Architectural Design Performance Through Computational Intelligence
A Comprehensive Decision Support Framework

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Ioannis Chatzikonstantinou

Architectural design is a prime example of a complex task. The associated complexity often poses significant challenges to human cognition. As such, a systematic approach to design space exploration must be undertaken, to maximize the potential for discovering optimal solutions to design problems.Recognizing the impact design complexity has on architectural design , this thesis proposes a comprehensive computational intelligence decision support system that combines components based on intelligence with ones based on cognition, with the ultimate aim of enabling decision-makers manage design complexity and improve decision making.
This thesis adopts the theoretical standpoint that efficient navigation of an unknown environment assumes a fusion of intelligence and cognition. In this sense, and given the already widespread adoption of intelligent approaches (such as Evolutionary Computation), the main contribution of this thesis is to endow the intelligent approach with cognitive facilities, so as to improve its efficiency to the point that it is readily applicable to the early stages of the architectural design process. Fusion of intelligent with cognitive approaches, as outlined herein, offers the unique advantage of a decision support approach that is both powerful, owing to the extensive search capabilities of intelligent search algorithms, and flexible, owing to the extensive knowledge modeling capabilities of cognitive approaches. As such, it is uniquely suited to the early conceptual design stage where the need to explore large design spaces, flexibly redefine the design problem, and satisfy preferences that are not included in the primary design goals, are all paramount.
The main output of this thesis is a comprehensive decision support framework; it is a framework, in the sense that it comprises a set of methods and implemented tools that seek to augment decision making in architectural design; it is termed comprehensive in that it employs computational cognition and machine learning to augment the intelligent decision support capabilities throughout the design decision support process. It is also generic and applicable as-is to a wide spectrum of architectural design problems. In the context of this thesis, validation of the proposed approach is performed mainly in case studies relevant to facade design, recognizing this design topic as a complexity-exhibiting exemplar in architectural design practice.

Ioannis Chatzikonstantinou

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Cover image (background) | Wolfgang Hasselmann on Unsplash

The author of this thesis attributes the following to the cover image:

> *Designing is exploring a landscape. Sometimes the landscape is smooth: its peaks and valleys visible from afar. At other times, it is rough and treacherous; we struggle to push ahead.*
>
> *The fog clears a bit and we discern that we've reached the highest peak; then, it clears more and we realize we're on top of a hill, a mountain standing tall across the valley.*

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Contents

Abstract

Identification of design solutions for a built environment that caters to the human needs at all levels, and more specifically, to the needs of the clients and the society, is the main task addressed by architectural design. Architectural design is a prime example of a design task that is characterized by a high degree of complexity. Architectural design problems by definition entail relationships between decisions and objectives that are all but transparent. For the decision-maker to be able to guide design towards fulfilling objectives, a 'closed-loop' approach where variations in design solutions are generated and evaluated in an iterative process is employed. Due to the sheer number of alternative solutions to problems of even a moderate scale (due to combinatorial explosion), it is only feasible to iterate over a minuscule fraction of possible solutions. Design intuition of the professionals involved in design is a strong driving force behind the identification of design direction, in which alternatives are explored as part of the preliminary design process. This is an approach that depends on the human cognitive capabilities to navigate the design space and identify potentially promising solutions. Regardless, the complexity associated with architectural design often poses significant challenges to human cognition. Human cognition, while formidable in its ability to flexibly and efficiently navigate challenging environments, is faced with difficulties in addressing the complexity factors outlined previously, namely: the excessive (combinatorially explosive) number of potential solutions to architectural problems, the complex and non-linear relations between objects and their properties and the conflicting nature of design goals that architectural design entails. Thus, design professionals are often faced with the real threat that their decisions may be biased due to the natural limitations of human cognition acting in complex environments.

Due to the reasons highlighted above, a systematic approach to design space exploration must be undertaken, to maximize the potential for discovering optimal solutions to design problems. Due to the nature of such problems that entail multiple conflicting objectives, a single best solution is generally not attainable. Nonetheless, best-tradeoff solutions are distinguished and highly desirable for such multi-objective design problems. The field of Computational Intelligence, and within that in particular Evolutionary Computation-based (EC) intelligent approaches, offer a lucrative option as decision-support tools in design, as they are able to efficiently address the aforementioned proponents of design complexity. EC approaches are able to navigate the design space efficiently and systematically, considering multiple conflicting objectives and hard constraints, and being able to deal with arbitrary relations between design decision variables and design objectives.

In today's setting, products of architecture must lead the way to a sustainable and environmentally friendlier society. As such, the performance of buildings has become the main driving force behind the design process, being referred to as "performance-driven design". This initiative emphasizes the quantitative evaluation of a design's function in accordance with established design objectives, related to aspects such

as energy performance, visual and thermal comfort, cost and environmental footprint, etc. Simulation-based tools that enable accurate design evaluation are gaining ground and offering valuable insight into the performance of buildings. Nonetheless, making decisions in this multi-objective environment is not trivial, and, as stipulated above, may be challenging to human cognition. Thus, in today's setting where the quantitative performance of buildings keeps gaining ground, the research on the application of EC in architectural design is high on the scientific agenda.

Recognizing the impact design complexity has on architectural design and the potential that EC-based approaches offer in addressing it, this thesis proposes a comprehensive computational intelligence decision support system that combines components based on intelligence with ones based on cognition, with the ultimate aim of enabling decision-makers manage design complexity and improve decision making. In particular, this thesis adopts the theoretical standpoint that efficient navigation of an unknown environment assumes a fusion of intelligence and cognition. In this sense, and given the already widespread adoption of intelligent approaches (such as EC mentioned above), the main contribution of this thesis is to endow the intelligent approach with cognitive facilities, so as to improve its efficiency to the point that it is readily applicable to the early stages of the architectural design process.

Fusion of intelligent with cognitive approaches, as outlined in the approach proposed by this thesis, offers the unique advantage of a decision support approach that is both powerful, owing to the extensive capabilities of intelligent search algorithms, and flexible, owing to the extensive knowledge modeling capabilities of cognitive approaches. As such, it is uniquely suited to the early conceptual design stage where the need to explore large design spaces, flexibly redefine the design problem, and satisfy preferences that are not included in the primary design goals, are all paramount.

Thus, the word "comprehensive" as it appears on this thesis' title obtains a twofold meaning: On one hand comprehension as in the combination of computational intelligence and cognition in a single approach; on the other hand, as in *comprehension* of the environment, the result of an intelligent and cognitive approach to understanding.

Firstly, it seeks to address the excessive computational burden associated with the use of modern high-fidelity simulation software in architecture, to render computational optimization more approachable. There is a clear trend in modern design practice to employ accurate simulation-based performance assessment tools from the very early stages of design. The use of such tools provides a valuable advantage to the decision-maker, in endowing objective awareness regarding the performance of a design solution. On the other hand, such tools are associated with a heavy computational burden, which may limit their application to the conceptual design stage. There exist methods to alleviate the computational burden through the use of computational cognitive machine learning tools, also known as surrogate modeling. However, training of surrogate models can be time-consuming itself, thus limiting the application. This thesis proposes a surrogate model that is modular in that it considers each space of the building in question as a separate entity, encoded through generic variables, and as such promotes model reuse in different design cases.

Secondly, it seeks to advance the state of the art on post-Pareto decision support by proposing a cognitive machine-learning based approach that enables the decision-maker to combine near-optimality with preferences regarding concrete features of the design solution. Post-Pareto decision making is an important step of the decision-making process, that seeks to identify a best-tradeoff solution among the possible ones that best matches the decision-maker's preferences in terms of performance. Such preferences are termed second-order because they follow design objectives in terms of importance. Nonetheless, it is often in architectural design that preferences are expressed in terms of design properties and not performance. Due to the non-linearity between the objective function space and the decision variable space that dictates object properties, it is challenging to exercise decision making using second-order preferences. Here the contribution of this thesis is a machine cognitive approach that learns the underlying relationships between object properties, distinguishing those that are relevant when the object is optimal with respect to design objectives. In other words, only imposing relations that are relevant to achieve optimality, it enables the expression of preferences by the decision-maker that are minimally constrained.

The main output of this thesis is a comprehensive decision support framework; it is a framework, in the sense that it comprises a set of methods and implemented tools that seek to augment decision making in architectural design; it is termed comprehensive in that it employs computational cognition and machine learning to augment the intelligent decision support capabilities throughout the design decision support process. It is also generic and applicable as-is to a wide spectrum of architectural design problems. In the context of this thesis, validation of the proposed approach is performed mainly in case studies relevant to facade design, recognizing this design topic as a complexity-exhibiting exemplar in architectural design practice.

Samenvatting

De identificatie van ontwerpoplossingen voor een gebouwde omgeving die voorziet in de menselijke behoeften op alle niveaus, en meer in het bijzonder in de behoeften van de opdrachtgevers en de samenleving, is de voornaamste taak die door het architectonisch ontwerpen wordt aangepakt. Architectonisch ontwerpen is een uitstekend voorbeeld van een ontwerptaak die wordt gekenmerkt door een hoge mate van complexiteit. Ontwerpcomplexiteit wordt door ontwerpprofessionals in de dagelijkse ontwerppraktijk ervaren, maar het is een fenomeen dat in de theorie geworteld is. Architectonische ontwerpproblemen brengen per definitie relaties tussen beslissingen en doelstellingen met zich mee die alles behalve transparant zijn. Om de besluitvormers in staat te stellen het ontwerp te sturen in de richting van het bereiken van de doelstellingen, wordt een "gesloten-lus" benadering toegepast waarbij variaties in ontwerpoplossingen worden gegenereerd en geëvalueerd in een iteratief proces. Door het enorme aantal alternatieve oplossingen voor problemen van zelfs maar bescheiden omvang (als gevolg van combinatorische explosie), is het slechts haalbaar om een minuscuul deel van de mogelijke oplossingen te itereren. De ontwerpintuïtie van de bij het ontwerp betrokken professionals is een sterke drijfveer achter het bepalen van de ontwerprichting, waarbij alternatieven worden verkend als onderdeel van het voorlopige ontwerpproces. Dit is een benadering die afhankelijk is van de menselijke cognitieve vermogens om door de ontwerpruimte te navigeren en potentieel veelbelovende oplossingen te identificeren. Hoe dan ook, de complexiteit van architectonische ontwerpen stelt de menselijke cognitie vaak voor grote uitdagingen. Hoewel de menselijke cognitie formidabel is in haar vermogen om flexibel en efficiënt door uitdagende omgevingen te navigeren, wordt zij geconfronteerd met moeilijkheden bij het aanpakken van de eerder geschetste complexiteitsfactoren, namelijk; het buitensporige (combinatorisch explosieve) aantal potentiële oplossingen voor architectonische problemen, de complexe en niet-lineaire relaties tussen objecten en hun eigenschappen en de conflicterende aard van ontwerpdoelen die architectonisch ontwerp met zich meebrengt. Beroepsbeoefenaren in de ontwerpsector worden dus vaak geconfronteerd met de reële dreiging dat hun beslissingen worden vertekend als gevolg van de natuurlijke beperkingen van de menselijke cognitie in complexe omgevingen.

Om bovengenoemde redenen moet de ontwerpruimte systematisch worden verkend, zodat optimale oplossingen voor ontwerpproblemen kunnen worden gevonden. Door de aard van dergelijke problemen, die meerdere conflicterende doelstellingen met zich meebrengen, is één enkele beste oplossing over het algemeen niet haalbaar. Niettemin zijn best-trade-off oplossingen voor dergelijke multi-objective ontwerpproblemen onderscheidend en zeer wenselijk. Het gebied van de computationele intelligentie, en daarbinnen in het bijzonder de op Evolutionary Computation gebaseerde (EC) intelligente benaderingen, bieden een lucratieve optie als beslissingsondersteunende hulpmiddelen bij het ontwerpen, omdat zij in staat zijn de bovengenoemde voorstanders van ontwerpcomplexiteit efficiënt aan te pakken. EC-benaderingen zijn in staat om efficiënt en systematisch door de ontwerpruimte

te navigeren, rekening houdend met meerdere conflicterende doelstellingen en harde beperkingen, en kunnen omgaan met arbitraire relaties tussen ontwerpbeslissingsvariabelen en ontwerpdoelstellingen.

In de huidige omgeving moeten architectuurproducten de weg wijzen naar een duurzame en milieuvriendelijker samenleving. Als zodanig zijn de prestaties van gebouwen de belangrijkste drijvende kracht achter het ontwerpproces geworden, wat wordt aangeduid als “prestatiegericht ontwerpen”. Dit initiatief legt de nadruk op de kwantitatieve evaluatie van de functie van een ontwerp in overeenstemming met vastgestelde ontwerpdoelstellingen, gerelateerd aan aspecten zoals energieprestatie, visueel en thermisch comfort, kosten en ecologische voetafdruk, enz. Op simulatie gebaseerde hulpmiddelen die een nauwkeurige evaluatie van het ontwerp mogelijk maken, winnen terrein en bieden een waardevol inzicht in de prestaties van gebouwen. Toch is het nemen van beslissingen in deze multi-objectieve omgeving niet triviaal en, zoals hierboven gesteld, kan dit een uitdaging zijn voor de menselijke cognitie. In de huidige context, waarin de kwantitatieve prestaties van gebouwen steeds meer terrein winnen, staat het onderzoek naar de toepassing van EC in architectonisch ontwerp dan ook hoog op de wetenschappelijke agenda.

