York, NY, USA, IESNA Lighting Measurement*.
[2] *Ibid.*
[3] C. Reinhart, 2013. "Daylighting Handbook-Volume I."

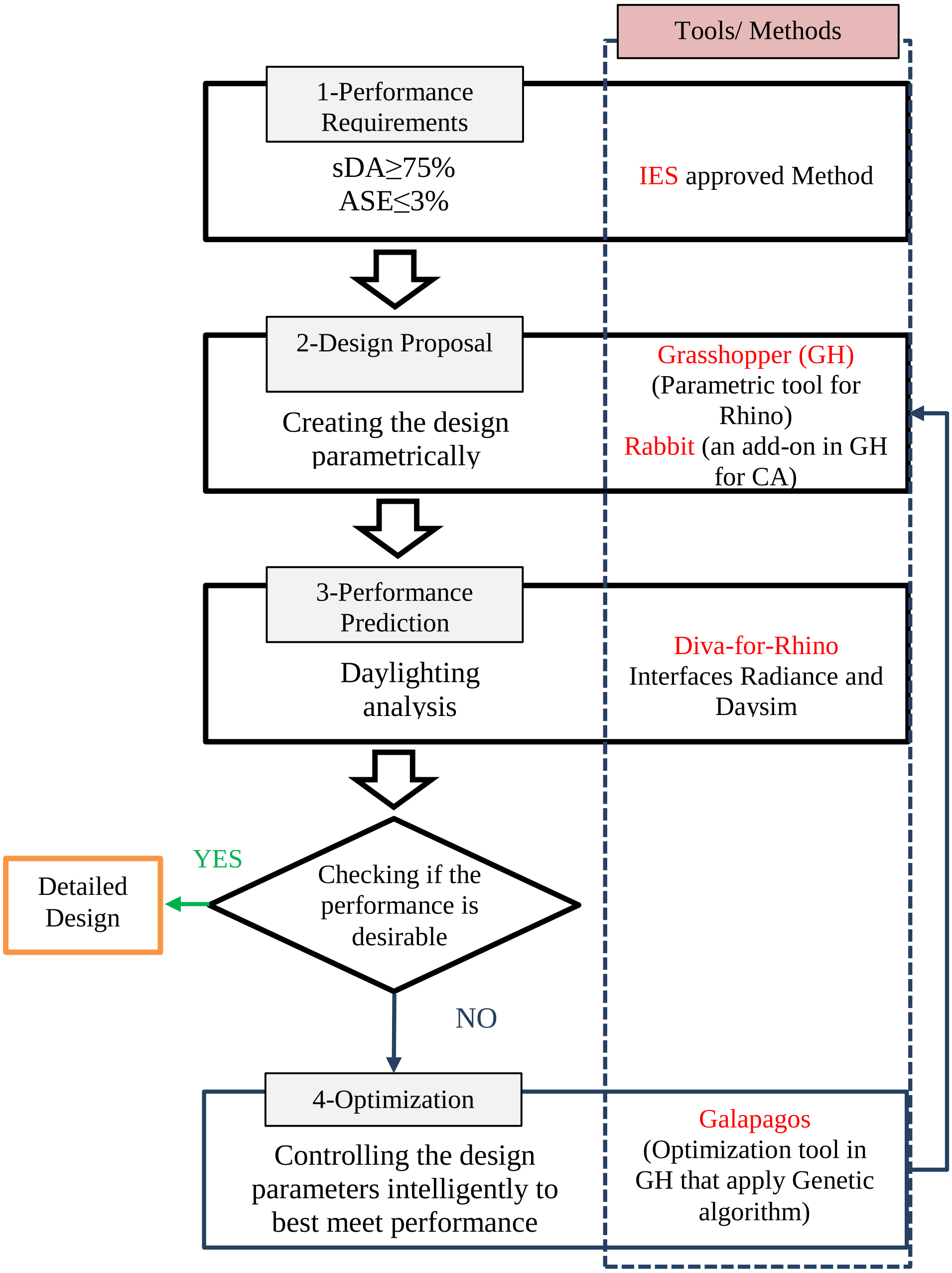


Figure 3-13 Design workflow proposed for daylighting optimization study

3.5 Classroom Configurations for Daylighting Design

Focusing on classrooms for the case study stems from the aim of enhancing the learning environment that could have a significant impact on both the students and staff performance. Different studies have proved the correlation between the students/staff performance and daylighting adequacy inside classroom.[1]-[2] It has a significant impact on the circadian system which is responsible for regulating some biological processes like sleeping and concentration. By taking a university classroom in one study, it is attempted to measure the quality of light in terms of its effect on the circadian system thus posing a new dimension for evaluating lighting quality.[3] In another study, an increase of 14% of students' performance is found to be in daylit schools and their rate of absenteeism has decreased by about 3.5 days per year.[4] A recent study has emphasized the influence of daylighting and detected the students' satisfaction with daylighting exposure. A questionnaire survey was conducted showing their tendency towards the perception of its significance in schools' environment and on their performance.[5]

A study was conducted that analyzes the condition of typical classrooms in the United Arab Emirates (UAE) in terms of visual performance. By focusing on different design aspects like, space size, depth to height ratio, orientation and desk position, it concluded with the necessity of the utilization of daylighting systems (i.e. solar shading) for mitigating the problems of glare and high solar radiation.[6]Another study intended to identify classroom configuration in a hot humid climate that meet with daylight performance criteria, regarding fenestration size and external louver configurations. Three windows to wall ratios were examined; 20%, 40%, and 60% ending with a recommendation of their corresponding shading louvers configurations.[7]

[1] L. Edwards and P. A. Torcellini, 2002. *A Literature Review of the Effects of Natural Light on Building Occupants*: National Renewable Energy Laboratory Golden, CO.
[2] G. Heath and M. J. Mendell (2002). Do Indoor Environments in Schools Influence Student Performance? A Review of the Literature. Proceedings of the 9th International Conference on Indoor Air Quality and Climate, Indoor Air 2002.
[3] L. Bellia et al., (2013). "Lighting in Educational Environments: An Example of a Complete Analysis of the Effects of Daylight and Electric Light on Occupants." *Building and Environment* 68: 50-65.
[4] M. H. Nicklas and G. B. Bailey (1996). Analysis of the Performance of Students in Daylit Schools. Proceedings of the National Passive Solar Conference, American Solar Energy Society INC.
[5] T.-w. Kim et al., (2014). "Daylight Evaluation for Educational Facilities Established in High-Rise Housing Complexes in Daegu, South Korea." *Building and Environment* 78: 137-144.
[6] K. A. Al-Sallal, (2010). "Daylighting and Visual Performance: Evaluation of Classroom Design Issues in the Uae." *International Journal of Low-Carbon Technologies* 5, no. 4: 201-209.
[7] A. Pedrini and J. Carvalho (2014 of Conference). Analysis of Daylight Performance in Classrooms in Humid and Hot Climate. 30th international PLEA conference, Ahmedabad, India.

In a city like Cairo, hot arid climate is experienced most of the year. Without taking proper shading of large glazed areas into consideration, a conflict between excessive heat gain and daylighting adequacy is sustained. One way is blocking direct sunlight while allowing the indirect to diffuse into the space through ceiling reflections or solar shading. In general, the north and south orientation were the first preference so that direct sunlight penetration could be avoided. According to the sun path diagram, only diffuse sunlight enter the space most of the time over the year. Whereas in the south, the sun angle is high, which facilitates the window treatment through horizontal louvers. The second preference is the north east or the south west and louvres should be utilized in both cases.[1] Besides orientation there are other factors affecting daylighting performance in classrooms as shown in Figure 3-14.

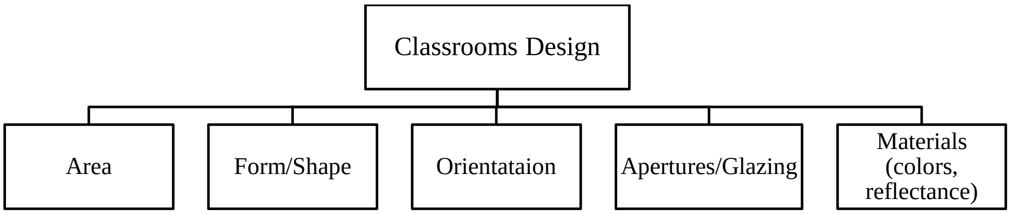


Figure 3-14 Classroom design factors affecting daylighting performance

Area of classroom can be calculated according to the following equation:

(Ca) = Ta + (Sn * Sa)[2]

Where Ca is the classroom area, Ta is the teacher's area, Sn is the number of the students, Sa is the area needed for each student.

According to the authority of educational buildings in Egypt[3], Ta ranges from 4.5 to 9m^2 and Sa ranges from 1.4 to 1.8m^2, and for the basic education the number of students ranges from 20-75 student. No limitations were imposed on how the shape should be like, it is left for the architect, so any shape is acceptable if it complies with the required area and the good distribution of furniture.

General terms imposed for classroom design can be summarized in: Common width not to be larger than 6m in case apertures are on one side of the room besides, length should

[1] MOE., 1990, *The Requirements of the General Authority for Educational Buildings for the Stage of Basic Education in Cairo*.
[2] Allen, Robert L. et al. 1996, Classroom design manual, 3rd edition, Academic information Technology services, University of Maryland, USA.
[3] *Op. Cit.: MOE., (1990).*

not be more than 9m. Room height should not be less than half its width and the recommended range is between 3.1 and 4.3m.