Ontwerpcomplexiteit heeft een groot impact op het architectonisch ontwerp. EC-gebaseerde benaderingen bieden een potentiële oplossing hiervoor. Deze scriptie stelt daarom een alomvattend computational intelligence decision support systeem voor dat onderdelen combineert die gebaseerd zijn op intelligentie en cognitie, met het uiteindelijke doel om besluitvormers en ontwerpprofessionals in staat te stellen ontwerpcomplexiteit te beheersen en besluitvorming te verbeteren. In het bijzonder gaat deze dissertatie uit van het theoretische standpunt dat efficiënte navigatie in een onbekende omgeving een samensmelting van intelligentie en cognitie veronderstelt. In deze zin, en gezien de reeds wijdverbreide toepassing van intelligente benaderingen (zoals EC hierboven vermeld), is de belangrijkste bijdrage van deze dissertatie de intelligente benadering te begiftigen met cognitieve faciliteiten, om zo de efficiëntie ervan te verbeteren tot het punt dat het gemakkelijk toepasbaar is in de vroege stadia van het architectonische ontwerpproces.

De fusie van intelligente met cognitieve benaderingen, zoals geschetst in de aanpak die in dit proefschrift wordt voorgesteld, biedt het unieke voordeel van een beslissingsondersteunende aanpak die zowel krachtig is, vanwege de uitgebreide mogelijkheden van intelligente zoekalgoritmen, als flexibel, vanwege de uitgebreide kennismodelleringsmogelijkheden van cognitieve benaderingen. Als zodanig is het bij uitstek geschikt voor de vroege conceptuele ontwerpfase waarin de behoefte om grote ontwerpruimten te verkennen, flexibel het ontwerpprobleem te herdefiniëren, en te voldoen aan voorkeuren die niet zijn opgenomen in de primaire ontwerpdoelstellingen, allemaal van het grootste belang zijn.

Het woord “begrip” zoals het in de titel van deze dissertatie voorkomt, krijgt dus een tweeledige betekenis: Enerzijds begrip als in de combinatie van computationele intelligentie en cognitie in een enkele benadering; anderzijds als in *begrip* van de omgeving, het resultaat van een intelligente en cognitieve benadering van begrip.

In de eerste plaats wordt getracht iets te doen aan de buitensporige computerdruk die het gebruik van moderne high-fidelity simulatiesoftware in de architectuur met zich meebrengt, om zo computationele optimalisatie toegankelijker te maken. In de moderne ontwerppraktijk is er een duidelijke tendens om vanaf de allereerste ontwerpstadia gebruik te maken van nauwkeurige, op simulatie gebaseerde hulpmiddelen voor de beoordeling van de prestaties. Het gebruik van dergelijke hulpmiddelen is een waardevol voordeel voor de besluitvormer, omdat het objectief inzicht verschaft in de prestaties van een ontwerpoplossing. Anderzijds gaan dergelijke instrumenten gepaard met een zware rekenlast, waardoor hun toepassing tot de conceptuele ontwerpfase kan worden beperkt. Er bestaan methoden om de computationele belasting te verlichten door gebruik te maken van computationele cognitieve machine-leermiddelen, ook bekend als surrogaatmodellen. Het trainen van surrogaatmodellen kan echter zelf tijdrovend zijn, waardoor de toepassing beperkt wordt. Deze dissertatie stelt een surrogaatmodel voor dat modulair is in die zin dat het elke ruimte van het gebouw in kwestie als een aparte entiteit beschouwt, gecodeerd door generieke variabelen, en als zodanig het hergebruik van het model in verschillende ontwerpgevallen bevordert.

Ten tweede wordt getracht de stand van de techniek op het gebied van post-Pareto-beslissingsondersteuning te verbeteren door een cognitieve, op machinaal leren gebaseerde aanpak voor te stellen die besluitvormers in staat stelt bijna-optimaliteit te combineren met voorkeuren met betrekking tot concrete kenmerken van de ontwerpoplossing. Post-Paretobesluitvorming is een belangrijke stap in het besluitvormingsproces, waarbij wordt getracht uit de mogelijke oplossingen een best-tradeoff-oplossing te vinden die qua prestaties het best aan de voorkeuren van de besluitvormers voldoet. Dergelijke voorkeuren worden tweede-ordevoorkeuren genoemd, omdat zij in termen van belangrijkheid op de ontwerpdoelstellingen volgen. Niettemin is het vaak in architectonisch ontwerp dat voorkeuren worden uitgedrukt in termen van ontwerpeigenschappen en niet van prestaties. Vanwege de niet-lineariteit tussen de ruimte van de objectiefunctie en de ruimte van de beslissingsvariabele die de objecteigenschappen dicteert, is het een uitdaging om besluitvorming uit te oefenen met behulp van tweede-ordevoorkeuren. De bijdrage van dit proefschrift is een machine cognitieve benadering die de onderliggende relaties tussen objecteigenschappen leert, en daarbij onderscheid maakt tussen die relaties die relevant zijn wanneer het object optimaal is met betrekking tot de ontwerpdoelstellingen. Met andere woorden, door alleen die relaties op te leggen die relevant zijn om optimaliteit te bereiken, maakt het de expressie van voorkeuren door de beslisser mogelijk die minimaal beperkt zijn.

Het belangrijkste resultaat van dit proefschrift is een uitgebreid beslissingsondersteunend raamwerk; het is een raamwerk, in de zin dat het een reeks methoden en geïmplementeerde hulpmiddelen omvat die trachten de besluitvorming in architectonisch ontwerp te vergroten; het wordt uitgebreid genoemd omdat het computationele cognitie en machinaal leren gebruikt om de intelligente beslissingsondersteunende capaciteiten te vergroten gedurende het gehele beslissingsondersteunende proces van het ontwerp. Het is ook generiek en toepasbaar als zodanig op een breed spectrum van architectonische ontwerpproblemen. In het kader van dit proefschrift wordt de validatie van de voorgestelde aanpak voornamelijk uitgevoerd in casestudies die relevant zijn voor het ontwerpen van gevels, waarbij dit ontwerponderwerp wordt gezien als een complexiteit-experimenteel voorbeeld in de architectonische ontwerppraktijk.

1 Introduction

§ 1.1 Background

Architecture has been long acclaimed as a paradigm of cultural enterprise, being uniquely situated in the intersection of art and science. Indeed, products of architecture need to cater to a wide range of diverse requirements: On the one hand, there are “hard” requirements that support functionality, feasibility, efficiency, and safety, aspects that are fundamental to a sustainable society. On the other hand, there are “soft” requirements that pertain to experiential aspects of the built environment, such as perception or aesthetics. At the same time, it is fair to say that the decisions made as part of the design process of a building are responsible for shaping the built environment we live in, and therefore have a profound and far-reaching influence on our lives. Therefore, it is certainly the case that the decisions made during the architectural design process are markedly important and therefore need to be founded on concrete assumptions and exercised in an informed manner.

Given the complex nature of architectural design, as well as the importance associated with the overall quality of its products, a considerable effort has been made up to this point from the scientific community to research and develop appropriate systems that are able to support decision making. One of the most recent developments in this direction is decision support systems based on Computational Intelligence (CI), whereby nature-inspired design optimization is a key representative. The research carried out in this thesis finds its place as part of this effort and aims to complement it, proposing advances that may further the usefulness of modern CI decision support systems.

§ 1.1.1 Design Complexity

Why is design complex? To begin understanding design complexity, one should begin understanding complexity itself as a phenomenon. Complexity is a phenomenon that is hard to describe and formalize, yet it is something that is encountered commonly every day. On every scale from micro- to macroscopic, the world is full of examples of complex behavior. Concerning artificial systems, in particular, cities, if seen in vertical integration, are considered one of the most complex human-made arrangements in existence. More recently, social networks have been found to display novel properties of emergent complexity and their study gives birth to novel methodologies for the study of complexity (Butts 2001). Other examples of complexity are abundant and may be found in the study of nature, society, materials, etc.

Identifying a definition for complexity as a phenomenon is a challenging question that has occupied the scientific community for a long time, especially since complexity is a ubiquitous phenomenon. The following excerpt from (Bechtel and Richardson 2010) offers an enlightening introduction to the topic of complexity and a sound definition:

> [...] Many machines are simple, consisting only of a handful of parts that interact minimally or in a linear way. In these machines we can trace and describe the events occurring straightforwardly. [...] Some machines, however, are much more complex: one component may affect and be affected by several others, with a cascading effect; or there may be significant feedback from "later" to "earlier" stages. In the latter case, what is functionally dependent becomes unclear. Interaction among components becomes critical. Mechanisms of this latter kind are complex systems.

As evident from the definition above, the nature of relationships between parts in a system is mainly responsible for the phenomenon of emergent complexity. In addition, the definition offered by Simon (Simon 1962) places importance on relationships between system components:

> [A complex system is] a system that can be analyzed into many components having relatively many relations among them, so that the behavior of each component can depend on the behavior of many others.

In a system that consists of several densely interconnected parts, local effects have the potential to affect the global state of the system, and, in turn, local states are affected by global fluctuations.

Design problems such as the ones encountered in real-world architecture practice involve making numerous design decisions, each of which is required to produce the final output, and also affects the satisfaction of design criteria and design constraints in ways that are difficult to anticipate. In a design context, complexity is evident in the dense and non-linear causal relationships between design decisions, design goals, and design constraints. In addition, another characteristic of the design process is that the effects of decisions taken in the early conceptual design stages may only be identifiable much later in the process, often when the project enters the detailed design stage. This important characteristic mandates a process that is ipso facto not linear, but rather entails one or more feedback loops, and is often required to backtrack and amend decisions taken during early design stages. This is a prime example of a complex system with delayed feedback, and the main reason that led to the emergence of performance-oriented design practices, where concrete, quantitative feedback on design goals is sought to be integrated as early as possible in the design process, through the use of advanced modeling techniques, rendering the design into a closed-loop system.

The abstraction of complexity that occurs as part of the architectural design process is beneficial because it allows one to study complexity in design without consideration of the specifics of each design case. This in turn leads to another benefit, namely the ability to apply tools, methods, and techniques developed as part of other research disciplines that deal with complex problems, to tackling complexity in architectural design, such as the representative example of Multi-Objective Evolutionary Algorithms (MOEAs).

FIGURE 1.1 London Aquatics Center, architect: Zaha Hadid. Large-scale complex projects with innovative forms and materials call for advanced decision support tools and methods to support complex decision making. Image source: Hélène Binet/Archdaily

§ 1.1.2 Performance-Based Design

Architectural design and the disciplines involved in it underwent a significant evolution throughout the 20th century, as a result of the ever-increasing complexity in design introduced by advancing technology and evolving design requirements. This resulted in a paradigm shift in the way that architectural design was approached. Up until the mid-20th century, the design of buildings and complexes was defined by prescriptive practices, which would stipulate design actions for commonly occurring design problems. This kind of accumulated knowledge would be found in design handbooks or would be part of the tacit knowledge of an experienced architect or engineer. Around the second half of the 20th century, and in the face of ever-increasing design complexity, it became clear to many that this practice would not be sustainable as design complexity increased. Thus the focus began to move away from acceptance and use of established means, including rule-of-thumb and common practices. The new focal point that the shift in design thinking brought revolved around the understanding of the design process as one that would put improvement towards achieving design goals first, focusing on how buildings would perform. Thus, performance became the driving force behind all of the aspects considered in the architectural design process, including aesthetics and construction methods. Performance-based design, as this novel approach would come to be called, formalized around a mission statement that is accurately outlined in Gibson (1982):

> [Performance-Based Design] is concerned with what a building or a building product is required to do, and not with prescribing how it is to be constructed.

Performance-based design introduces a new way of design thinking, which promotes efficiency and innovation in architecture and building design. The Performance-based design approach goes beyond the application of pre-existing expert knowledge in design, rather adopting investigation and evidence-based practices as its primary tool, therefore also generating novel design knowledge as part of its process. An important part of the Performance-Based design process is the evaluation of performance and validation of results concerning constructed products. Solutions can be evaluated and validated against demand using many different approaches and tools. In practice, a key feature of a contemporary performance-based design process is that it involves advanced computational simulation tools to inform the design process with valuable data on a design's performance according to different criteria (Kolarevic and Malkawi 2005). In general, there is no specification of the type of criteria that may be involved in a performance-based design process. However, it is often that criteria related to energy consumption, indoor comfort, daylighting, project cost and sustainability are part of the performance-based design use case.

In addition to improvement in building performance, such a shift in design thinking, and the use of advanced modeling and simulation tools also targets the reduction in failure costs, which at the moment amounts to 20% of the construction budget (Love et al. 2018). This utilization is a direct result of the shift in design thinking as described previously. In a performance-based design approach the application of investigative design practices, to identify designs that cater to the requirements of a given brief would generally be preferable to the application of rule-of-thumb and heuristic design approaches.

§ 1.1.3 Softness in Design Criteria

The ability to quantify design criteria in engineering disciplines, in general, is considered a cornerstone of modern engineering, and it is a fundamental requirement for enabling widespread application of computational methods and techniques, which has brought forth tremendous advancements in engineering. Architecture is differentiated from other design and engineering disciplines in that it incorporates design criteria that are not easily quantifiable, yet they form a fundamental quality of the envisioned design products. Such criteria are termed 'soft', in contrast to 'hard' criteria where a mathematical expression is readily available. Some soft criteria can be expressed verbally, e.g. when it is claimed that a building is 'transparent', there is a more-or-less common understanding of the corresponding quality. Or, when one refers to a building's architecture as 'monumental', even without having seen the building, it is possible to deduce its qualities. There exist still other criteria that are expressed as part of a designer's tacit knowledge, and these are only revealed as part of design activity, or evident in the design result. In cases where such criteria are involved, which is quite common in architecture, it is difficult to even verbally communicate a design quality, let alone quantify it. Consider, for instance, the case of aesthetics. Aesthetics is a fundamental design quality in architecture, however, it is widely acknowledged as an elusive concept, which defies concrete definition (Arnheim 1976; Hassenzahl 2008). As a result, reaching a consensus on aesthetic terms is generally a challenging task. Even more so is the quantification of such criteria as aesthetics, which is met with great difficulty in practice. In the face of an ever-increasing design complexity brought forth by intensification and diversification of design criteria, there exists the risk that design qualities that are not readily quantifiable and based on tacit knowledge, such as but not limited to aesthetics, are not treated to the extent corresponding to their importance in architectural design. As such, in researching and developing a suitable decision support framework, it is necessary to consider a systematic and scientific approach that fully addresses both hard as well as soft and subjective design criteria in an integrated manner.