Based on the aforementioned requirements, this study was conducted on a generic south oriented classroom space located in the desert climate of Cairo, Egypt (30°6'N, 31°24'E, alt.75m) with no external obstruction. The classroom configuration and parameters for the classroom space, window and screen are shown in Figure 3-15 and Table 3-2 respectively. Radiance parameters used for sDA and ASE calculations were set according to the Illuminating Engineering Society (IES) as shown in Table 3-3.

For this case study, all window to wall ratios from 20% till 90% (with 10% increment) were evaluated, but none has passed the assigned criteria. Thus, after testing the daylighting conditions, it proved the necessity of implementing a design treatment for the openings. The main objective of this study is to find optimal solution that passes the daylighting performance criteria (sDA≥75% and ASE≤3%) through the suggested workflow of the CA screen pattern. This optimization study focused on the assigned parameters and variables (Screen Depth, Blackcount or the Opennes factor); However, other factors were neutralized like the internal material finishes, screen thickness, and external obstructions.

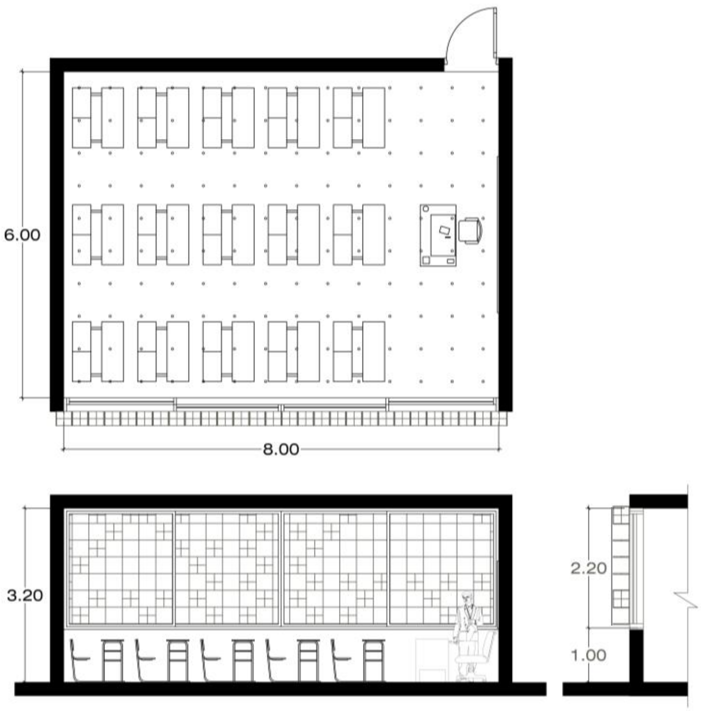


Figure 3- 15: Classroom Configurations

Table 3-2: Parameters of the classroom, window and screen

Space Parameters	
Floor Level	1st floor (+365cm)
Room Area	$48m^2$
Floor Height	320cm
Internal Surfaces Reflectance	
Ceiling	White color paint with 80% reflectance
Walls	off-white color paint with50% reflectance
Floor	Wooden floor with 20% reflectance
Window Parameters	
Window to wall ratio (WWR)	70%
Sill	100cm
Window height	220cm
Window width	800cm
Glazing	Double Clear Pane (VT=80%)
Window Frame	Metal Diffuse
Screen Parameters	
Screen Reflectivity	35%
Cell Size	30cm

Table 3-3: Radiance Parameters

Evaluation Metrics	Ambient Bounces	Ambient Divisions	Direct Threshold
sDA	6	1000	0
ASE	0	1000	0

3.6 Summary

Increasing tendency towards the adoption of generative systems in architectural design returns to a number of reasons; its automated non-monotonic form generations; exploration capabilities of large design space; possibility of design optimization; high efficiency; reduction of labor and time and hence decreasing cost.[1] Besides, generative models offer a high level of interaction and control over the digital representation and their operative part.[2] However, they lack the capability of modifying design elements to meet performance requirements without the feedback from the simulation tool. Thus, a generative performative approach was adopted where exhaustive search then Genetic Algorithms (GAs) was integrated with the generative system Cellular Automata (CA). Within this suggested workflow, Radiance (through Diva-for-Rhino) was utilized for daylighting performance prediction.

In this study, the goal was to achieve adequate daylighting illuminance levels in a south oriented classroom space using CA patterns. The generative flexibility of CA was capitalized on in order to set the resulting design alternatives free from monotonous and static prototypes, where geometrical forms are defined by fixed numerical values to produce and evaluate multiple alternatives. The rules and instructions that govern the geometric attributes and their relationships were based on two main aspects: daylighting adequacy and avoiding direct sunlight. Thus, capturing performative constraints to encode them by using CA parameters that comply with the IES approved method while controlling visual aspects.

[1] V. Singh and N. Gu, (2012). "Towards an Integrated Generative Design Framework." *Design Studies* 33, no. 2: 185-207.
[2] R. Oxman, (2006). "Theory and Design in the First Digital Age." *Design studies* 27, no. 3: 229-265.

CHAPTER 4

CLASSROOM CASE STUDY: RESULTS AND DISCUSSION

- EXPLORING CA RULES UNDER THE REPETITIVE CLASS PATTERNS
- EXPLORING CA RULE 210 BY EXHAUSTIVE SEARCH
- EXPLORING CA RULE 210 BY GENETIC ALGORITHMS

4.1 Introduction

Generative design systems have contributed in liberating the limits of design exploration, allowing designers to explore various design solutions. First, the 18 CA rules under the repetitive class were explored in terms of sDA and ASE values through an exhaustive search. Then, CA rule number 210 was specifically employed for form generation where 847 different cases were examined. Having the performance of all possible configurations, it was possible to evaluate the performance of GA in reaching the optimal solutions. At last, genetic algorithm GA was utilized to examine its efficiency in reaching optimal solutions with an appropriate convergence velocity. Results of this study demonstrated the potential of CA and GA in achieving the intended visual aspects and daylighting requirements efficiently.

4.2 Exploring CA Rules: Phase 1

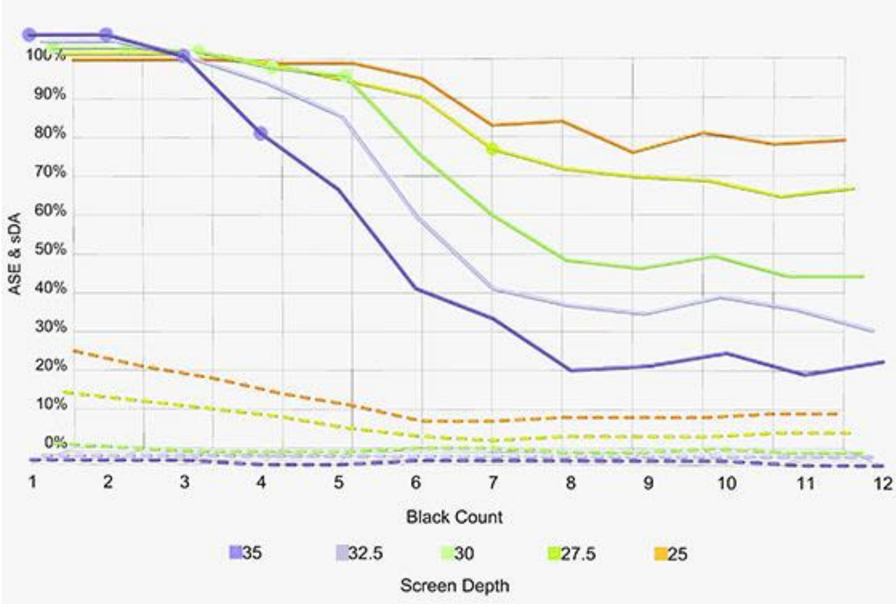
Cellular automata has proven its applicability in reaching a range of satisfactory solutions for static building facades. In this phase, 18 CA rules were explored which were classified under the repetitive class patterns and were considered appropriate for shading applications.[1] For the assigned range of values, all possible combinations were explored forming 1080 cases. For each rule 60 alternatives were examined. Parameters were confined to cell depth and black count. For cell depth, the range of values started with 25 cm to 35 cm with an increment of 2.5 cm. As for the black count, it ranged from1 to 12. The effect of black count and rule selection on CA pattern generation was explicated. Merely two random CA rules were given as shown in Table 4-1; as the rest showed a similar effect on the overall performance.

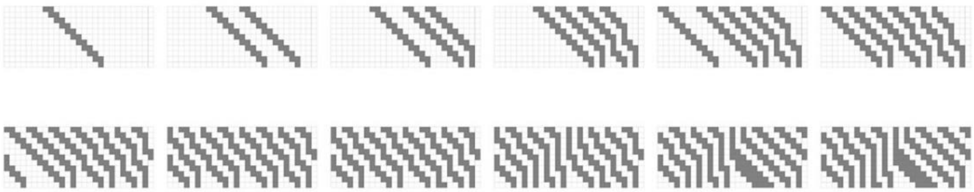
It was noticed that for all CA rules the effect of black count in decreasing sDA which was magnified by large depth lengths. For instance, in rule 142, sDA remained at its peak value at depth length 35cm till black count 3 then it was subjected to a sharp decrease where it reached 20% at black count 12. On the other hand, at smaller depth lengths, the effect of black count was much smaller. For instance, at depth length 25cm, sDA was constant at its peak till black count 5, then a slight decrease was experienced till it reached 80% at black count 12. As for ASE, black count had no relevant effect on ASE values. They remained almost constant at all black counts; however, at small depth lengths, a slight decrease can be noticed with the black count increase.