§ 1.1.4 Conflicting Nature of Design Objectives

Design performance is not defined by a single design objective, rather it is defined by a set of objectives, and in many cases these objectives are conflicting. The presence of conflicting objectives by definition precludes "utopic" solutions, where all objectives are fully satisfied. Of interest in such problems are so called "best-tradeoff" solutions, or Pareto-optimal solutions, owing to the seminal study of Pareto Pareto (1896) that defined the term. A solution is termed Pareto-optimal, Pareto-efficient or non-dominated, if none of the objective functions defined in the optimization problem can be improved in value without degrading some of the other objective function values.

The importance of identifying Pareto-optimal solutions is that during the decision-making process, it is possible to sample a set of solutions that represent what is optimal given the problem definition at hand, thus allowing the acquisition of knowledge regarding problem-related optimality prior to decision making Bittermann (2010).

§ 1.1.5 Computational Intelligence and Cognition

The terms computational intelligence and cognition have a significant role in the context of this thesis, however it is often that the distinction between these terms is inconspicuous. This section will attempt to clarify the distinction between the two terms, in the context that they serve to support the arguments presented within this thesis.

An agent is tasked to perform a goal-oriented exploration of an environment. Examples of such an environment and task may be considered as diverse as an illustrative, simplistic problem where a person is trying to find an object within an office, to real-world problems where a design professional is exploring the design space, striving to identify well-performing solutions to an architectural design problem. For an intelligent search approach, it is merely enough that an objective function exists, in other words, the agent should be able to receive feedback on the fitness of their actions concerning the goal at hand. In the case of the design problem, such actions would be to make decisions to produce a design solution; the reward would be the performance of that solution. The intelligent approach hints at a search strategy for performing actions within the design space. In general, an intelligent approach aims to achieve exploration of the environment, minimizing the effort required to arrive at an optimal result. Such a strategy is made of rules that may be simple or involved, with intelligent approaches such as Evolutionary Computation involving complex rules that make up their strategy. Nonetheless, in the intelligent approach there is no knowledge of the particular properties of the environment at hand, which suggests that to identify the relations between properties of solutions in any design environment, it is necessary to instantiate the solution (i.e. visit the corresponding point in the design space) every time.

But what if indeed knowledge regarding the environment could be obtained and exploited? After all, the intelligent search is a process that readily produces knowledge, in the form of establishing relations between object properties for every point in the environment that is visited. Exploitation of such readily available knowledge hints at a cognitive approach. Cognition, in this respect, is understood as the ability of a technical system to perceive the environment as well as to aggregate and abstract knowledge (Ahle and Soffker 2006; Ciftcioglu and Bittermann 2015b). Whereas the intelligent approach performs an unbiased search of the environment, the cognitive approach exploits already accumulated knowledge to derive generalized rules regarding relations between solution properties in the environment, which are embedded in a *model* of the environment. The computational cognitive model, as such, presupposes the existence of information regarding the environment — and is biased by it. The clear advantage in this case is that the relations present in the environment are *embedded* in the cognitive model — insofar as the knowledge used to generate the model is expressive of those relations. As such, instantiation of solutions is no longer necessary as in the case of intelligent search, which results in an instantaneous response.

Knowledge for computational cognition may come from many sources, however it has been established that intelligent search is a knowledge producing process, generating high-quality knowledge that is extremely relevant to the design goals at hand. In other words, considering a design problem, the intelligent search would output solutions that are well-performing concerning the goals put forward. It is therefore reasonable to utilize the knowledge embedded in those solutions to derive the cognitive model. In this sense, the output of the cognitive model forms a suitable action for satisfying required design performance, and in addition to that, produces a desirable design with respect to its properties. This action, then, is suggestive of a state of *comprehension* of the environment (Ciftcioglu and Bittermann 2015b).

§ 1.2 Research Outline

§ 1.2.1 Background Information

The complexity arising out of factors outlined in the previous section gives rise to significant challenges in decision making. The sheer amount of design variables at play, the complex non-linear relations between decisions, design criteria and constraints, as well as the multitude and conflicting nature of design criteria themselves places an unprecedented burden to human cognition during design (Bittermann 2009; Chatzikonstantinou and Sariyildiz 2017). To address such challenges and support the cognitive decision making during design, a broad research effort has been targeted towards the development of methods, tools and techniques for decision support in architectural design. The dissemination of Information, Communication and Knowledge Technologies (ICKT) throughout the last half of the 20th century has resulted in increased research interest for applications of computational methods, tools and techniques towards realizing advanced decision support systems. One of the most recent developments along this research direction has been Computational Intelligence-based techniques, and specifically MOEAs. MOEAs have been applied to a series of architectural design problems (Chatzikonstantinou et al. 2015; Ekici et al. 2016; Kirimtat et al. 2016a; Yufka et al. 2017; Chatzikonstantinou et al. 2019) achieving promising results, and an increasing interest towards this technology is an evident trend.

As an intelligent approach, MOEAs have been proven able to identify promising solutions to challenging design problems in various engineering fields. However, concerning their application in the field of architectural design, a fundamental limitation exists, namely the difficulty in applying MOEA-based decision support methods to early, conceptual-stage decision making. This is the main limitation that constitutes a starting point for the research conducted as part of this thesis, which aims to propose methods and techniques to tackle it. In particular, following an analysis that is based both on the current State of Art (SoA) in relevant fields of Computational Intelligence (CI) as well as personal experience of the author in application of MOEAs in real-world design projects, two issues are identified that contribute to the limitation outlined above, which are identified henceforth.

Accounting for the complex nature of relationships between design decisions and criteria satisfaction, as well as the fidelity of simulations required to ensure accurate estimation of building performance, in general it is the case that in architectural design numerous simulation iterations are required. This is also the case when MOEAs are used as decision support tools, for the algorithm to reach optimality. The cost associated with those simulations is often prohibitive for application to real-world problems. This is especially true for the stage of conceptual design where design iterations are fast-paced and decision support tools are often not able to keep up with constant changes. This issue has been empirically documented by the author during participation in a design project concerning the design of a large-scale facade shading device in the Netherlands, where it was necessary to carefully plan design iterations and stakeholder meetings to allow a cluster of computers to perform the costly optimization process in the meantime, and obtain results for decision making. It is obvious that this should not be the case in conceptual design stage, as the flexibility that characterizes it is severely compromised. To this end, a system is developed whereby computational cognitive machine learning models of relevant simulation figures are used instead of the actual simulation, to approximate those figures at a fraction of the computational cost.

Besides, another issue is identified focusing on post-Pareto decision making in architectural design and in cases where MOEAs are used as decision support systems. Even though MOEAs naturally offer a series of best-tradeoff design solutions as a result, the process of inspection for selecting the most desirable solution is generally a tedious undertaking, while the result is often an unfavorable compromise of preferences of stakeholders, as the latter are expressed in terms of concrete design attributes. To amend this situation, computational cognitive a method and tool is envisioned herein, whereby second-order preferences will be able to be expressed by directly manipulating design variables. At the same time, the tool itself, informed by the properties of optimal designs as determined by multi-objective optimization, will provide a "guiding system" that responds accordingly with complementary variable adjustments as necessary, and that ensures that the preferences are satisfied to the best degree possible, while optimality of the design is not compromised.

Throughout the manuscript, the term "decision-maker" is extensively used. This term is used in the context of the design process, to denote, in the context of a project, the group of agents that influence design-related decisions. Such agents may be project stakeholders, architects, engineers, experts, or any combination thereof. A singular form of the term (i.e. "decision-maker" vs "decision-makers") is used in order to enhance the illustrative power of explanations found throughout this thesis, by assuming that a single agent interacts with the system at hand. This does not constrain application of discussed systems to a single agent. An exception to the single-form rule occurs when referring to a specific group of decision-makers, or when referring to the decision makers as a generic category of agents.

§ 1.2.2 Problem Statement

Through the above, the concrete problem that is dealt with by this thesis is brought forward. Despite the powerful nature of CI-based decision support methods and techniques, application to early-stage architectural design is problematic, owing to limitations in being able to support preference-intensive design decisions, in a rapidly changing problem definition context. It is stipulated that these limitations call for an augmentation of the intelligent capabilities of CI methods and specifically MOEAs, in order to be able to combine intelligence offered by the methods with cognition required for rapid decision making in conceptual design stages.

§ 1.2.3 Research Questions

Under the scope of the problem definition discussed above, this thesis stipulates the following research questions.

Main Research Question:

How can Computational Intelligence (CI)-based methods and techniques (including intelligent as well as cognitive methods) better support decision making during architectural design, especially in the early conceptual design stage?

To elaborate the above general research question, two urgent focus areas are identified, namely: The need for managing computational complexity of simulations and the need for addressing design preferences beyond the satisfaction of concrete design goals. These areas are deemed to be the ones having the greatest importance with the aim of proposing computational decision support systems that can respond to design problems comprehensively, accurately addressing the high-level needs of contemporary design research & practice. Under this assumption, a number of sub-research questions have been further stipulated with the aim of better focusing the research. Those are as follows.

Sub-research Questions:

- How can cognitive methods augment intelligent decision support tools, in order to lead to better and more agile decision making in design?
- How can methods and techniques borrowed from the field of machine learning contribute to alleviating computational complexity of simulations?
- How can decision-maker preferences be effectively incorporated alongside design goals in computational multi-objective optimization?
- At which stage should decision-maker preferences be addressed (before, during, after optimization)?
- How can the above specifically be applied to current and challenging design problems in architecture?

§ 1.2.4 Research Objectives and Scope

The research reported herein belongs broadly to the field of design computing. In accordance with the specific challenges stipulated previously in section 1.2.2, it is aimed at developing tools, methods, and techniques for improving the usefulness and extending the application of computational decision support methodologies in the application area of architectural design, and specifically early design stages. More specifically, assuming the stipulations regarding design complexity mentioned and considering computational optimization as a viable candidate for decisively addressing complexity; the focus of the research is two-fold. On one hand, to propose methods to alleviate the computational complexity of complex simulations through the application of machine learning techniques, and on the other hand to enrich post-Pareto decision making through ample consideration of decision-maker preferences. In both cases, the research output consists of both the elaboration of a method as well as a tool in the form of an application or plugin that allows the proposed method to be readily applied to design tasks.

§ 1.3 Methodological Overview

Research methodology refers to the principles of the methods by which scientific research can be carried out (Fellows and Anita 2008). In this sense, this section aims to elaborate on the principles of the methods considered in this thesis. The research methodology applied throughout the elaboration of this thesis comprises several stages. A preliminary research stage is followed in order to identify issues of interest and formulate a concrete research framework, including research question formulation. Following this, a model development stage takes place focusing on identification of the approach and specific methods to address the research questions. This is followed by an experimental research part where the proposed methods are comprehensively validated through application to real-world case studies. An overview of the applied research methodology is available in figure 1.2 and elaborated hereon.

§ 1.3.1 Preliminary Research

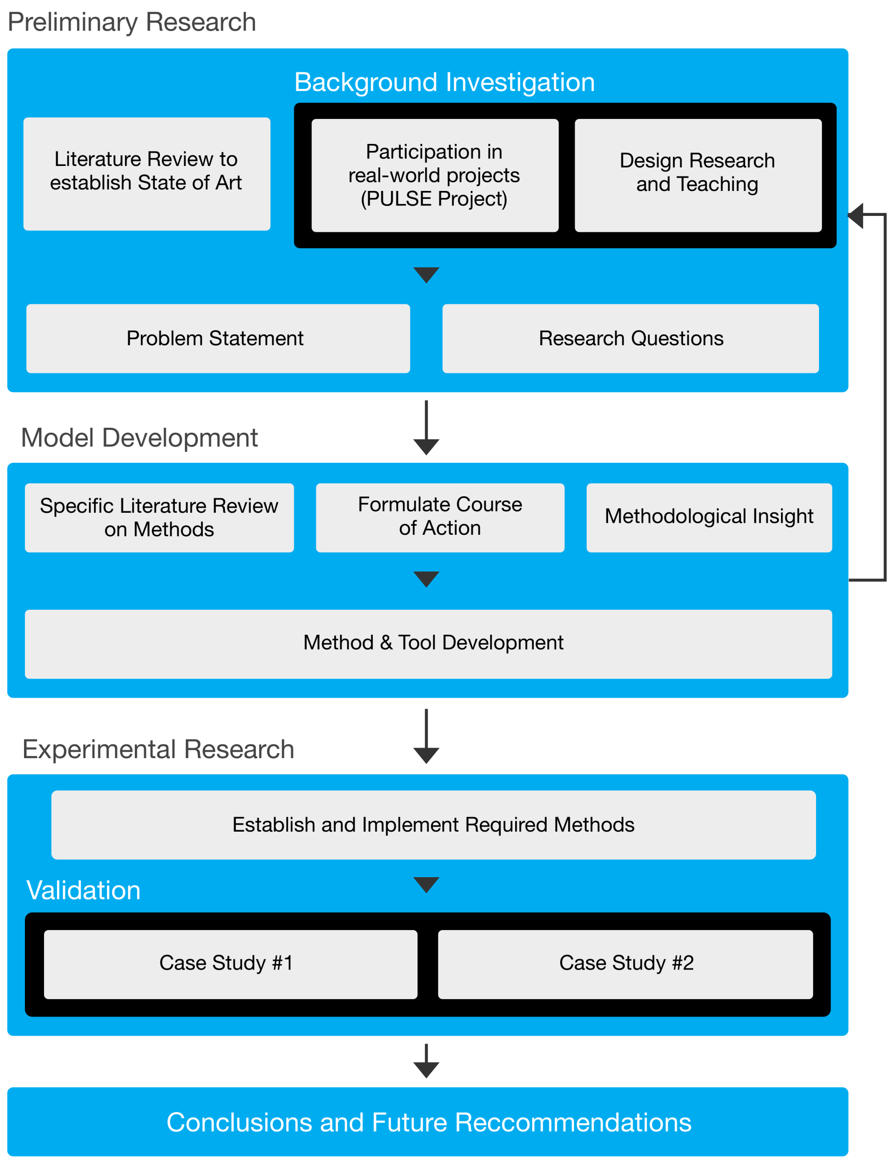


FIGURE 1.2 Research Methodology

Through the preliminary research stage, the main aim has been to generate insights about the needs of design agents in the context of architectural design. This has been based on two main poles: On one hand, extensive literature review, and on the other hand, qualitative data and empirical observations. This initial research step is a form of exploratory research (Fellows and Anita 2008) that aims to put forward the fundamental ideas that guide the next research steps. This initial step has been more than often carried out as a form of action research, in the sense that the author of this thesis is an active participant in the processes that are being observed. This has occurred with several cases, and this thesis reports one of them, as the most significant. It is noted that among all cases this particular one took place later in the research timeline.

The application of computational decision support in academia and architectural practice undeniably opens up novel opportunities that enable treatment of complexity in large-scale, real-world projects and complex, multi-faceted performance requirements and constraints. Despite the potential brought forward, there exist challenges in effectively applying computational decision support in contemporary education and practice. As stipulated previously in this thesis and specifically within section 3.2, two fundamental challenges are related to the following two issues:

- Unmanageable computational complexity of stochastic optimization due to use of accurate simulation models, and,
- the lack of an efficient approach that allows decision-maker preferences to be integrated with design objectives.

Identification of these two challenges and substantiation through real-world education and design experience has been the main output of the preliminary research, which leads to the concrete methodological specification of the next step.

An extensive review of the state of art in computational decision support and applications in architectural design has been performed. The result of this investigation is presented in chapter 2. The main aim here, as related to the research methodology applied, is to identify existing approaches that may potentially be helpful in addressing the issues identified in the previous research stage. This procedure consists of the identification of works, establishing usefulness in addressing issues, pinpointing potential shortcomings, and, finally, establish the potential for improvement of the identified work with the aim of better addressing issues at hand.

this stage comprises formulating specific research questions and hypotheses, as well as developing the necessary methodological insight to enable the establishment of specific methods that will be implemented in the next experimental research stage to address the research questions.

§ 1.3.2 Model Development

The second part of the overall research methodology is concerned with the development of the model, which encompasses the development of the approach and the formulation of the concrete method, as well as the development of software tools that implement the theoretical findings. This part of the research focuses on the use of insights gained previously in the initial research stage as well as in a more focused review the of state of art, in order to formulate a course of action for addressing the issues identified as part of the preliminary research.

It is noted that this focused review of literature, in contrast to the general state of art established in the Preliminary Research, will often be found alongside model development within the structure of the thesis. This has been a conscious decision on the part of the author for two reasons. The first is to allow some degree of fidelity to the timeline of performed research, which consists of a series of publications that encompass both establishing of state of art as well as development, and the second is that content-wise, it is really fitting to combine these specific investigations into the state of art with the development that they are related to.

§ 1.3.3 Experimental Research

In previous research stages, and based on the needs and requirements established and the investigation of the state of art, a proposed approach is formulated, and its elaborations in specific methods, tools, techniques are proposed, and their implementations are developed.

As a next step, the main goal of this research stage is to implement and validate the applicability and performance of proposed methods in addressing the issues of concern. As part of this goal, a two-fold experimental research endeavor is undertaken that focuses on the following:

- The research and implementation necessary to establish the proposed methods and techniques, supporting infrastructure, functional testing components, as well as integration thereof in a software framework.

- The planning and implementation of case studies that aim to ultimately validate the performance and applicability of the proposed approaches. Validation of proposed approaches is performed through the application to design case studies that are inspired by real world complex design problems.

The results of the experimental research stage, together with previous stages are evaluated in order to formulate research conclusions and recommendations for future research directions.

The overall outline of the research methodology followed in this thesis is presented in figure 1.2.

§ 1.4 Limitations

No claim is made as to the validity or accuracy of design objectives as they are established in the context of an architectural design project. Through the proposed approach it is possible to satisfy DM preferences insomuch as they are not in direct conflict with design objectives; in this sense, it is proper to use the term “second-order preferences”, in order to denote the precedence of design objectives in the post-Pareto analysis. Concerning the above, the establishment of specific soft criteria as they could be introduced in a design problem is an important aspect, however one that is not dealt with in this thesis.

§ 1.5 Contributions

Computational optimization offers tremendous potential for improving decision making in the field of architectural design. Under this assumption the main contribution of the work described herein is the identification of proposed methods and techniques to extend the generic computational optimization framework so as to:

i improve adoption of simulation-based testing in the initial phase of design, by alleviating arduous computational effort spent on design performance evaluation, especially in the early, conceptual design stage,

ii enable decision making that is closer to the needs of project stakeholders, by extending post-Pareto decision support with emphasis on the satisfaction of preferences pertaining to concrete object attributes.

iii overall, improve informed decision making throughout the design process, which can provide benefits such as overcoming building failures during the construction stage (calculated to be 20% of the building costs).

The aforementioned contributions are expected to serve in promoting informed decision making and, ultimately, through the improvement of the design process, to a better-built environment. It is to be noted that, while focusing on architectural design, the products of this thesis apply to other fields of design where qualitative criteria have a key role, such as product design, graphic design, Human-Machine Interface (HMI) design, and so forth.

§ 1.6 Expected Output

The expected output of this thesis is two-fold: On one hand, it comprises the methodological and technical novelties that are proposed herein. This includes i. descriptions of the proposed methods including mathematical or algorithmic formulations where relevant, and ii. descriptions of methods to validate the performance of the former. The above have been incorporated in a series of journal and conference publications, some of which have been distilled into parts of this thesis. On the other hand, it comprises the concrete software implementations of the proposed methods and techniques, which are fully functional components, at TRL 5 and above, that are ready to be used in practice.

§ 1.7 Scientific and Societal Relevance

Computational optimization constitutes a powerful tool that carries the potential for groundbreaking advances in design research and practice. However, applications still fall behind as crucial aspects present challenges in applying said methods, tools, and techniques to real-world architectural design problems. This research aims at identifying prominent said problematic areas and proposing the necessary advancements to alleviate related shortcomings. The proposed advancements constitute a novel body of knowledge, that focuses on the research of specific aspects involved in the application of existing CI methods in the field of architectural design, as well as the technical advances necessary to enable successful application thereof. The contribution to knowledge comprises advances in cognitive methods to enable the seamless application of intelligent decision support methods in architectural design. Besides, the tools, methods, and techniques proposed as part of this work are expected to yield advancements in the application of computational decision support in real-world architectural design problems by making them more applicable and able to more accurately address high-level problems faced by decision-makers in the field of architectural design, which constitutes significant dissemination of scientific research.

The societal relevance of this work resides in the premise that through the adoption of the proposed tools methods and techniques, decision-makers in the field of architecture will obtain powerful assets that can orchestrate a better application of computational decision support tools overall, with emphasis on computational multi-objective optimization, which is the most relevant for architectural design. The societal relevance is thus directly evident, in that complex architectural design problems as those commonly tackled in contemporary architectural practice will be addressed with greater confidence due to the augmented cognitive capabilities that the synergy of man (decision-maker) and machine (optimization algorithms and cognitive models) is expected to offer. As a result, increased efficiency in design and construction is expected to translate into the reduction of costs associated with the built environment, which in itself is a clear benefit both for the individual as well as for society. Ultimately, it is expected that furthering the state of the art in this field will lead to a better-built environment, where, not only technical but also qualitative aesthetic and individual/cultural preferences may be readily addressed in everyday design practice.

§ 1.8 Thesis Outline

A significant portion of the content of this thesis is based on a series of publications that have been published throughout the course of the author's PhD research, and which have lead up to the definition of the methodological and technical findings outlined hereafter.

The thesis is structured as follows. In chapter 2, an extensive literature review on the state of the art on design Decision Support Systems, and in particular Computational Intelligence-based decision support is presented. In chapter 3, the first stages of research are presented. This preliminary research has been carried out as part of the author's participation in architectural education and practice, and culminated in the stipulation of the problem statement and research questions of this thesis. Chapter 4 focuses on model development, elaborating on the individual components that make up the proposed approach as well as their integration in a consistent and comprehensive decision support method. Chapter 5 elaborates on two case studies, each focusing on different aspects of the proposed approach; in the first case, the application of a machine learning surrogate model to accurately model indoor daylight distribution is discussed. In the second case, the application of an auto-associative neural network that models the distribution of Pareto-optimal solutions to a multi-objective facade design problem is presented, and application to preference modeling is discussed. Finally, chapter 6 presents concluding remarks and future recommendations.

The structure of the thesis, including relevant publications, is outlined in figure 1.3.

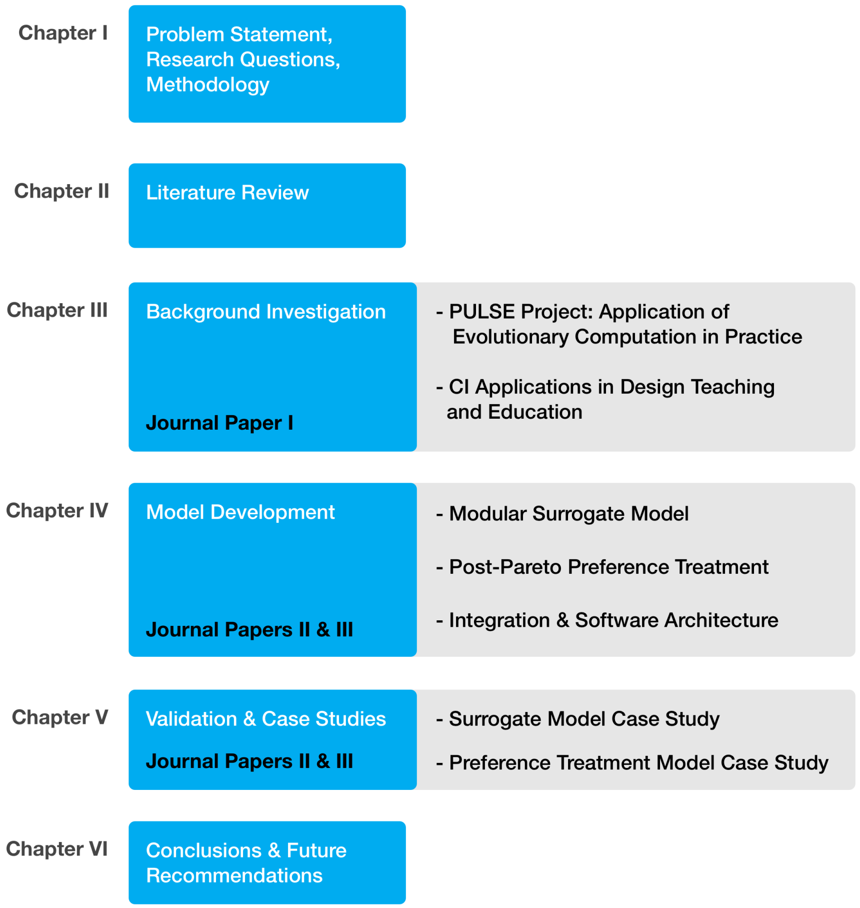


FIGURE 1.3 Outline of the thesis structure in relation to the research activities throughout the thesis.

2 Literature Review and State of Art

This chapter aims to provide a concise outline of the technologies that are related to the present research, present an overview of the state of the art in related fields, and identify the required developments in the state of art, to be able to propose relevant methods, tools and techniques that can address the research questions posed in chapter 1. The focus of this chapter is on approaches that belong to the field of Computational Intelligence. In particular, the emphasis is two-fold: On one hand, on the state of art in design decision-support approaches, focusing on developments in Evolutionary Computation approaches for decision support in architectural design, and on the other hand in research and applications of Machine Learning in the same field.

§ 2.1 Decision Support Systems

Decision making is a central activity in architectural design that is characterized as much by its ubiquity as by its importance in the design process. The complexity involved in the design of architectural projects renders decision making in the context of design a challenging task for human cognition. The main sources of design complexity have been previously outlined in section 1.1.2. Together with their effects on the design process they may be summed up as follows:

1. The excessive number of possible design solutions (due to combinatorial explosion); exhaustive enumeration of design solutions is thus impossible.

2. The presence of multiple conflicting design objectives; identification of a single best performing design is thus unattainable.

3. The presence of complex, non-linear relations between decision variables, objectives and constraints; exploration of the design space is thus perplexed.

4. The presence of tacit design preferences, independent of design objectives; exploration cannot be guided by objectives alone.

In order to alleviate excessive cognitive burden, and effectively support cognitive decision making, a wide range of devices has been utilized throughout the history of design. The very act of sketching or drafting can be seen as a device that supports decision making. This is achieved through providing an external memory mechanism where cognition can readily offload and reacquire information, thus reducing the amount of information that needs to be retained in cognition at any time. The use of external media as a cognitive extension mechanism has been described in the literature (Clark 2001). The act of physical model-making belongs to the same category, in that it aids in visualization of the projected design result, and therefore facilitates a task that would otherwise prove to be a significant burden to cognition. In a modern interpretation, contemporary Building Information Modeling (BIM) systems serve a similar but extended purpose, namely to store rich, hierarchical information pertaining to a multitude of building and construction aspects, which allows knowledge to be managed in a much more transparent manner, therefore leading to better collaboration among stakeholders as well as an overview of the design process and improved decision making.