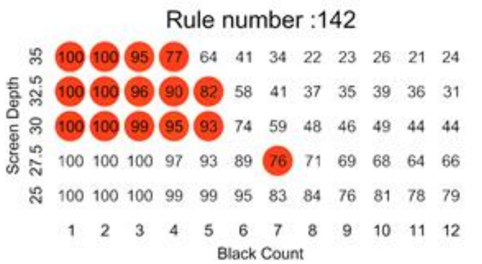
[1] M. Zawidzki, (2009). "Implementing Cellular Automata for Dynamically Shading a Building Facade." *Complex Systems* 18, no. 3: 287.

Table 4-1: Performance of screen patterns of rule 142 and rule 154 in terms of sDA and ASE showing their interaction with cell depths and black count

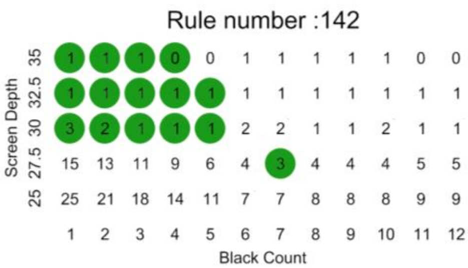
Rule 142





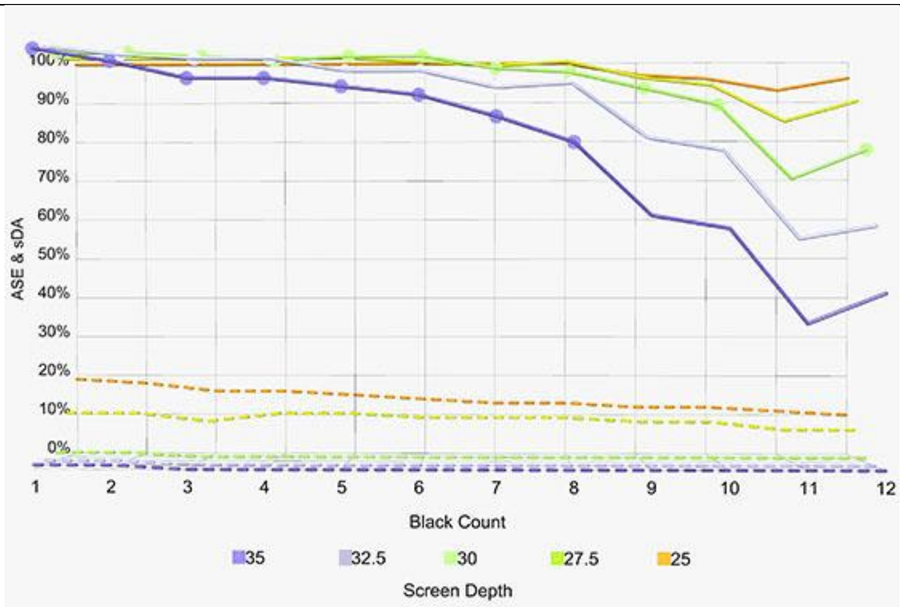


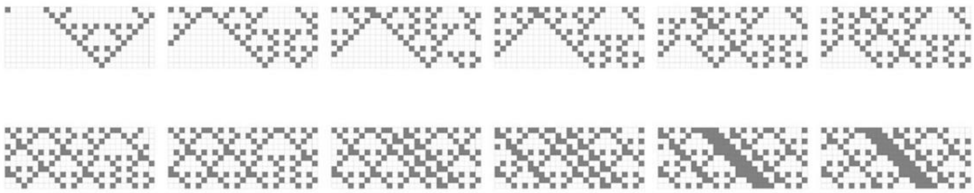
sDA≥75%

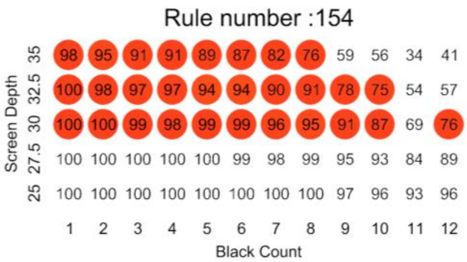


ASE≤3%

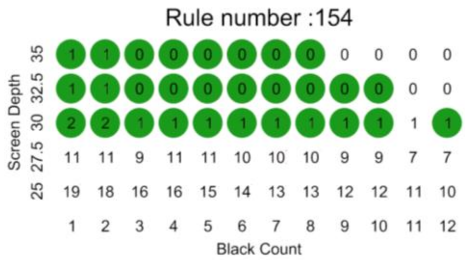
Rule 154







sDA≥75%



ASE≤3%

By comparing the performance of all rules, it is found that all rules showed promising results where both sDA and ASE passed the predefined criteria. This was demonstrated in Figure 4-1 and Figure 4-2, where all successful cases that passed the criteria: sDA $\geq$75% and ASE$\leq$ 3%, were highlighted. It can be noticed that solutions reached for all the18 rules were at depth length ranged from 30 to 35cm across all black counts.

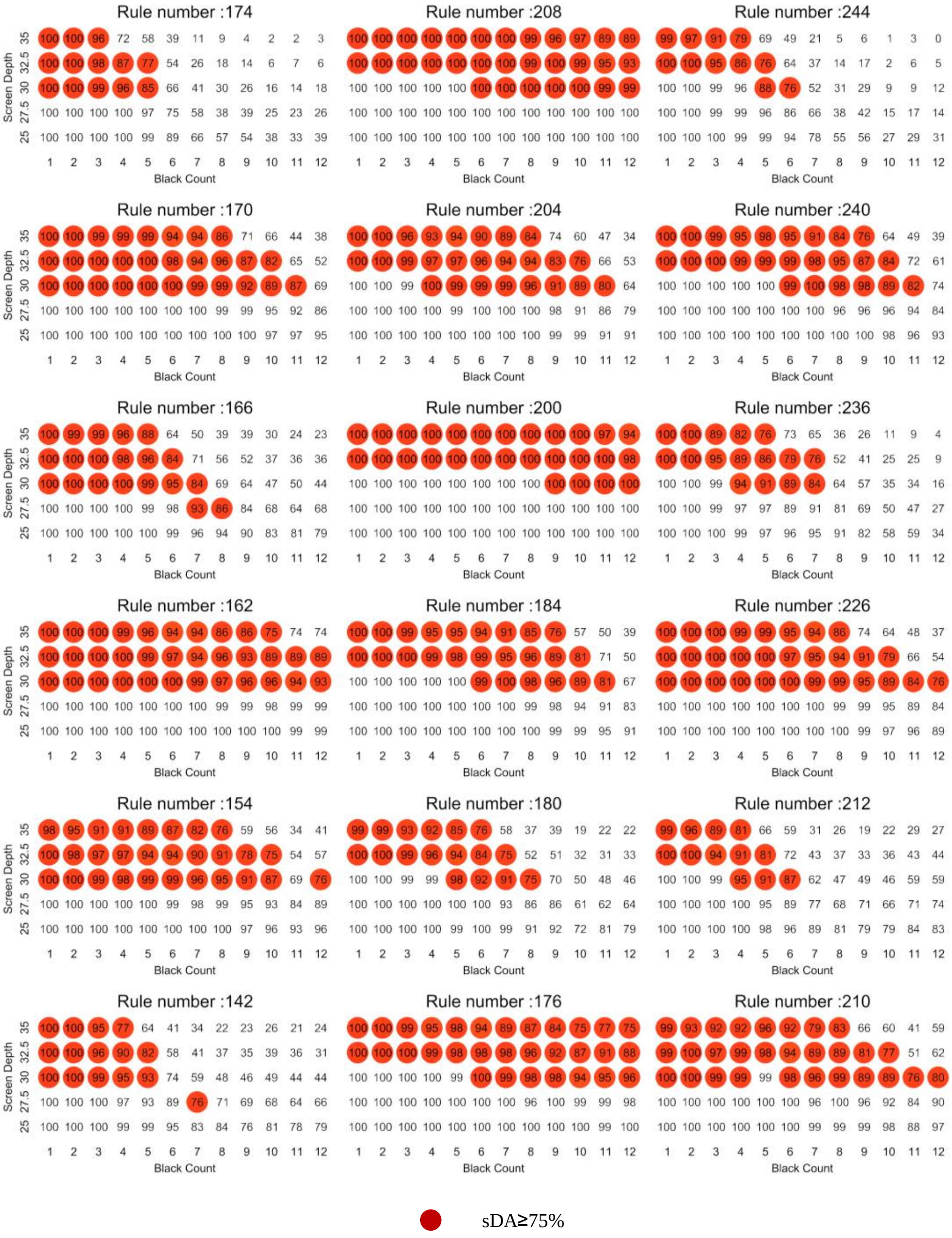


Figure 4-1: sDA values for all screen configurations of the 18 CA rules highlighting the successful ones

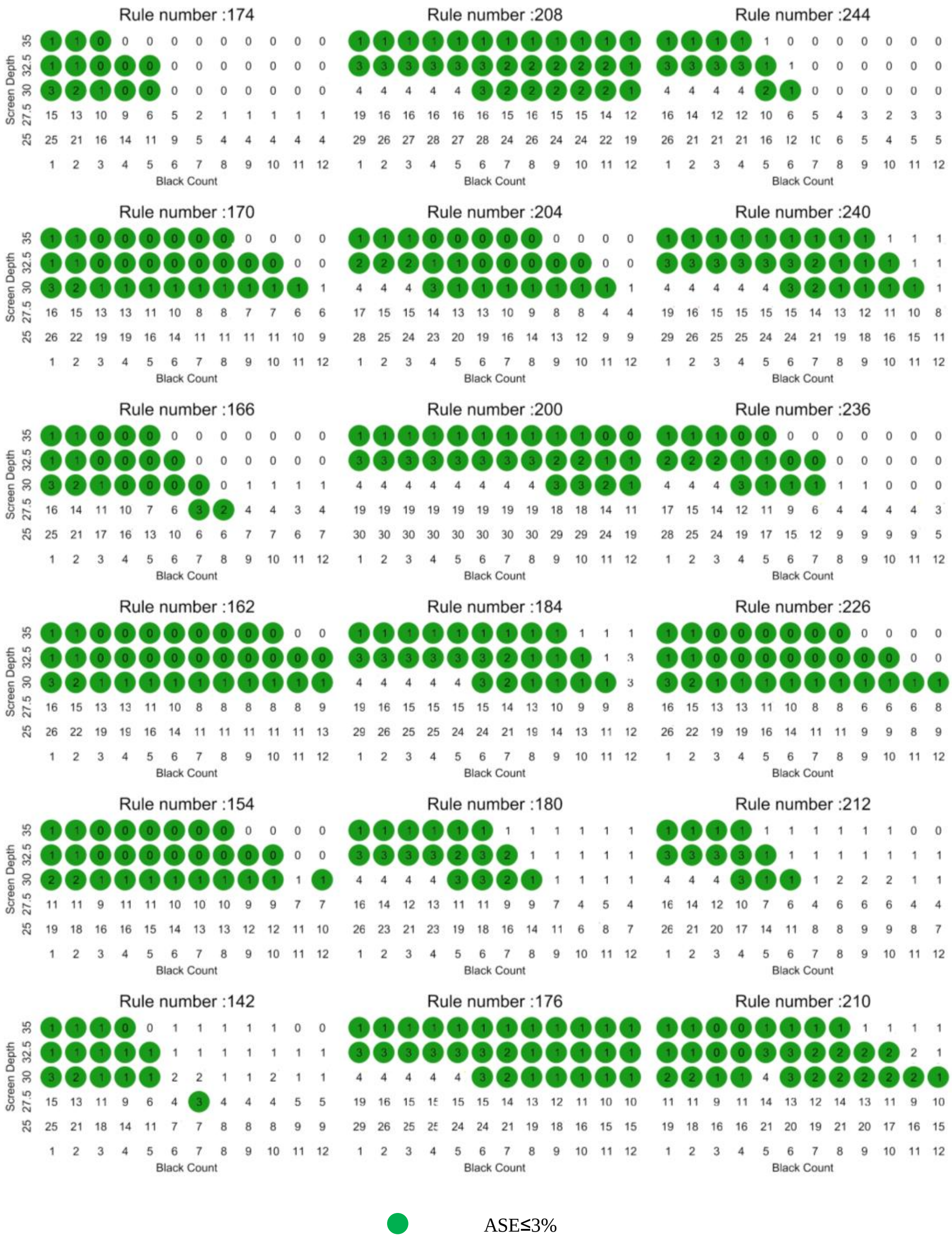


Figure 4-2: ASE values for all screen configurations of the 18 CA rules highlighting the successful ones

4.3 Exploring CA Rule 210 by Exhaustive Search: Phase 2

In this phase, one CA rule was chosen to be explored in more detail using the same exhaustive search method. Examining all possible combinations allowed for investigating the impact of each variable and their interaction on the required daylighting performance. One new variable was added which is the displacement value to see its effect on performance. It is intended to explore a larger range of depth length and black count values, where the range of depth length started from 15 to 45 cm with an increment equal 5. At the same time the range of black count was increased to reach 15; however, less than 5 black count was discarded for visual intentions. By combining all possible values for each variable, seven values for depth lengths, and eleven values for black count and displacement, 847 different cases were evaluated in total as shown in Figure 4-3.

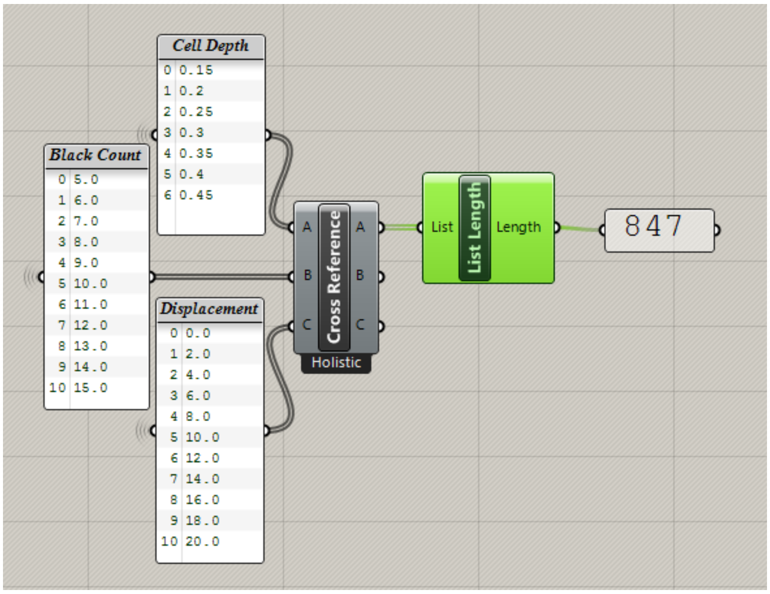


Figure 4-3: Values of the three investigating variables forming 847 different alternatives

4.3.1 Cell Depth Effect

A number of findings emerged from the simulation process. First, cell depth proved a large impact on daylighting performance. Both sDA and ASE decreased as the depth increased, as shown in Figure 4-4. However, it was required to decrease only ASE while increasing sDA. For large depths ranging from 35 to 45 cm, ASE succeeded to maintain its maximum threshold (3%); however, sDA did not exceed the minimum required value (75%). sDA exceeded 75% while maintaining the low ASE level only at a depth value of

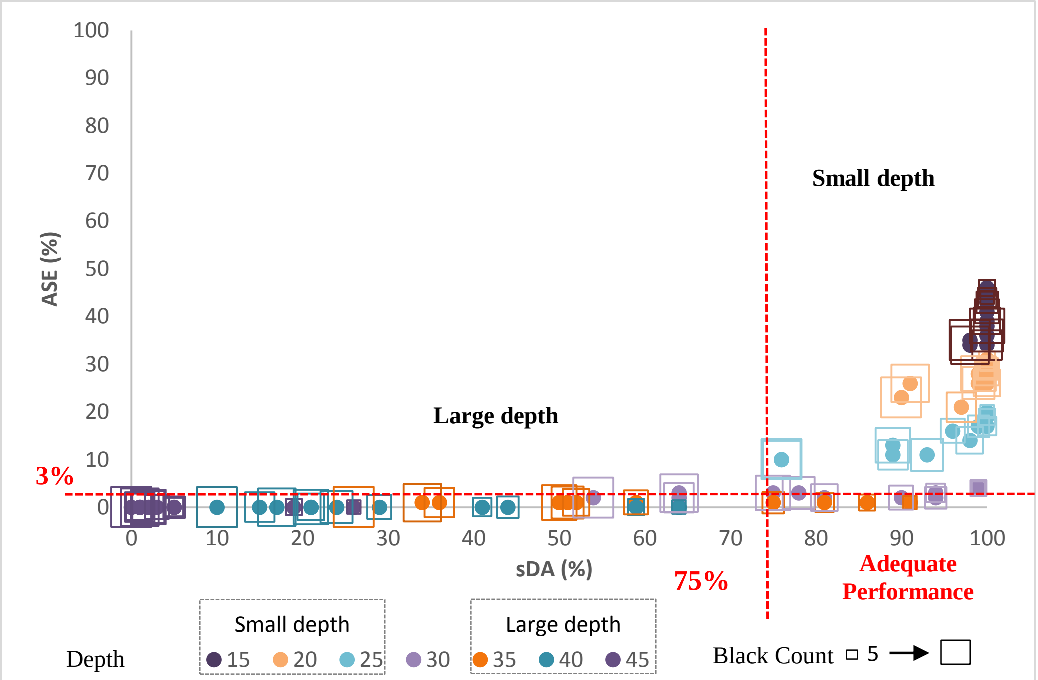


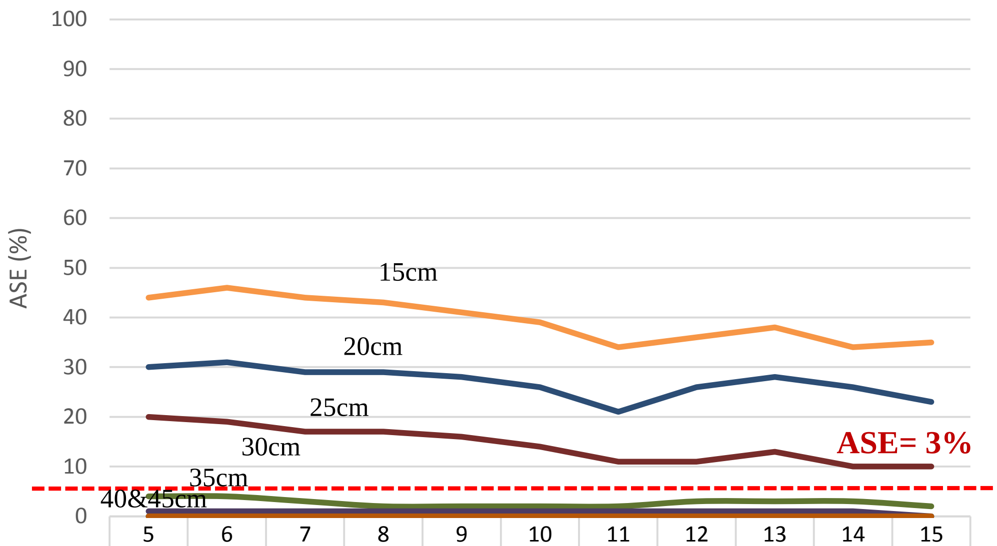
Figure 4-4: sDA and ASE values for all depth lengths and black counts at displacement 2

35cm and by decreasing black count as illustrated in the adequate performance area. As for small depths ranging from 15cm to 25cm, sDA exceeded 75% at all black counts; on the other hand, ASE was too high reaching up to 46%. A compromise between the advantage of large depths in decreasing ASE and small depths in increasing sDA was found at a depth value of 30cm. About 76% of the solutions were reached at this depth value. Since the cell size was fixed at 30cm, a correlation between cell size and cell depth was deduced, where the optimal results were realized mainly at depth ratio 1:1. However, it needs more verification by varying and testing other cell sizes. Searching all possibilities, sDA and ASE passed their benchmarks at both cell depth of 30cm and 35cm, as shown in Figure 4-4.