§ 2.2 Information, Communication and Knowledge Technologies

Architecture, just as many other engineering disciplines, has undergone a profound transformation with the introduction of digital machines. Developments on ICKT have persisted throughout most of the 20th century, and have had an unmistakable effect on designing at multiple levels, including but not limited to representation, collaboration, modeling and management (Sariyildiz and Stouffs 2001, 2002). Original work on the topic of ICKT dates back to the seminal dissertation of Ivan Sutherland on Human-Machine Interface (HMI) and in particular HMI for design tasks, which culminated to the well-known Sketchpad program (Sutherland 1963). Sketchpad has been a pioneer work in many levels. Some of the innovations introduced as part of that work include: the use of a novel "light-pen" interface for sketching on screen; basic associative functionality through the use (and re-use) of "symbols", i.e. associative groups of line and arc elements that share changes; extendability with new kinds of shapes and functionality; and innovations in storage of drawings. Beginning in the 1980s, commercial Computer Aided Design (CAD) programs had already found their way outside the academia and into architectural design practice. Beginning with 2D drawing operations, and later on extending to 3D drawing, animation and Building Information Modeling (BIM) software, ICKT technologies have provided a groundbreaking transformation of the architectural design workflow, facilitating mundane tasks and providing novel management, collaboration and visualization capabilities.

The majority of ICKT applications in architectural design concern representation and explicit design knowledge management. CAD software, visualization, representation and Virtual Reality applications, BIM applications, as well as the recently popularized analysis tools such as computational simulation tools belong to this category. Barring the cognitive support offered through facilitating information management, including representation, there is no further involvement in decision making of the tools described above. Besides, recent developments in CAD, such as building information modeling (BIM) and simulation-based design, have mainly affected the later stages of the design process, where the support offered by computer tools is focused on decisions on specific aspects of the design (Strobbe et al. 2011).

§ 2.3 Computational Intelligence and Optimization

Of greater relevance to the scope of this thesis though, are decision support systems that are making use of computation to directly support decision making through systematic search of the design space in the early stages of the design process, where fundamental design decisions are still taking place. These are mainly tools that rely on computational optimization. It is important to stress the difference between analysis and optimization. In analysis, the employed model is responsible for providing an accurate figure of the performance of a design, whereupon a decision-maker iteratively performs adjustments that are either informed by previous knowledge (e.g. through heuristic rules), own design or engineering experience, or through trial-and-error, to improve performance according to one or more design criteria. While the use of simulation offers a picture that is much closer to reality than simplified calculations, rules of thumb or even speculation could offer, decision making is still left up to the cognition of the decision-maker to perform. On the other hand, in optimization, the iterative improvement is performed as part of the algorithm, and the decision-maker is responsible for defining design goals and the design space. Optimization-based approaches offer a clear advantage in that the human-in-the-loop trial-and-error process is eliminated and in turn cognitive limitations are alleviated. The decision-maker is thus free to exercise their choice on designs that are proven to be well-performing, significantly reducing the burden associated with design decision making overall.

Computational Intelligence (CI) is an umbrella term that encompasses several diverse approaches to intelligence, which comprise Machine Learning (ML), Evolutionary Computation (EC) and Fuzzy Logic (FL) (Jang et al. 1997). CI became a formal area of study in the early 1990s, and is very close to the term Soft Computing (SC) (Zadeh 1994). SC as a term comes in contrast to Hard Computing, the essential difference being that SC and methods thereof can tolerate imprecision, can function using partial truth and may handle uncertainty as part of the process (Jang et al. 1997). It is interesting to note that these are similar qualities as those found in the mental processes underlying behaviors in natural organisms. Nature has become in many cases the inspiration behind approaches that belong to the domain of Soft Computing, such as Evolutionary Computation and Artificial Neural Networks. Concerning the aims of the present research, the two most relevant Soft Computing methods are those of Evolutionary Computation, especially it's Multi-Objective counterpart, as well as Artificial Neural Networks.

§ 2.4 Computational Optimization in Building Design

Computational optimization in building design is a topic that has recently gained attention by both academia as well as design practice. To clarify, the topic of computational optimization in building design is a performance-based design approach that is not limited to the use of analysis tools, rather it goes further to integrate those tools with meta-heuristic optimization algorithms, such as Genetic Algorithms, therefore automating the design search process. Hereby an indicative number of relevant studies are shortly reviewed.

It is noted that applications of presented studies tend to focus on facade design, as this topic has been intensively researched due to its relevance with the case studies that will be presented later on in this thesis. In addition, this particular topic is a prime example of complex design, as it combines performance aspects that are related to several different design objective including daylighting, climate comfort, cost and aesthetics.

Von Buelow (2008) discusses a digital tool, “Intelligent Genetic Design Tool” that aims to support in design exploration through presenting decision-makers with design alternatives that are discovered through genetic exploration in the design space. The tool is claimed to promote creativity through considering more than one alternative “near-optimal” solutions. It is worthwhile noting that the genetic algorithm described in the paper is single objective. The tool is applied in a case study that involves the design of a truss bridge, for which several alternatives are presented.

Rusovan and Brotas (2012) propose a method that uses genetic algorithms to optimize an external shading screen based on a modular system of three-dimensional elements gradually changing throughout the façade. The objective of optimization is indoor daylight distribution, glare reduction and energy expenditure reduction. Paper authors use Evalglare, Daysim and EnergyPlus simulation software to evaluate shading screen designs.

Choi et al. (2013) develop a method for optimizing sets of rectangular louvers for thermal performance using genetic algorithms to alternate the angle of rotation, spacing, projection length, and inclination.

Ercan and Elias-Ozkan (2015) propose a performance based parametric design approach for the design explorations of shading device, which could optimize daylight and block excessive amount of solar heat gain.

González and Fiorito (2015) focus on the optimization of external shadings for visual comfort and energy efficiency in a typical office space; the research tackles solutions popularly adopted in standard practices, such as blinds and overhangs.

Futrell et al. (2015) compare the performance of four different optimization algorithms to optimize building design, including exterior shading, for daylighting performance to minimize lighting loads. The results indicate the region of optimal performance is found quickly by all algorithms, but the converge has shown it can be slow.

Omidfar (2015) presents a set of designs based on optimization of complex architectural facades using generative algorithms for daylight and structural analysis, with explicit focus on the value of ornament. Paper authors use a Genetic Algorithm to optimize the Daylight Autonomy of indoor space, however no further information regarding either the algorithm at use of the optimization results is given.

Elghazi et al. (2013) focus on origami to generate geometries of modular patterns. They first studied and then optimized with genetic algorithms a set of kaleidocycle rings that can be morphed to change the daylight performance in indoor spaces.

Lee et al. (2016) advocate a similar standpoint, by highlighting computer-assisted parametric techniques can be utilized for daylighting design in a more accurate way than design considerations based solely on prior knowledge and experience. Paper authors compare conventional design approaches with indoor lighting conditions obtained by adjusting louver shapes and window patterns using genetic algorithms.

Mahdavinejad and Mohammadi (2018) proposes a method for optimizing a louvre system in hot climates based on daylight metrics and energy consumption, using a genetic algorithm. Paper authors use the Strength Pareto Evolutionary Algorithm - II (SPEA2) (Zitzler et al. 2001) and aim to minimize energy consumption while maximizing the Useful Daylight Illuminance metric of natural lighting quality indoors. Furthermore, they discuss the resulting Pareto optimal distribution and draw useful design conclusions from the decision variables of the best-tradeoff designs.

Mangkuto et al. (2018) focus on daylight admission in an open-plan. The admission was optimized using a genetic algorithm alerting the external and internal widths, external tilt angles, and specularity of the light shelves with or without overhangs. The objectives were to maximize the spatial daylight autonomy and minimize the annual sunlight exposure.

§ 2.5 Multi-Objective Evolutionary Computation

Optimization problems minimize some function of decision variables subject to hard or soft constraints and are divided into two types:

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

Single objective problems can be solved by exact methods to achieve an optimal solution for problems with small-size and a strict mathematical formulation, which does not match real-world problem characteristics (Cui et al. 2017). However, it is more than often that design problems in architecture and elsewhere are defined by more than one design criteria. In addition, design criteria may be conflicting with each other, so that performance improvement according to one criterion leads to degrading performance according to another. In such cases, a design that satisfies all design criteria to the full extent is by definition impossible.

As an example, one may consider the case of designing an office building. The building stakeholders may wish to maximize profit by maximizing the usable floor area of the building. On the other hand, it is expected that they may wish to minimize the investment cost. Satisfying both of these criteria to the fullest is impossible by definition. Thus, one has to settle for compromises between them. Problems like the one mentioned, characterized by more than one conflicting objectives, are commonly known as Multi-Objective Problems. The field of optimization that deals with such problems is known as Multi-Objective Optimization (MOO). Multi-Objective Optimization in particular, has enabled efficiently addressing problems of significant design complexity in engineering (Ravindran et al. 2006), and more recently also in architecture (Evins 2013; Machairas et al. 2014; Ekici et al. 2019). The rest of this chapter focuses on these methodologies and the state of the art of their applications in architectural design.

§ 2.5.1 Multi-Objective Evolutionary Algorithms

Most real world optimization problems are naturally posed as multi-objective optimization problems. One approach to addressing multi-objective problems is known as the weighted sum or scalarization technique, where a minimization problem is expressed as (Deb 2001):

$$\min \sum_{i=1}^{n} \gamma_i f_i(x) \tag{2.1}$$

$$\sum_{i=1}^{n} \gamma_i = 1 \tag{2.2}$$

$$\gamma_i > 0, i = 1, \ldots, n \tag{2.3}$$

In the above equation, γ_i is the *ith* weight value and f_i the *ith* objective function. An alternative technique entails converting all but one of the problem objective functions to constraints, and trying to optimize the functions subject to said constraints. Despite the simplicity of the above techniques, the performance of the optimization solutions in both approaches is heavily dependent on the chosen weights or constraint limits (Zitzler 1999).

In the application of these approaches, it is difficult to decide the degree of importance of each objective whether it is previously determined (weighted-sum method). Considering the drawbacks of these approaches, multi-objective optimization (MOO) algorithms, and especially Multi-Objective Evolutionary Algorithms (MOEAs) are referred to. MOEAs introduce the notion of dominance to effectively deal with multiple objectives. Simplified, the notion of dominance introduces definitions for comparing solutions in the presence of multiple objectives. Namely, considering a minimization problem, a solution x_A is said to dominate another solution x_B if the following conditions are both true (Deb 2001):

Solution x_A is no worse than x_B in all objectives, Solution x_A is is strictly better than x_B in at least one objective.

If any of the above conditions are violated, then solution x_A does not dominate x_B. Since the concept of dominance allows for a comparison of designs in a multi-objective context, most MOEAs rely on dominance, or an indicator thereof, to identify and evolve promising solutions.

Besides Evolutionary Algorithms, other algorithms dealing with stochastic optimization, including MO problems, have been developed through inspiration from behaviors and communication mechanisms in nature (Cui et al. 2017), such as biology-inspired algorithms, physics-inspired algorithms, geography-inspired algorithms, and social culture-inspired algorithms (Cui et al. 2017). Indicatively, a few popular MOEAs are outlined as the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) (Deb et al. 2002), the Strength Pareto Evolutionary Algorithm-II (SPEA-II) (Zitzler et al. 2001), the Multi-Objective Evolutionary Algorithm with Decomposition (MOEA/D) (Qingfu Zhang and Hui Li 2007) the Hypervolume Estimation Algorithm (HypE) (Bader and Zitzler 2011) and the Multi-Objective Differential Evolution (DEMO), outlined below.

§ 2.5.1.1 Non-Dominated Sorting Genetic Algorithm II

NSGA-II is an exclusive multi-objective Genetic Algorithm and it is an improved version of NSGA. It behaves as to preserve variations by not having any variable. It incorporates a fast and robust non-dominated sorting approach (Deb 2001). The algorithm demonstrates complexity $O(MN^2)$ in finding all members of the first non-dominated stage in the population. M represents the number of objectives and N the population size.

In the main loop, P_0, which represents an initial random parent population, of size N, emerges. It contains D-dimensional vectors and it is symbolizing decision variables. In order to produce an offspring population Q_0 of size N, binary tournament selection, recombination, and mutation operators are applied. On the other hand, elitism is not applied in this stage. In advance, a combined population $R_t = P_t Q_t$ gets formed. Here, size of $2N$ is the population of R_t. Later on, with nN being the total number of ranks of the combined population upon non-domination, the Rt population is sorted into sets $F_1, ..., F_n$. As from the set of non-dominated individuals, F_1, attachment of individuals to P_{t+1} is applied. Iteration for each consequent phase set is the period of insertion. When there is an addition of set F_k, it makes inferences the size of P_{t+1} in order to be greater than N, F_k is sorted upon the crowded-comparison operator n, and is trimmed to suit the sustaining places in P_{t+1}. In order to generate an offspring population Q_{t+1}, for the next generation, P_{t+1} is used along with binary tournament selection, recombination, and mutation.

In order to acquire an approximation of the depth of solutions encircling a specific formula in the population, the average distance of two points on either side of this point along each of the objectives is computed. In this step, there is an approximation of the perimeter of the cuboid. It gets formed by using the closest neighbors as the corners, and this fact is named as "crowding distance" (Deb 2001)If two solutions a and b have different ranks, the one with the lower rank is selected. On the other hand, when there is equality between ranks, the one with the biggest crowding distance is selected.

§ 2.5.1.2 Hyper-volume Estimation Algorithm

The Hyper-volume Estimation Algorithm, abbreviated HypE, was developed by Bader and Zitzler (Bader and Zitzler 2011). It is based on an effective fitness assignment strategy. As can be seen in figure 1, the main loop of HypE started with a standard evolutionary algorithm process, then continued with the successive application of mating selection, variation, and environmental selection procedures

(Algorithm 1).