4.3.2 Black Count Effect

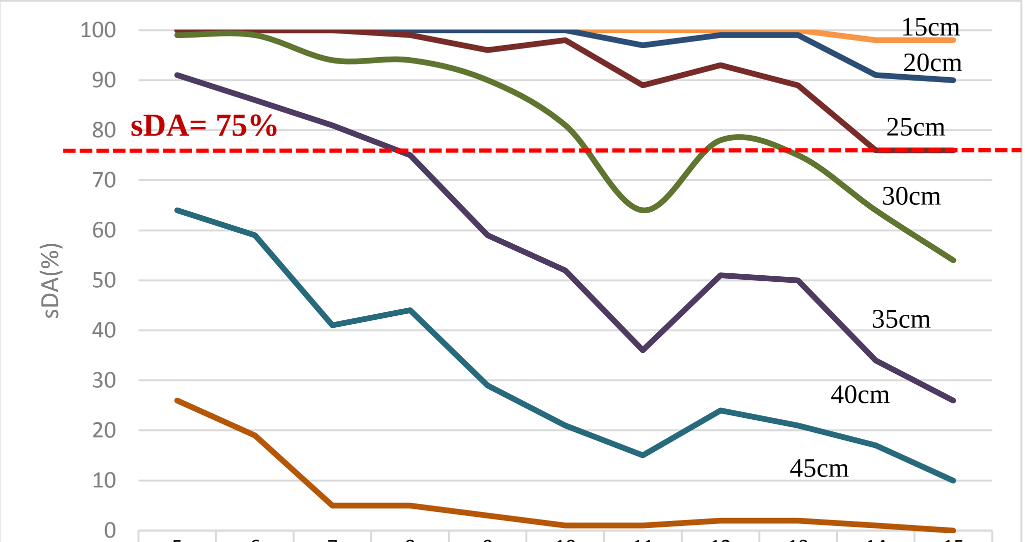
Second, the black count, which denotes the openness degree of the whole array, showed its remarkable effect on decreasing sDA at large depth values, where it suffered a sharp decrease at large depth values. On the other hand, it had a little effect on ASE, where it appeared constant at large depth values, as shown in Figure 4-5 and Figure 4-6. For instance, at depth length 35cm, sDA decreased from 91% at black count 5 to 26% at black count 15, while ASE decreased by only 1%. Conversely, at small depth values, increasing black count had a significant effect on decreasing ASE. However, it was not large enough to reach the required value.

In contrast, sDA slightly decreased and still maintained its large values. For instance, at depth length 15cm, ASE decreased from 44% to 35% while sDA decreased by only 2% to reach 98% at a black count of 15. The only case where black count had no considerable impact on both sDA and ASE was at depth value of 45cm, where sDA was too low; even at the lowest openness where sDA reached only 26%. Besides, it had no impact on ASE at large depth values where ASE reached a bottom. In short, black counts ranging from 5 to 13 showed a success in reaching a balance between the required low ASE value and large sDA value at depth values 30cm and 35cm, as shown in Figure 4-5and Figure 4-6. These values implied screen openness factor ranges from 20% to 50%.



	5	6	7	8	9	10	11	12	13	14	15
15	44	46	44	43	41	39	34	36	38	34	35
20	30	31	29	29	28	26	21	26	28	26	23
25	20	19	17	17	16	14	11	11	13	10	10
30	4	4	3	2	2	2	2	3	3	3	2
35	1	1	1	1	1	1	1	1	1	1	0
40	0	0	0	0	0	0	0	0	0	0	0
45	0	0	0	0	0	0	0	0	0	0	0

Figure 4-5: The effect of black count on ASE at all depth lengths showing successful cases at displacement 2



	5	6	7	8	9	10	11	12	13	14	15
15	100	100	100	100	100	100	100	100	100	98	98
20	100	100	100	100	100	100	97	99	99	91	90
25	100	100	100	99	96	98	89	93	89	76	76
30	99	99	94	94	90	81	64	78	75	64	54
35	91	86	81	75	59	52	36	51	50	34	26
40	64	59	41	44	29	21	15	24	21	17	10
45	26	19	5	5	3	1	1	2	2	1	0

Black Count

Figure 4-6: The effect of black count on sDA at all depth lengths showing successful cases at displacement 2

4.3.3 Displacement Effect

The last variable examined was pattern displacement. This variable showed no effect on daylighting performance, where 95 cases succeeded to pass the required criteria across all the eleven displacement values. Since they had a similar effect on daylighting performance, the previous analysis was concerned with explaining only one displacement value. In Table 4-2, one optimal solution with 100% sDA and the lowest possible ASE (1%) was exemplified to show the effect of screen configuration on daylighting distribution.

Optimal solution was found to be at 6 black count, 30 cm depth length and 18 for the displacement value. To confirm the irrelevance of the displacement, a comparison is drawn between the performance of all cases having this black count and depth length but with different displacement value as shown in Table 4-2. It is illustrated that displacement value showed a trivial impact on both sDA and ASE, where they ranges from 98% to 100 % and 1% to 4 % respectively.

Table 4-2: The effect of screen configuration on daylight distribution showing the optimal CA pattern of rule 210

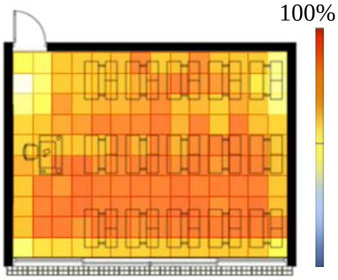
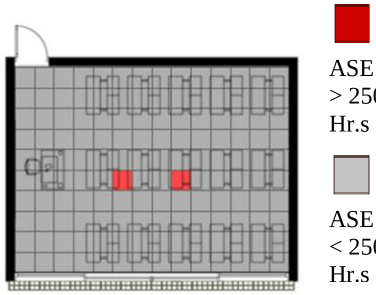
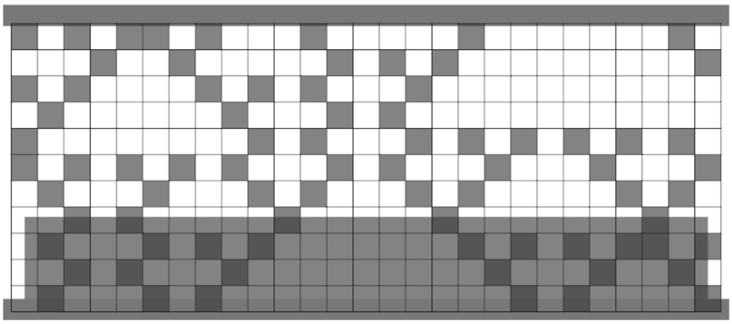
<table>
<tr><th colspan="2">Daylight Distribution</th></tr>
<tr>
<td>sDA= 100%
100% sDA

0% sDA</td>
<td>ASE= 1%

ASE > 250 Hr.s
ASE < 250 Hr.s</td>
</tr>
<tr><td colspan="2">
Depth length= 30cm, Black count= 6
Displacement = 18</td></tr>
</table>

Table 4-3: Performance of optimal configurations in terms of black count and depth length showing the indifference of displacement value

Displacement	sDA(%)	ASE(%)	Daylit (%)	Partially (%)	Overlit (%)	Black count	Depth (cm)
0	99	3	96	1	4	6	30
2	99	4	94	1	5	6	30
4	99	4	94	1	4	6	30
6	98	2	94	2	4	6	30
8	99	2	96	1	3	6	30
10	99	1	97	1	2	6	30
12	99	1	96	1	2	6	30
14	99	2	95	1	4	6	30
16	99	1	96	1	2	6	30
18	100	1	99	0	1	6	30
20	100	1	97	0	3	6	30

To sum up, searching all possible alternatives could sometimes be impractical due to computational capabilities; however, it provided the advantage of finding a large range of solutions that can be further refined using any other criteria or constrains. Besides, it indicated the implicit relationship between geometric attributes and the intended performance criteria. In this phase, three parameters were varied: screen depth, opacity, and displacement. Through a predefined set of ranges and their correlation with daylighting performance, they were explicitly stated.

Both screen depth and opacity proved their significant influence on daylighting and their interrelation in reaching a trade-off between the two conflicting objectives: providing sufficient daylight and avoiding direct sunlight. Displacement value however had no relevant effect on daylighting performance.

For the following phase the exhaustive search method was replaced by genetic algorithm GA. By taking advantage of knowing performance of all solutions, GA robustness was evaluated.

4.4 Exploring CA Rule 210 by Genetic Algorithm GA: Phase 3

In this last phase, for the same variables and their range of values for rule 210, it is intended to explore the robustness of genetic algorithm GA search method in reaching near optimal solutions. It is sought to find the optimal or near optimal solutions with a minimum number of simulations without the need for simulating all the 847 possibilities.