Result: P_g of Pareto optimal solutions
Initialize population P by choosing N solutions from X uniform at random where N: popsize, M: nosamplingpoints;
$g \leftarrow 0$
while $g \leq g_{max}$*, where* g_{max} *is number of generations* **do**
  $P' \leftarrow matingSelection(P, R, N, M)$;
  $P'' \leftarrow environmentalSelection(P \cup P'', R, N, M)$;
  $g \leftarrow g + 1$;
end

Algorithm 1: HypE algorithm main loop (Bader and Zitzler 2011)

During the mating selection process, if the number of objectives is equal or smaller than three, the hypervolume values are computed exactly; otherwise, these values are estimated based on a Hypervolume-based Fitness Value Estimation algorithm. Then, binary tournament selection is realized with several tournaments among a few individuals that are randomly selected from the population. In the variation process, mutation and recombination processes are combined to produce an offspring population. Finally, in the environmental selection process, the most promising solutions are chosen from the parent population and offspring. Then, a new population is created for the next generation (Algorithm 2).

Result: Mating pool Q
where P: population, R: referenceset, N: popsize, M: nosamplingpoints;
if $n < 3$ **then**
  $\phi \leftarrow computeHypervolume(P, R, N)$;
else
  $\phi \leftarrow estimateHypervolume(P, R, N)$;
end
$Q \leftarrow \emptyset$;
while $|Q| < N do$ **do**
  choose $(a, v_a), (b, v_b) \in \phi$ uniformly at random;
  if $v_a > v_b$ **then**
    $Q \leftarrow Q \cup \{a\}$;
  else
    $Q \leftarrow Q \cup \{b\}$;
  end
end

Algorithm 2: HypE mating algorithm (Bader and Zitzler 2011)

§ 2.5.1.3 Multi-Objective Differential Evolution

Differential Evolution, first presented in (Storn and Price 1995) is a successful Evolutionary Algorithm that uses a greedy selection strategy and a recombination operator that combines a parent with several other individuals within the population. The original Differential Evolution algorithm is single-objective, and several strategies are reported to extend it to the Multi-Objective domain. Among those, a particularly successful one is Differential Evolution for Multiobjective Optimization (DEMO) (Robič and Filipič 2005). DEMO proposes an elitist scheme for handling the problem of deciding on parent replacement when parent and offspring are non-dominated. DEMO proposes that in this case, the offspring is added to the population, growing its size. Following recombination and selection, the population is truncated following dominance and crowding distance criteria, similar to the approach followed in NSGA-II. The algorithm is shown in figure 3.

Evaluate the initial population P of random individuals;
for $P_i(i = 1, ..., popSize)$ *in* P **do**
  Create candidate C from parent P_i;
  $evaluate(C)$;
  if $C \succ P_i$ **then**
    C replaces P_i;
  else if $C \prec P_i$ **then**
    C is discarded;
  else
    C added to P;
end
if $|P| > popSize$ **then**
  $truncate(P)$;
end
Initialize population P by choosing N solutions from X uniform at random where $N : popSize$, $M : nosamplingpoints$;
Randomly enumerate the individuals in P;

Algorithm 3: Outline of one variant of DEMO algorithm, DEMO/parent (Robič and Filipič 2005)

§ 2.5.2 Multi-Objective Optimization in Building Design

In this section, an indicative number of studies are presented that focus on the application of Multi-Objective Evolutionary Computation (MOEC) as a decision support tool in architectural design.

Sariyildiz et al. (2008) report a novel system with the aim of pursuing Pareto-optimal designs in multi-objective problems in the application domain of architectural design. The system is capable of quantifying qualitative, linguistic information through the use of fuzzy neural trees and thus it is able to incorporate qualitative knowledge of design experts as an objective function for optimizing. In addition, paper authors present a probabilistic visual perception model which they use to address privacy concerns in architectural design. Finally, they report promising results with a neighborhood planning case study, where objectives are to maximize garden area with specific orientation and maximize visual privacy.

Gagne and Andersen (2010) report a tool based on a Genetic Algorithm that facilitates the exploration of facade designs considering objectives of improving illuminance and minimizing glare. Paper authors present a bi-objective study where one objective is related to illuminance and the other is related to glare, where both are computed through simulation. It is interesting to note that despite the fact that an efficient lighting engine (Lightsolve Viewer) is employed, the computation time for a single scene is reported at 10 seconds. As such, a significant time cost is associated with the whole endeavor, which may scale to the range of many hours if not days, for large populations and many generations. Paper authors combat this cost through the use of a small population “Micro Genetic Algorithm”, and through limiting the total generation number. However, it is seen from the results that with such limitations convergence to the Pareto front is not achieved. Nonetheless, they report interesting and novel architectural facade solutions.

Khoroshiltseva et al. (2016) employ as objective functions reducing the overheating time of the building, providing a high level of visual comfort, and minimizing the level of energy consumption for heating, cooling, and lighting and formulate a bi-objective optimization problem thereof.

Zhang et al. (2017) propose a multi-objective approach for the design of either Venetian blinds and roller shades in the design variables (comprising orientation, room depth and corridor depth, the window-to-wall ratio of different interfaces, glazing materials in addition to shading type) of a school in mainland China. The proposed approach make use of the SPEA2 algorithm and aims to minimize the energy use for heating and lighting and the summer discomfort time and to maximize the useful daylight illuminance, in a cold climate.

Wright et al. (2014) reports a Multi-Objective Evolutionary Algorithm-based design tool for the design of cellular fenestrations in building facades, considering the objectives of minimizing energy consumption and capital cost for an interior atrium of a three-story commercial building. The author employs a matrix of binary values denoting the presence or absence of types of elements on a grid on the building facade. Energy consumption is derived through EnergyPlus simulation. In addition to the multi-objective constrained optimization, paper authors also report the results of a sensitivity analysis as well as perform comparisons between the optimization performance of different design encodings. There are no figures reported regarding the computational cost of running simulations.

Turrin et al. (2013) report an application of multi-objective optimization to the free-form design of thermal mass panels, similar in concept to a Trombe wall, located in a multi-story atrium in Shenyang, China. Paper authors make use of simulation to define a bi-objective optimization problem with objectives of minimizing panel mass and energy costs for heating and cooling the atrium. A series of emergent designs is achieved, however selection is performed through manual inspection and selection, i.e. no post-Pareto optimality analysis is performed.

Kirimtat et al. (2016a) report on the design of exterior facade shading devices using two different Multi-Objective Evolutionary Algorithms, with the objectives of improving indoor daylighting distribution (as indicated using the Useful Daylight Illuminance (UDI) metric Nabil and Mardaljevic (2005)) and minimizing energy consumption. This is one of the few studies that report detailed figures of the optimization time, and it is surprising to see that the total optimization time for an evolutionary run of 30 generations extended to 3.75 days. This extreme computational complexity brings forward the demand for methods to alleviate the computational burden. As a conclusion, paper authors demonstrate design solutions that are picked from the ultimate population through manual inspection.

Zani et al. (2017) propose the design of a high-performance concrete static shading

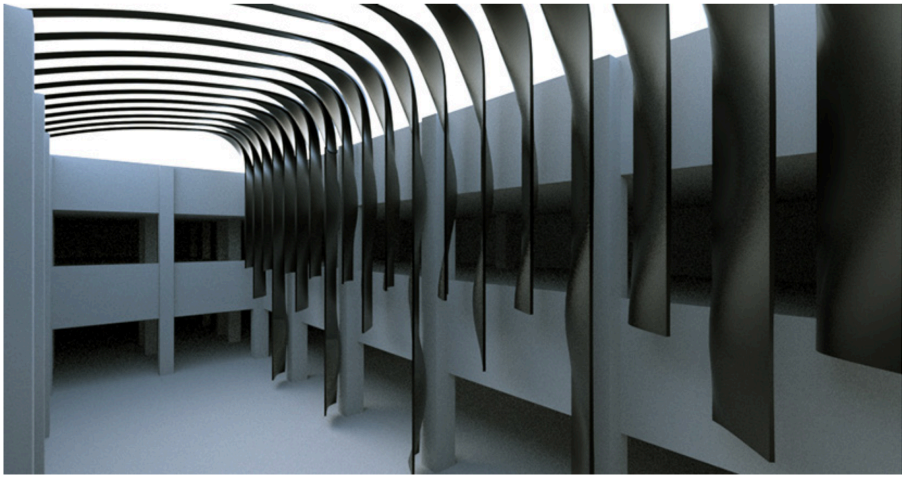


FIGURE 2.1 Evolutionary design of thermal mass panels for a multi-story atrium (Turrin et al. 2013).

system using a parametric design approach based on radiation control, outdoor view, daylight indexes, and energy performance. Optimization by genetic algorithms is used to define the openness' sizes and cutting angles to minimize solar radiation entrance throughout the year, maintaining an outdoor view. The result includes geometries with gradient changes and smooth transitions.

Manzan and Clarich (2017) focus on the optimization of an external fixed inclined panel combined with deployable internal Venetian blinds for an office room with a south exposed window. The problem definition includes three continuous decision variables and two objectives, namely the primary energy consumed during a whole year for maintaining healthy internal conditions and the total number of hours in a year, computed during the occupancy time, with internal blind deployed with an inclination of 45 degrees. Their research focuses on the application of a Response Surface Model algorithm termed FAST, designed to reduce long simulation times, during optimization. FAST fits several different models, among which neural networks, radial basis function networks and support vector machines, and uses the most accurate meta-model for each objective and constraint evaluation. The algorithm starts from an initial dataset derived through Design of Experiments (DoE) and refines the results near the area of optimal solutions. Paper authors compare FAST with NSGA-II and report that results are similar, i.e. Pareto fronts are similar, while FAST offers significantly reduced computational times.

It is seen through the above works that there is increased interest in the past years in the applications of Multi-Objective Optimization (MOO) in architectural design. The use of MOO algorithms in itself is a significant decision support tool that may reveal a wealth of design solutions to the decision-maker, contributing significantly to informed decision making during the early stages of design. The sections that follow aim to attempt to discuss the important issues that application of computational optimization and especially Multi-Objective Optimization is facing in its application to architectural design, to set the foundations for researching contributions that may improve the efficiency of such decision support techniques, and widen the field of potential applications.

Table 2.1 provides a concise summary of studies that have been reviewed as part of the previous sections. In the table in question, “S.O.” corresponds to a single-objective problem, “M.O.” to a multi-objective problem, and the “Galapagos” Genetic Algorithm is a GA implementation incorporated in the popular “Grasshopper” parametric design platform. To the best of the author’s knowledge, this algorithm has not been published.

§ 2.5.3 Computational Complexity

A significant concern with the application of EAs in complex problem-solving is the increased requirements in computation. EAs approximate optimal solutions by iteratively improving on a population of candidate solutions, and as such they require continuous evaluation of solutions according to the prescribed design criteria. If those criteria involve evaluation of computationally demanding models, such as the elaborate daylighting or thermal models employed in contemporary practice, the computational complexity of an optimization run can easily become unmanageable, especially in the early stages of design, where radical design changes are frequent and may incur re-definition of the optimization problem or change in objective functions and constraints.

§ 2.6 Decision Making and Multi-Objectivity

As previously mentioned, Multi-Objective problems comprise more than one conflicting objectives, and as such, there is no single attainable solution that can fully satisfy all objectives. Decision making in the context of MOO concerns the settlement on an optimal objective function tradeoff that best satisfies the preferences of the stakeholders. According to (Zitzler 1999), referencing (Horn 1996; Hwang and Abu Syed Md. Masud 1979) there are three main approaches to treating preferences, in general:

- Decision making before search (a-priori decision making): The objectives of the MOO problem are aggregated into a single objective by determining weighting factors, or alternatively by selecting a single objectives and selecting constraint violation thresholds for the remaining ones. In both cases, preferences and design knowledge of the decision-maker are implicitly expressed through the weighting factors or constraint violation thresholds

- Decision making during search (interactive decision making): The DM can articulate preferences during the optimization process through interaction. After each optimization step the DM specifies further preference information whereby the search is further guided towards preferred areas in the design space. This approach is also termed “Interactive Optimization” (Takagi 2001; Meignan et al. 2015), with applications also in architectural design.

- Search before decision making (a-posteriori decision making): Optimization is

TABLE 2.1 Summary of Reviewed Computational Optimization Approaches in Architectural Design and their Characteristics

Study	Type	Algorithm	Topic	Objectives
Choi et al. (2013)	S.O.	”Galapagos” GA	Sunshading Facade	Thermal Performance
Ercan and Elias-Ozkan (2015)	S.O.	”Galapagos” GA	Sunshading Facade	Solar Irradiation
Elghazi et al. (2013)	S.O.	Not mentioned	Sunshading Facade	Daylight Distribution
Futrell et al. (2015)	S.O.	Simplex (O’Neill, 1971), Hooke Jeeves (Hooke and Jeeves, 1961), Particle Swarm Optimization (Kennedy and Eberhart, 1995)	Sunshading Device	Visual Comfort & Energy Efficiency
Gagne and Andersen (2010)	M.O.	Micro-GA (Coello Coello Coello and Toscano Pulido, 2001)	Sunshading Facade	Illuminance & Glare
González and Fiorito (2015)	S.O.	”Galapagos” GA	Sunshading Element	Visual Comfort & Energy Efficiency
Lee et al. (2016)	S.O.	”Galapagos” GA	Sunshading Facade	Daylight Distribution
Khoroshiltseva et al. (2016)	M.O.	Harmony Search (Lee and Geem, 2005)	Composite Shading Device	Energy Consumption, Overheating, Device Area
Mahdavinejad and Mohammadi (2018)	M.O.	SPEA2 (Zitzler et al., 2001)	Internal Louvre	Daylight Distribution, Energy Consumption
Mangkuto et al. (2018)	M.O.	SPEA2 (Zitzler et al., 2001)	Light Shelf Geometry	Daylight Distribution
Manzan and Clarich (2017)	M.O.	FAST, NGSA-II (Deb et al., 2002)	Shading Device	Energy Consumption, Daylight
Omidfar (2015)	S.O.	Gene Arch (Caldas, 2008)	Sunshading Device	Daylight Distribution
Rusovan and Brotas (2012)	S.O.	”Galapagos” GA & Interactive	Sunshading Element	Daylight Distribution
Sariyildiz et al. (2008)	M.O.	Own implementation	Urban Block Spatial Configuration	Visual Privacy, Outdoors Area
Turrin et al. (2013)	M.O.	NGSA-II (Deb et al., 2002)	Indoor Thermal Mass	Thermal Mass Distribution, Exposure to the South, Deflection
Von Buelow (2008)	S.O.	CHC-GA (Eshelman, 1991) & Interactive	Truss Design	Weight
Wright et al. (2014)	M.O.	NGSA-II (Deb et al., 2002)	Facade Design	Cost, Energy Consumption
Zhang et al. (2017)	M.O.	SPEA2 (Zitzler et al., 2001)	Spatial Configuration	Heating, Discomfort, UDI

performed without any preference information given. The result of the search process is a set of (ideally Pareto-optimal) candidate solutions from which the final choice is made by the DM.

In this thesis, the focus is on the third paradigm as outlined above. Decision making before search (first paradigm) requires a-priori domain knowledge that is usually not available, let alone in the early stages of architectural design, which is the focus of this thesis. Decision-making during search is a promising alternative, however, it presents drawbacks such as increased uncertainty, cognitive drift, and cognitive fatigue, that usually prohibit application to complex design scenarios such as the ones found in real-world architectural design problems. Thus the focus is on a-posteriori decision making, where preference-oriented decision making is postponed until the design solutions that are of interest, namely the best tradeoff solutions, have been established through multi-objective optimization. For more information on this type of approaches, the reader is invited to study references (Coello 2000; Jaimes 2011; Wagner and Trautmann 2010; Carrese et al. 2012; Koksalan and Karahan 2010), among others. Besides, a brief review of recent post-Pareto optimality analysis approaches is presented next.

§ 2.6.1 Approaches to Post-Pareto Optimality Analysis

§ 2.6.1.1 In Engineering Design

Surpassing the common practice of exhaustive inspection and empirical selection of solutions, several approaches to post-Pareto optimality exist in literature. An indicative set of works is briefly reviewed hereby.

Obayashi and Sasaki (2003) propose the application of Self-Organizing Maps (SOM) to address the problem of post-Pareto optimality analysis in the case of the aerodynamic wing and fuselage design. Paper authors apply SOM as a dimensionality reduction technique to manage the high-dimensional objective function distribution of the resulting Pareto-optimal solutions to a quad- and bi-objective problem respectively. Following an initial derivation of a two-dimensional SOM encoding objective function distribution, they derive cluster-averaged codebook vectors and use those for the generation of a second SOM revealing interactions and trends of decision variables in objective function values.

Wagner and Trautmann (2010) introduce Desirability Functions (DFs), previously introduced by Harrington (Harrington 1965) in multi-objective problem solving as a non-linear mapping of objective function values to the $[0, 1]$ range, parametrized by decision-maker preference information regarding exemplary objective function values. Besides, paper authors develop the Desirability Index which is an aggregate of individual objective function DFs into a single index representing the desirability of a solution. Finally, they present an integration into an indicator-based MOEA and experimental results.

Carrillo et al. (2011) present the non-numerical ranking preferences method as an approach to post-Pareto optimality preference treatment. In particular, through the proposed algorithm the paper authors seek to progressively prune Pareto optimal solutions that are of less relevance to decision-maker preferences that are expressed through non-nominal ranking of objective functions. Paper authors demonstrate application to a Pareto-optimal set identified from a multi-objective problem from literature.

Bandaru and Deb (2011) propose an automated method for identifying innovative principles through analysis of Pareto-optimal sets in multi-objective problems. The paper authors aim to derive basis functions that are characteristic of the set of Pareto optimal solutions, in an automatic manner. In doing so, paper authors propose an evolutionary algorithm that evolves mathematical relationships aiming to maximize their generality, applicability, and validity over the set of Pareto optimal solutions. Applications to several engineering problems is presented.

Carrese et al. (2012) introduce a Particle Swarm Optimization (PSO) algorithm that makes use of a reference point, determined through decision-maker preferences, to focus the search on a particular region of interest on the Pareto front in multi-objective problems. The paper authors apply the proposed method to an aerodynamic design problem and propose the reduction of computational complexity through the use of a Kriging model.

Through the above brief review, it is deducted that in the general field of multi-objective problem solving and decision support for engineering the focus is on solution performance as expressed in the objective function space and less so in the decision variable space. Even when some emphasis is on the latter, such as in the works of Obayashi and Sasaki (Obayashi and Sasaki 2003) and less so Bandaru and Deb (Bandaru and Deb 2011), the goal is to derive principles that support high performance and less so to explore preferences in terms of object properties.

Despite the existence of a wealth of methods for post-Pareto optimality analysis, it is stressed that addressing preferences on object properties is not achievable purely by examining the objective function space, due to the complex non-linear relations between objectives and constraints. As such, handling of such kind of preferences is non-trivial, as will be further elaborated in chapter 4.

§ 2.6.1.2 In Architectural Design and Related Disciplines

The aforementioned approaches form useful contributions concerning post-Pareto optimality analysis and decision making. In engineering applications, the domain of importance is that of the objective function space, and effective treatment of preferences therein is enough to conclude decision making and identify an optimal choice among best-tradeoffs. However, a significant difference exists when the application domain is not engineering but also comprises soft, qualitative aspects. In such a case,

It is underlined that, despite the importance of the subject, especially in the domain of architectural design, few authors report attempts at addressing this issue. It is surmised that the elusive nature of the topic is the reason behind the seemingly limited research interest, which does not corroborate with the importance of the issue at hand. Some relevant studies are hereby briefly summarized.

Ansuini et al. (2012) report on a methodology for the design of decision support systems in conceptual design phases capable of fostering the exploration of design alternatives through statistical inference. The approach is probabilistic, based on Bayesian Networks (BNs). In the proposed BN, graph nodes represent design parameters and performances, and graph edges represent relationships among parameters, parameters, and performances, or performances. Relationships are obtained through statistical analysis of simulation results. In the paper authors' paradigm, a design decision is translated to value assignment in a node, which corresponds to a 100% likelihood for the given value. The remaining nodes in the graph obtain probability distributions corresponding to probabilistic conditional dependency relations among them. Paper authors make the case for building knowledge through linking of multiple BNs, and present an extended example in energy-conscious architectural design.

Thomsen (2014) propose a method for post-Pareto optimality taking into account design intention. The method is based on k-means clustering. The novelty of the approach lies in that clustering is performed in a modified design space that is generated by transforming the original through decision-maker defined functions. Paper authors present application in the case of designing a vault structure.

§ 2.6.2 Preferences in Multi-Objective Decision Making

In the context of MOO where conflicting objectives are present, the notion of preference is usually associated in literature with the relative importance among problem objectives (Jaimes 2009). As Obayashi puts it, "Design is a process to find a point in the design variable space that matches with the given point in the objective function space" (Obayashi and Sasaki 2003). As such, preferences in the canonical meaning pertain to the objective function space. In a-priori decision making, preferences are implicitly embedded in the combination of weight vectors. In interactive decision making, preferences are expressed via the selection performed throughout the optimization process. In a-posteriori decision making, the full front of trade-off solutions is available, and the decision-maker expresses preferences by selecting a Pareto optimal solution. Through this selection, the relative importance among objective functions is implicitly established.

Through multi-objective optimization, it is generally feasible to achieve a set of solutions that are evenly distributed along the Pareto surface in the objective function space. These are termed non-dominated solutions. However, relationships in the objective function space do not extend to the decision variable space and vice versa. The reason behind this phenomenon is rooted in the non-linearities introduced by the objective functions defined in the context of the design problem. As a result, neighboring relationships between solution representations in the objective function space do not necessarily correspond to relationships in the decision variable space. Two solutions that demonstrate similar decision variable compositions (neighboring solutions) may occupy far-away points in objective function space. Similarly, solutions nearby in the objective function space may occupy two distant points in the decision variable space. It is thus impossible to make comprehensive design decisions by considering the similarity of solutions in either space alone since similarity in the other of the two spaces is not guaranteed. Fig. 2.2 graphically outlines this condition.

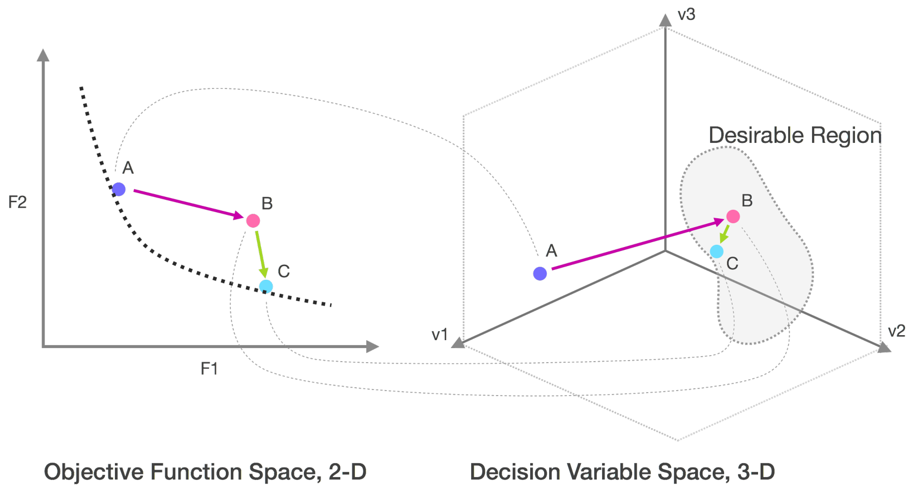


FIGURE 2.2 Description of a possible decision making process in architectural design. On the left, the Objective Function Space is depicted. On the right the Decision Variable space. Note that in both cases, the spaces are low dimensional, in order to aid representation. Solution A is a best-tradeoff, that is lacking desirable features. The decision-maker may choose to adjust decision variable values to impose desired properties. This generally is expected to lead to a sub-optimal solution, B. Ideally, the goal would be to guide the decision-maker to obtain a solution that combined both performance and desirability, C.

§ 2.6.3 Preferences on Object Properties

In this section, an alternative notion of preferences is introduced, namely preferences on the decision variable space, in place of objective function space. In architectural design, the ultimate decision of the architect lies in determining the concrete properties of the designed objects, that is establishing values for the decision variables of the problem at hand. This is a process that is guided by the satisfaction of goals as much as by the satisfaction of preferences in terms of concrete object attributes. Thus in many cases, decisions are guided to ensure that desirable attributes are present.

In other words, identifying a point in decision variable space that corresponds to a given (optimal) point in objective function space, as per the statement of Obayashi, does not tell the whole story, when it comes to architectural design.

An example of this is often seen in a-posteriori decision making, where the examination of Pareto-optimal solutions is carried out to identify visually interesting ones. On the contrary, expressing decision variable preferences in a-priori decision making is near impossible, as it pertains to multiple optimization iterations with different sets of weights.

Generally speaking, designing is about identifying compositions of physical features that are generally desirable and suitable. Here, "suitable" and "desirable" reflect two distinct criteria, namely: suitability of a particular design is evaluated concerning first-order design goals and objectives, that have been predetermined e.g. as part of a design brief, and are mostly unyielding and essential for the acceptance of a design solution. Simply put, suitable solutions are those that maximize performance concerning design goals or objectives while satisfying constraints. The role of goals and objectives on the domain of object properties is that of imposing certain relationships between them. Designs that possess properties that adhere to the relations established by design goals are those that maximize design suitability for the intended purpose. Through the establishment of such relations, decision-makers are provided with the necessary mechanism to abstract away the excessive complexity that arises in design problems such as those in the field of architecture, for example, when dealing at the level of detailed properties of the objects.

On the contrary, desirability is a design quality that is to be found at the lowest abstraction level, which is that of design features. At this level, designers generally express preferences concerning some or all the decision variable values that are involved in the design task at hand. These preferences are notwithstanding the design goals mentioned above, which need to be satisfied with maximum priority.

Through establishing goals and constraints in design, explicit relationships are formed between concrete object properties, design goals, and constraints. These relationships are generally complex and are not known by decision-makers at the time of designing. It should be understandable, nonetheless, that successful designs combine the requirements for suitability and desirability; in other words, they are well-performing designs that are characterized by desirable feature compositions.

While plain selection out of a set of Pareto optimal solutions is a widely adopted practice, given the above realizations it is hardly an efficient one if both suitability and desirability are to be considered. A limited set of solutions, such as those present in the Pareto front may miss desirable attributes entirely, and as such a decision-maker examining it will not be introduced to solutions of interest concerning decision variable preferences. This is especially true in the case of complex objective functions or problems of high-dimensional design spaces. Besides, due to the non-linear and multi-modal relationships between objective functions and decision variables, an extensive inspection of every single best-tradeoff solution is often required to ensure comprehensive identification of desirable attributes. This is cumbersome in large population sizes and may result in cognitive fatigue and subsequent suboptimal decision making.

Through the above, the need for a better approach to decision making for the satisfaction of preferences on physical object attributes is clear and underlines the importance of the associated research goal of this thesis.

§ 2.7 Machine Learning Algorithms

The field of machine learning is concerned with the question of how to construct computer programs that automatically improve with experience. On the definition of learning from experience, (Mitchell 1999) presents the following definition:

> A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if it's performance at tasks T, as measured by P, improves with experience E.

It is noted that this is a form of learning which is much closer to the way humans and animals learn through stimulation from and reaction to the environment, and in contrast to traditional machine programming, where knowledge and reasoning are embodied in the form of explicit instructions.