A large number of iterations was needed in order to examine their performance and their improving rate. Besides, a small number of simulations was also sought, so the population size was set to only 5. Then, the number of iterations (generations) was set to 46 forming a total number of simulations equal 230. The robustness of GA was judged by its convergence along the 46 iterations and comparing the results with the true optimal found by the exhaustive search. Having to combine between maximizing sDA while minimizing ASE is not possible using a single objective function, so another daylighting metric was exploited.

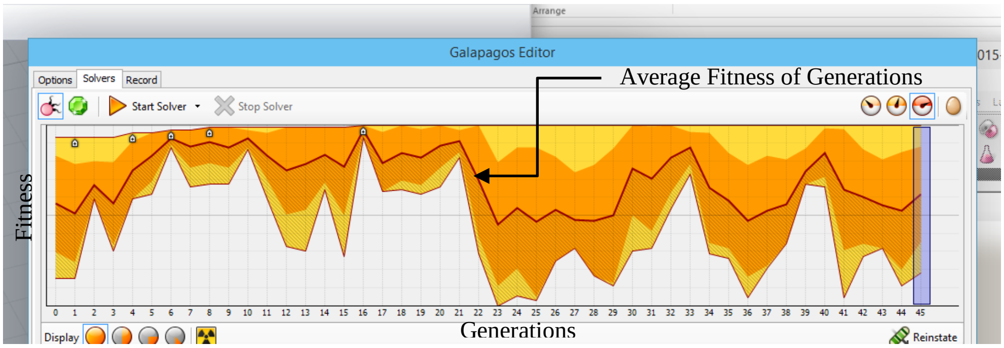


Figure 4-7: GA Optimization in Galapagos solver maximizing the 'daylit' area showing the performance of 46 generations

Daylight Availability (DA) was calculated to utilize the 'daylit' value as the fitness value to be maximized. It represents the area of space where illuminance levels exceeds 300Lux for more than 50% of the time while still a maximum threshold of 3000Lux more than 5 % of the time. Thus, it is assumed that the increasing value of 'daylit' area signifies the higher sDA with lower ASE. Both sDA and ASE are the two intended metrics that have to pass the criteria: 75% or more for sDA and 3% or less for ASE.

The interface of GAs solver in Grasshopper (Galapagos) was represented in Figure 4-7 showing the fast convergence of GAs in reaching near optimal solutions starting from iteration 4. Average performance of selected solutions continued to increase till generation number 16, then it decreased constantly away from optimal till generation 29. Afterwards, average performance fluctuates, but couldn't reach better solutions than what was found in generation 16. However, good solutions can still be found. The fitness of all solutions in the 46 generations regarding daylit area percentage and sDA and ASE are shown in Figure 4-8 and Figure 4-9 respectively and solutions that passed the benchmarks are represented in red colored circles.

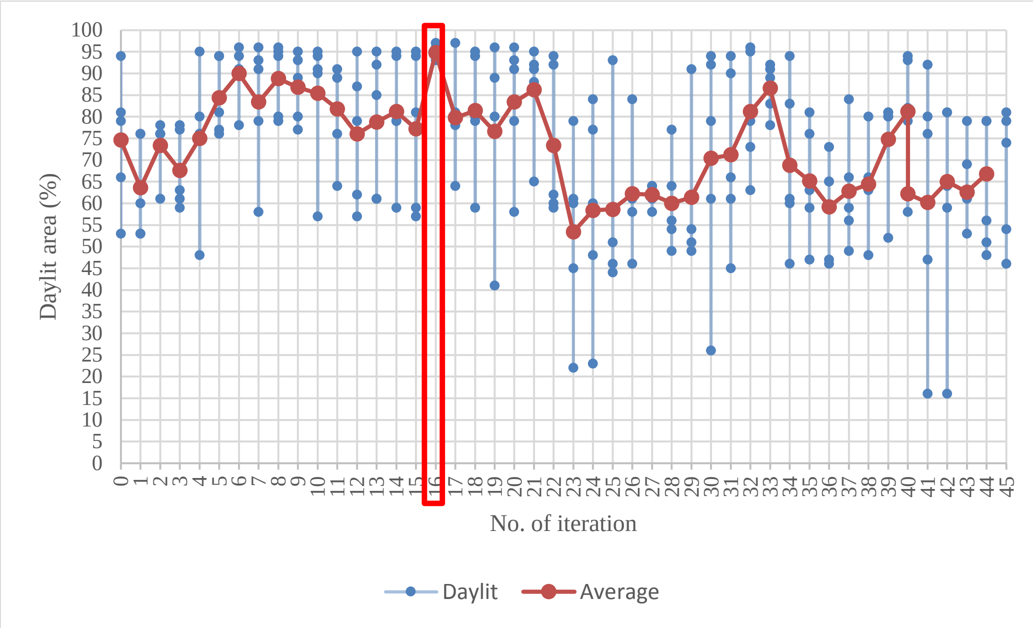


Figure 4-8: Fitness value along the generations showing the average fitness for each generation

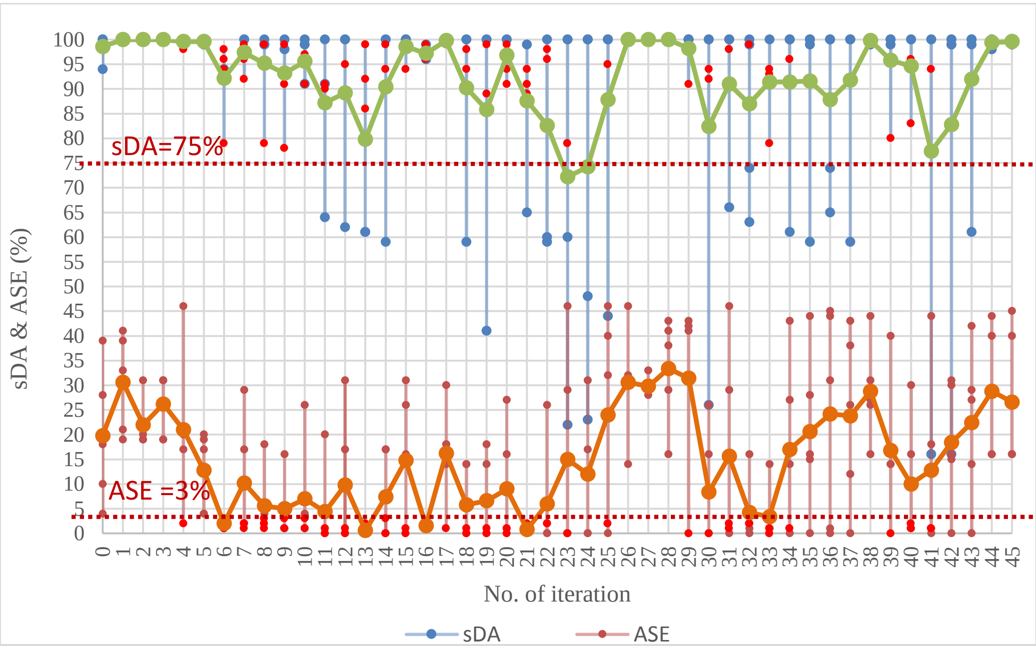


Figure 4-9: sDA & ASE values along the generations showing the average fitness for each generation

For each generation, 5 solutions were generated representing 0.006 % of all solutions. So, it can be deduced that after 16 generations about 10% of the possible solutions were merely simulated. Thus, reaching near optimal solutions from the early generations highlighted the GA robustness in finding good solutions with adequate convergence velocity. In similar cases, a smaller number of generations can be enough to reach satisfactory solutions.

4.5 Summary

Results of this case study has contributed in revealing the potentials of the exhaustive search method in evaluating genetic algorithm in finding optimal or near optimal solutions. It can also be used in benchmarking other heuristic search methods; however, its applicability was limited. In this study, a parallel computing algorithm was exploited which was developed and applied in a previous study.[1] This procedure, where multiple Radiance simulations can be run, have much reduced the computational burden. In the first phase, 18 CA rules under the repetitive class patterns were explored; all possible combinations in terms of cell depth and openness factor were examined. All rules have proven their applicability in reaching satisfactory solutions in terms of the assigned daylighting criteria. Since all rules were equally efficient regarding this criteria then, one rule which is rule 210 was chosen based on the designers' visual intentions for further investigation. This rule was exhaustively examined in terms of the same parameters in addition to displacement effect. However, it showed to have no relevant effect afterwards. In this stage, 874 possible combinations were formed and their performance was explicated. Having all the results, optimal and near optimal solutions were identified and thus, any other search method can be judged based on reaching these predefined solutions. Indeed, genetic algorithm was detected. It proved its robustness in finding satisfactory solutions with less computational demands than the exhaustive search method which could be impractical in other cases.

[1] A. Wagdy and F. Fathy, (2015). "A Parametric Approach for Achieving Optimum Daylighting Performance through Solar Screens in Desert Climates." *Journal of Building Engineering* 3: 155-170.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

- CONCLUSION
- RECOMMENDATIONS
- FUTURE RESEARCH

5.1 Conclusions

The conceptual design is an important design phase where many decisions are made so, it affects the whole design process. Making decisions based on the designers experience alone may lead to a lot of penalties and if they are made on performance only, the design may lack the sense of integrity. However, digital technologies have invaded the design practice in the early phases, where ideas are articulated in the digital media not only for visualization, but also for analysis and synthesis. The development of the digital design process implied a paradigm shift which imposes a number of requirements on the whole process:

1. Parametric modeling; where a large number of design solutions can be automatically generated and controlled through a number of variables related to each other by a certain rule.
2. Utilizing an appropriate optimization algorithm for finding optimal solutions.
3. Implementing analytical simulation tools for performance evaluation.

This study elaborated the potentials of parametric modelling coupled with Genetic Algorithms (GAs) as an optimization tool in reaching highly efficient solutions. According to the intended performance criteria -which was set in chapter two to be daylighting performance- multiple solutions can be found. The guiding approach aimed at reaching this result was *'Performative design'*, by which optimal solutions were reached through the feedback of the simulation engine.

However, another aspect was needed to provide the interaction and flexibility of design, by controlling and modifying the rule algorithm in a way that meets designers' visual aspirations. Thus, generative systems were explored and found to have potentials in articulating design ideas in a way that endows visual appeals. Integrating generative systems within the optimization work flow allows creating design variations that meet designers' subjective visual intentions and the intended performance criteria as well. This approach -called *'Generative Performative Design'*- empowered the designers with a number of design possibilities underlying within their own crafted visual boundaries.

Making use of this approach in a daylighting case study, has revealed the potentials and limitations of generative systems (in particular Cellular Automata) and optimization algorithms (Genetic Algorithms and exhaustive search) applied. In this case study, Radiance -the daylighting calculation engine- was found to be the most prominent daylighting simulation method as being validated and used in many studies for daylighting performance prediction.

Cellular Automata (CA), was employed for the generation of solar screen patterns mounted on a south oriented classroom space in Cairo. As a representative of generative systems; they revealed their characteristics and potentials through:

1. The non-monotonic screen patterns generated.
2. Exploring large design space where 1080 cases were explored in phase one then, 847 cases in phase two and three.
3. The possibility of design optimization; CA was integrated within the optimization workflow.
4. High efficiency; CA succeeded to generate screen patterns that meet daylighting performance criteria and reaching optimal solutions.
5. High level of interaction and control over the design variables and the rules relating them together.

The CA patterned screen was considered a functional façade element that provides daylight shade without ignoring visual appeal. The goal of achieving efficient daylighting performance in a south oriented classroom space using was actually reached. Based on two main aspects: daylighting adequacy and avoiding direct sunlight, Radiance inform the optimizer (GAs) with the performance prediction, then GAs were able to govern the CA variables in a way that best meet that criteria. Besides, the interaction of the designer was not violated where the rule selection was based on visual requirements after ensuring its performance validity.

In particular, CA rule 210 was selected among the other 18 investigated rules after ensuring its high performance. It was exhaustively examined in terms of black count (openness factor), cell depth, and displacement effect. In this stage, 874 possible combinations were formed and their performance was explicated. Both screen depth and openness factor proved their significant influence on daylighting and their interrelation in reaching a trade-off between the two conflicting objectives: providing sufficient daylight and avoiding direct sunlight (sDA and ASE values). As for the displacement, despite showing no relevant effect, this proved the applicability of the random arrangement of black cells without adversely affecting the performance. By having all possible solutions and their level of performance, GA were then utilized to show their effectiveness in selecting optimal solutions among a diverse population of solutions.

To sum up, the success of early decision making in the design process relies on paying attention to performance aspects without neglecting the subjective design requirements. These visual constraints could play an important role in guiding the selection criteria. Results of this study demonstrated the potential of combining Cellular Automata (CA) and Genetic Algorithms (GAs) in achieving the intended visual aspects and daylighting requirements efficiently. GAs proved its robustness in finding satisfactory solutions among CA patterns with less computational demands than the exhaustive search method which could be impractical in other cases. The suggested workflow for such an optimization study to balance between performance and visual intentions is shown in Figure 5-1.

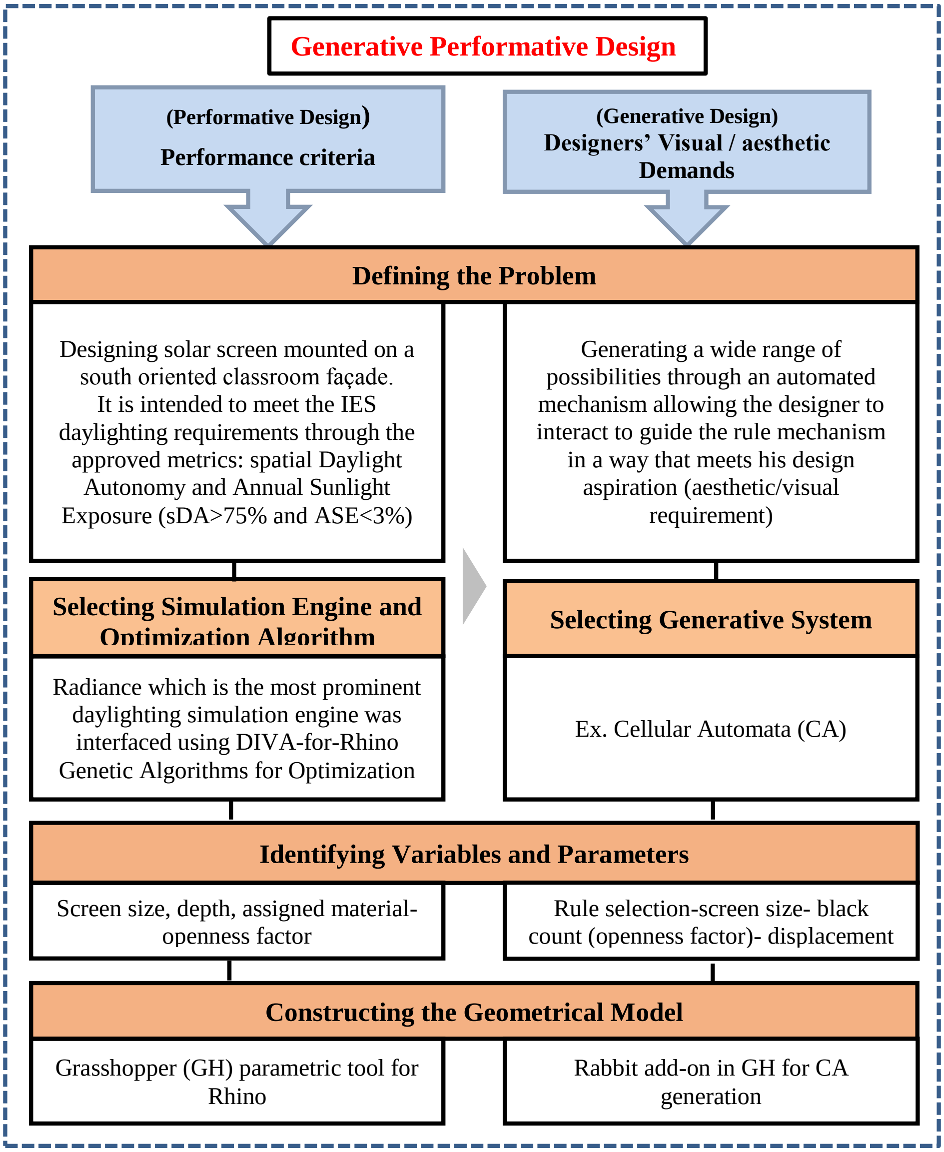


Figure 5-1: Workflow suggested for a generative performative design approach

5.2 Recommendations

Incorporating performance criteria in the design process have started with a trial and error approach to show the effect of a specific variable on the overall design objective. This process was inefficient especially when there is a large number of variables. Then, parametric modelling was introduced as a solution to reduce the design cycle latency. However, still the automated design workflow was required for design efficiency. This was overcome by incorporating optimization algorithms which transform the concept of performance based design to performative design.

Still, performative design lacks sense of integrity as it disregards the designers' own visual aspirations. So, to integrate both aspects without dominating one on the other, Generative Performative design was suggested. This could mean integrating the appropriate optimization algorithm with a generative system chosen based on the designer's visual requirements.

Genetic Algorithms (GAs) have been widely used for building performance optimization, this study is an additional contribution that emphasizes its suitability for building design problems. Thus, it is recommended to be used for finding optimal solutions for daylighting design through a limited number of simulation runs. However, further research is needed for evaluating other stochastic optimization methods to ensure its superiority for such kind of design problems.

The enumeration exhaustive method can be exploited in benchmarking other optimization methods. It also provided a larger range of solutions that can be further refined using any other criteria or constrains. In addition, it is recommended for understanding the effect of each variable and their interaction on the overall performance. It can clarify the implicit relationship between geometric attributes and the intended performance criteria. However, it could be impractical without the use of parallel simulation, which was used in this study through SpeedSim tool[1].

Introducing solar screens in façade designs controls daylighting provision through the space; their function go beyond being a decorative façade element. Basically, the success of this design element requires balancing between the functional performance and the designers' subjective constrains. In essence, achieving this balance is the main objective behind introducing any design element. Thus, pattern mapping through generative systems was recommended. Generative patterns need to be evaluated, offering designers

[1] A. Wagdy, "Speedsim for Diva".http://www.aymanwagdy.com/#!speedsim/cjg9 (accessed 21-12-2015).

a wide range of variations that could meet their aspirations. However, concern should be on screen depth, openness factor, and desired appearance.

Particularly in this study, the generative system selected was Cellular Automata. The openness factor -which was controlled by the number of solid cells entered in the initial row (black count) - plays an important role in meeting the overall design objectives. From the daylighting perspective as well as visual aesthetic demands, the openness factor should range from 20% to 50%. This range could change when incorporating other constraints like: energy requirements, air circulations, or privacy needs. The degree of being more or less open differs when other performance criteria are integrated. The distribution of solid to void areas is also important even for the same openness factor, the uniform distribution is needed. The irregularity of solid distribution could cause problems of glare or high contrast inside the space. This is the case except if it was intended to endow a dramatic shadow/light effect throughout the space.

5.3 Future Research

Generally, future research related to optimization studies are suggested. The utilized optimization algorithms were exhaustive search and Genetic Algorithms (GAs). The exhaustive search -which is more efficient using parallel Radiance simulation (SpeedSim)- allows all possible solutions to be reached, so the performance of other heuristic algorithms can be evaluated and compared to GAs, whether for the same case study or other building optimization problems. It is suggested to employ the same methodology to benchmark other optimization algorithms.

The generative system selected in the case study was Cellular Automata (CA). However, other generative systems such as L-systems, Shape Grammars, and Voronoi can be exploited for façade treatments. In terms of their capabilities in pattern mapping, a comparison study could be useful. This analysis can show the flexibility of each system in response to the required performance and the designers’ interaction level.

Generative systems have a range of applications for building design which are not confined to pattern generation. Besides façade treatments, these systems can be utilized whether on the urban or building scale (ex. Layout Formation).

Moreover, adding other aspects or constrains like energy consumption, fabrication, and cost would give another dimension to the selection criteria. Paying attention to performance priorities and how to balance them with the designers’ subjective demands, this methodology could be developed.

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هيكل البحث:

الفصل الأول: بداية نماذج الأداء في التصميم

في الفصل الأول، تم التركيز على نماذج الأداء (Performance models) و جوانب الأداء في المباني التي يمكن إدراجها في العملية التصميم لتكون بمثابة المحرك لاستكشاف بدائل مختلفة. النموذج التوليدي (Generative model) هو من ضمن النماذج التصميمية و الذي له خصائص شكلية، فللجمع بين هذه الخصائص مع ضمان الأداء الأمثل، تم تسليط الضوء على النهج المتكامل للتصميم "التصميم الأدائي التوليدي" (Generative Performative design). الى جانب ذلك، تم استكشاف أهمية الخوارزميات في الوصول الى الحلول المثلى لتصممصم عالي الأداء.

الفصل الثاني: الأداء من منظور الإضاءة الطبيعية

في الفصل الثاني، تم تحديد معايير الأداء لتكون كفاءة اداء الاضاءة الطبيعية. تصميم الفراغ المعماري بناء على معايير الاضاءة الطبيعية هو جانب مهم يحتاج الاهتمام في المراحل المبكرة من عملية التصميم. فإن النجاح في الوصول لهذه المعايير لا تزال مهمة صعبة بسبب المتطلبات المتعارضة و ذلك لتحقيق التوازن بين كمية الاضاءة اللازمة والراحة البصرية. علاوة على ذلك، فإن الطبيعة المتغيرة للاضاءة الطبيعية على مدار اليوم والسنة تعقد العملية التصميمية. وبالتالي، هذا البحث يناقش أهمية دمج الخوارزميات للوصول للحلول المثلى لكفاءة أداء الاضاءة الطبيعية.

الفصل الثالث: التصميم الواجهات اللأداء الأمثل للإضاءة الطبيعية: دراسة حالة لفصل دراسي

في الفصل الثالث، تم استكشاف النماذج التوليدية المختلفة لايجاد أنماط تشكيلية مختلفة، مع التركيز على نموذج واحد و هي خلايا الاوتوماتا (Cellular Automata-CA). بما أنها تفتقر إلى القدرة على تحقيق كفاءة الأداء، تم دمج خلايا الاوتوماتا (CA) مع الخوارزميات الجينية (GA) لاستكشاف مدى فعاليتها في تشكيل أنماط مختلفة للكواسر الشمسية و التي تشبه المشربيات. والمقصود منها هو تلبية متطلبات الاضاءة الطبيعية داخل فراغ معماري لأحد الفصول الموجهة جنوبا في القاهرة. أولا، تم تطبيق بحث شامل(Exhaustive Search) لتقييم جميع البدائل التصميمية ثم استخدام الخوارزميات الجينية (GA) لتقييم أداءه في الوصول للحل الأمثل. وتم استنتاج فعاليتها في إيجاد حلول مرضية في وقت أقل من طريقة البحث الشامل الذي يمكن أن يكون غير عملي في حالات أخرى.

الفصل الرابع: مناقشة نتائج دراسة الحالة للفصل الدراسي

في الفصل الرابع، تم عرض نتائج دراسة الحالة للفصل الدراسي وصولا لأهم العوامل و المتغيرات المؤثرة في أداء الإضاءة الطبيعية بالإضافة الي استكشاف كفاءة النهج التصميمي. و اخيرا تحليل مدى تطابق هذه النتائج مع الفرضية البحثية.

الفصل الخامس: النتائج و التوصيات

في الفصل الأخير، تم الوصول الى نتائج عامة و تسليط الضوء على أهمية النهج المتبع "النهج الأدائي التوليدي" لتحقيق التوازن بين كفاءة أداء الإضاءة الطبيعية و المتطلبات التشكيلية للمصمم. و ذلك مع عرض بعض التوصيات للأبحاث المستقبلية.

الأهداف الثانوية:

- استعراض التحول في اتباع النهج المختلفة في العملية التصميمية، وكيف تم التركيز علي النهج الأدائي.
- إبراز قدرات النظم التوليديه في تشكيل أنماط المعالجة المعمارية (Screen Pattern) و التي تتوافق مع المعايير المحددة مسبقا.
- استكشاف إمكانيات الأوتوماتا الخلوية (CA) كأداة لتكوين أنمط المعالجة(Screen Pattern) وصولا لكفاءة أداء الإضاءة الطبيعية.
- تقييم أداء الخوارزميات الجينية (GA) في التوصل إلى الحلول المثلى.

مقدمة

تستخدم أدوات المحاكاة في العديد من المجالات لتقييم معايير الأداء المختلفة للمباني. نظرا للاحتياج الى مباني صديقة للبيئة وذات كفاءة عالية، أصبح هذا الاتجاه اكثر استخداما و تطورا من أي وقت مضى و خاصة بعد التقدم الذي أحرز مؤخرا في التقنيات الحاسوبية. ومع ذلك، فإن مشاكل التصميم لا يمكن استكشافها بالكامل فقط من خلال أدوات المحاكاة. فهي مفيدة في تحليل وتقييم تصميم معين، أو عدد محدود من البدائل وفقا لمعايير معينة ولكن هي ليست فعالة لتقييم عدد كبير من الحلول. وبالتالي، تم دمج التصميم البارمتري مع الخوارزميات الجينية (Genetic Algorithms-GA) كنهج للتغلب على هذه المشكلة. وكان محور هذا التكامل في مرحلة التصميم المبدئي، حيث انها المرحلة التي لها تأثير كبير على كفاءة التصميم، فالقرارات التي تتخذ في هذه المرحلة يكون لها الصدى الاكبر على المراحل اللاحقة.

المشكلة البحثية:

الإضاءة الطبيعية هي عنصر هام في تصممصم الفراغات المعمارية و الذي من المحتمل إهماله في مرحلة التصميم المبدئية. تصميم فراغ معماري مبنيا على معاير الإضاءة الطبيعية هي عملية صعبة بسبب التغيرات على مدار اليوم والسنة، إلى جانب إمكانية اكتساب الحرارة الزائدة. بشكل عام، العملية التقليدية في التصميم تكون معقدة عندما نواجه عدد كبير من المتغيرات. فان الأخذ في الاعتبار الجوانب و الأهداف المتعارضة وصولا إلى الحل الأمثل من شأنه أن يؤدي إلى الكثير من التجارب والأخطاء.

والسؤال هو: ما هو النهج التي يمكن أن يؤثر على النواحي التشكيلية بطريقة تلبي كل من تطلعات المصممين ومعايير الأداء المنشودة؟ الى جانب ذلك، على أي أساس يمكن أن يكون اختيار الخوارزميات لتكون متكاملة مع التصميم البارامتري؟ ثم، كيف يمكننا استكشاف فعالية هذا الاختيار لدراسة أداء الإضاءة الطبيعية؟

الفرضية:

استخدام النهج الأدائي التوليدي (Generative Performative design) يمكن أن يكون ايجابيا في التأثير على كفاءة الإضاءة الطبيعية داخل الفراغ. و اتخاذ القرارات التصميمية في مرحلة التصميم الأولي، لها التأثير الأكبر على نجاح التصميم. و هكذا يكون اقتران الخوارزميات الجينية مع التصميم البارمتري هو الاختيار السليم للتعامل مع مشكلة الإضاءة الطبيعية حيث ان الحلول المثلى يمكن الحصول عليها مع عدد محدود من عمليات المحاكاة.

الأهدف الرئيسية:

الهدف الرئيسي من هذا البحث هو استعراض إمكانيات ومحددات الخوارزميات الجينية (GA) كأداة تهدف للتوصل إلى أداء أمثل للإضاءة الطبيعية في الفصول الدراسية. بالإضافة الى تحديد العلاقة الضمنية بين الأنماط التشكيلية للمعالجة المعمارية المقترحة و كفاءة الإضاءة الطبيعية من خلال تصميم الأدائي التوليدي.

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كلية الهندسة
قسم الهندسة المعمارية

إسم الطالبة : فاطمة محمد فتحي أحمد عبدالعزيز
عنوان الرسالة : استخدام الخوارزميات الجينية والتصميم البارامتري لكفاءة أداء الإضاءة الطبيعية في الفراغات التعليمية
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ختم الإجازة: أجيزت الرسالة بتاريخ

/ / / /

موافقة مجلس الكلية موافقة مجلس الجامعة

/ / / /

جامعة عين شمس
كلية الهندسة
قسم الهندسة المعمارية

استخدام الخوارزميات الجينية والتصميم البارامتري لكفاءة أداء الإضاءة الطبيعية في الفراغات التعليمية

رسالة مقدمة للحصول على درجة ماجستير العلوم في الهندسة المعمارية

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كلية الهندسة- جامعة عين شمس

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