In the sections that follow a brief, general introduction to a series of machine learning algorithms that have been used in the context of this thesis is presented.

§ 2.7.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are a category of machine learning algorithms that draw inspiration from the functioning of the neural system in living organisms. In principle, ANNs belong to the machine learning paradigm of connectionism (Rumelhart and McClelland 1986). In this paradigm, the processing of information is performed within massive networks of simple interconnected units in a parallel and distributed manner. Such an architecture bears direct resemblance to the neural networks that are ubiquitous in higher animals, although the artificial counterpart performs computation at a smaller scale. In such networks, knowledge is stored in the weights of the connections, and learning occurs by adaptation of said weights. One of the most compelling characteristics of ANNs is that it is proven that they can universally approximate any continuous function (Hassoun 1995; Haykin 2005) although it is accepted that complex functions may require vast networks for efficient approximation. For the purposes outlined in the present research, two types of ANNs are relevant namely the Feed-Forward ANN and the Radial Basis Function ANN (RBFN), which will be briefly outlined henceforth.

FEED-FORWARD NETWORKS A Feed-Forward ANN (FFN) is a network that is organized in layers of neurons of variable size. The only connections in this type of network are between adjacent layers, and in particular connections between any layer to the next one, hence the term “Feed-Forward”. The neurons in each layer receive as input a weighted summation of the output of each neuron in the previous layer. This is termed the propagation function and is expressed as:

$$p_i(t+1) = \sum_i o_i(t) w_{ij} \tag{2.4}$$

Where $o_i(t)$ is the output of a neuron of layer t. Each neuron produces its output by transforming the input through an activation function f. A common activation function is the sigmoid:

$$S(x) = \frac{1}{1 + e^{-}x} \tag{2.5}$$

FFNs are trained using the backpropagation algorithm (Rumelhart et al. 1985) or variations thereof. A gradient descent algorithm is used to adapt the connection weights based on the gradient information derived from backpropagation. The optimization objective is usually minimization of the squared error over the training dataset.

RADIAL BASIS FUNCTION NETWORKS Radial Basis Function Networks (RBFNs) (Moody and Darken 1989) are a different category of ANNs that are based on Radial Basis Functions (RBFs) as activation functions. RBFNs have two layers: The first layer comprises RBFs that act as pattern detectors at the input space, and the second layer forms the output of the network through a linear combination of the RBF outputs. The output of an RBFN is formed as follows:

$$f_r(x) = \lambda_0 + \sum_i^{n_r} \lambda_i \phi(||x - b_i||) \tag{2.6}$$

Where λ_0 forms the network bias, λ_i the linear weight values and ϕ is the radial basis function.

The conspicuous property of RBF networks is that the output of the network, as shown in the formula above, is a linear combination of the radial basis function outputs. This property is significant as it allows linear least-squares techniques to be used to determine the output weights, without resorting to non-linear optimization, which may be costly and lead to local optima. Thus the problem of fitting an RBF network is reduced to selecting suitable basis functions given a dataset. In turn, this task can be performed very efficiently through algorithms such as

Orthogonal Least Squares (Chen et al. 1992). Thus RBF networks offer a sound alternative to other neural network types.

§ 2.7.2 Random Forests

A Random Forest (RF) is a prediction model based on ensembles of decision trees. Decision trees are hypotheses created by constructing a binary tree with simple decision functions at the internal nodes and output values at the leaves. The definition of RFs for classification according to is as follows (Breiman 2001):

> A random forest is a classifier consisting of a collection of tree-structured classifiers h(x, k), k = 1, . . . where the k are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x.

An important concept in training RFs is that of bagging. Bagging, short for "bootstrap aggregating", was introduced in (Breiman 2001) as a device for reducing the prediction error of learning algorithms. Bagging is performed by generating new training datasets through sampling from a dataset with replacement. In RF training, several of those datasets are generated, and each one is used to grow a tree-structured predictor. The ensemble of these predictors forms the RF model.

§ 2.7.3 Support Vector Machines

SVM is a machine-learning approach based on the principle of structural risk minimization (Vapnik 2000), which enables better prediction generalization while enabling limiting of the number of learning patterns. For the scope of this study, the variant of SVM that is suitable for regression, support vector regression (SVR), will be used to approximate the visual comfort values.

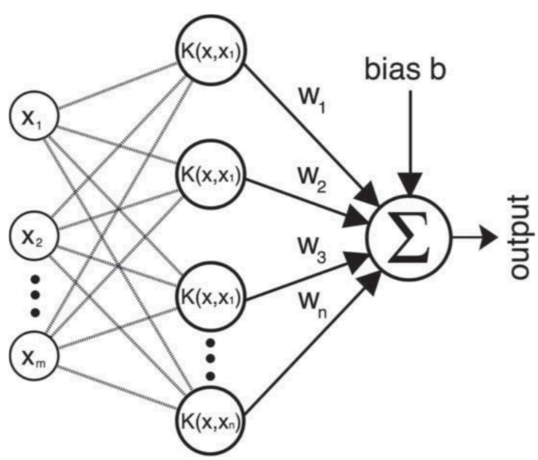


FIGURE 2.3 Schematic illustration of a support vector machine, showing input, kernels and linear output.

The method will hereby be very briefly outlined. In the simplest case, the problem of fitting a linear function f to data in $\mathbf{R}^n$ is considered. In -SVR, the goal is to find a (linear) function f that has at most deviation from each point in the dataset and is at the same time as "flat" as possible (Basak, Pal, and Patranabis 2007), that is, the values of the linear weights of the model are minimized. A schematic diagram of a regression SVM is presented in Figure 2.3.

Let w denote the vector of first-order coefficients in the linear function. Then, the learning problem is formulated as follows:

Minimize

$$||w||^2 \tag{2.7}$$

s. t.

$$\begin{aligned} y_i - \langle w, x_i \rangle - b \leq \epsilon \\ \langle w, x_i \rangle + b - y_i \leq \epsilon \end{aligned} \tag{2.8}$$

The above formulation suggests a quadratic optimization problem where the objective is to minimize model weights, subject to prediction error being smaller than a value ϵ. Thus, the conspicuous difference in the objective function between ANNs and SVMs is evident: While the prediction error is introduced as a minimization goal in the case of ANNs, the objective function in the case of SVMs is to minimize the values of the model weights thus maintaining model parsimony, while the model error is introduced as a constraint. In other words, SVM attempts to identify the most parsimonious model that demonstrates an error no greater than ϵ. The parsimony of generated models introduces an advantage in model generalization performance.

§ 2.8 Surrogate Modeling

Surrogate modeling is an application of the field of Machine Learning (ML) in optimization problems where repeated sampling of the objective function is nontrivial due to computational complexity. Simulations of complex phenomena (including building performance aspects such as daylight and thermal modeling) require enormous processing power and take a large amount of time. Repetition of such phenomena for hundreds or thousands of times, as required by most stochastic optimization algorithms, becomes infeasible even for problems of moderate size. Therefore in complex engineering applications, it is common to fit an ML model with previously gathered examples and make use of it in optimization. Thus the evaluation of the original function (which may entail costly simulation) is only seldom required, which results in a significant reduction of computational complexity related to performance evaluation.

§ 2.8.1 Surrogate Modeling in Building Performance Simulation

The topic of surrogate modeling has gained significant attention concerning architectural design, in particular as related to attaining reduction of computational complexity in simulations of building energy consumption, daylight performance, and visual comfort. A number of indicative studies are briefly reviewed hereby.

In a relatively early study in function approximation, Bhatnagar et al. have illustrated the applicability of FFNs, trained using backpropagation, in the problem of thermal design of wall and roof sections (Bhatnagar et al. 1997). The study focused on fitting a model that could suggest suitable dimensions for building components, given input regarding environmental conditions.

Dong et al. (2005) have successfully applied Support Vector Machine Regression (SVM-R) in predicting the landlord energy consumption of four commercial buildings situated in Singapore, based on consumption figures derived from utility bills. The application of SVM has outperformed existing approaches to landlord energy consumption, reaching a % error ranging from 3.44 to 0.68 in their test cases.

Neto and Fiorelli (2008) have compared the accuracy of an approximation model based on FFNs and a simulation model based on Energy Plus for forecasting building energy consumption. Their findings indicate a slightly better performance of the ANN-based approach when trained on actual building consumption data.

Kazanasmaz et al. (2009) propose a feed-forward artificial neural network for estimating daylight illuminance levels of buildings, based on time, weather and building-related parameters, for a total of 13 inputs. A single output gives the estimated illuminance in lux. The employed model is a single hidden layer neural network with seven hidden nodes and *tanh* activation function both at the hidden nodes as well as at the output. In addition to model derivation, authors perform a sensitivity analysis on the model intending to identify the most significant inputs, where four inputs are identified, however, authors concede significant model performance deterioration with just these four inputs considered.

Ekici and Aksoy (2009) examined the applicability of FFNs trained by backpropagation in predicting energy needs of buildings benefiting from orientation, insulation thickness, and transparency ratio. Their study focused on buildings in the Elazig region in Turkey, and they managed to achieve an accuracy of 94.8–98.5% in their predictions.

Hawkins et al. (2012) have introduced an FFN trained by backpropagation to recognize patterns between building early-stage design parameters and display energy certificate energy use data and subsequently performed a causal strength analysis to determine the effect of independent variables on the energy use change. They reported satisfactory but improvable results in prediction.

Wilkinson et al. (2012) propose an inductive model for approximating the distribution of wind surface pressure on a building's facade surface. The proposed approach entails the derivation of a local shape descriptor for each sampling point and the subsequent input to a machine learning model, where the estimated pressure output is derived. Authors train the model using derived data from an actual CFD simulation and perform cross-validation, where a cross-validation error of 4.8% - 18.3 % on real buildings is reported.

Tsanas and Xifara (2012) aim to identify the statistical relation between eight independent variables describing a total of 768 residential buildings and two dependent variables corresponding to the heating and cooling load of said buildings. Authors report on the use of descriptive statistical techniques. Besides, given pairs of input and output variables, authors derive and compare two regression models, one using iteratively reweighted least-squares (IRLS) and one using the random forest (RF) technique, introduced by Breiman (Breiman 2001), where they find that the non-linear Random Forest regression significantly outperforms its linear counterpart.

Melo et al. (2014) propose an ANN-based surrogate model for building energy certification use, focusing on the use case of a Brazilian city. Authors make use of actual data used in energy certification as input to a single hidden layer network with nine hidden nodes and a sigmoid activation function, which is trained through backpropagation. In addition to deriving the model, authors perform sensitivity analysis on each model input as well as an analysis of model performance for different building types and finally compare the performance of the proposed model to the surrogate approach found in the existing certification approach in Brazil, where they highlight the potential of the ANN-based approach.

Hu et al. (2015) discuss evaluating lighting performance risk in retrofit scenarios, using a neural-network surrogate model trained using simulation data from EnergyPlus. Authors consider independent variables of occupancy level, weather conditions, control strategy, and lamp type, which they term risk factors in the context of lighting retrofit. Training of the surrogate model is reportedly performed through an adaptive sampling technique, however, no further details regarding this technique are reported. Results of the study indicate a negligible error in lighting energy consumption prediction ($R^2 = 0.9999$) and a small error in HVAC energy consumption prediction ($R^2 = 0.946$).

Wortmann et al. (2015) present an argument pro the use of surrogate models as a means of guiding design exploration and contrast this approach to the use of metaheuristic algorithms in design. Admittedly, the author of this thesis is unable to fully comprehend the state of contrast between the two as expressed by the paper; especially since metaheuristic algorithms often employ surrogate models as a means of managing computational complexity. In turn, authors define an optimization problem of Useful Daylight Illuminance and compare two alternative software in deriving optimized solutions: The "RBFOpt" library (Costa and Nannicini 2018), and the "Galapagos" program, which is an implementation of a genetic algorithm. It should be noted that the algorithm implemented in the Galapagos program does not constitute published work. Authors find that the results of the "RBFOpt" library are superior.

Yang et al. (2016) present a study on the effects problem scale and sampling strategy have on the accuracy of the surrogate model approximating Useful Daylight Illuminance (UDI) and Energy Usage Intensity (EUI). Authors evaluate the effect of the above in a series of different surrogate models, namely Polynomial Singular Value Decomposition (SVD); Stepwise Regression (STEP); Kriging (KR); Shepard K-Nearest (KN) and Radial Basis Functions (RBF), and using a series of model accuracy indicators. In comparing the above algorithms for different problem scales, namely a design problem with two and another one with 41 variables, authors find that RBF performs best in the low-dimensional problem, while SVD performs best in the high dimensional one. In comparing different sampling strategies, authors report results that lean in favor of the adaptive sampling strategies.

Chen et al. (2017) propose a two-stage optimization approach for improving energy usage in residential buildings. The first step of the proposed method is the derivation of the surrogate model based on detailed energy usage simulations using EnergyPlus, and simulating building HVAC control through a control algorithm. Authors report that a Support Vector Machine-based surrogate model performs best in minimizing the Generalized Cross-Validation (GCV)-adjusted training error. In the next step, the surrogate model is used in a bi-objective optimization problem formulation with the objectives of minimizing lighting demand and cooling demand, and which is optimized using the NSGA-II genetic algorithm. It is interesting to note that authors report varying Pareto fronts according to the different surrogate models in use; this highlights the importance of an accurate surrogate model in achieving realistic optimization results.

Chen and Yang (2017) develop a surrogate model using Multivariate Adaptive Regression Splines (MARS) to approximate lighting levels, air change rate, and ASHRAE55 comfort time in energy-efficient building designs. The proposed model has nine inputs. Authors perform a sensitivity analysis to evaluate the effect of each independent variable on the dependent variables of the model. In addition, authors examine the effects of sample size for predicting illuminance levels and report a sufficient sample size of 1000 examples. Finally, formulas of predictive models with R^2 values ranging from 0.703 to 0.926 are reported.

For a comprehensive review of recent advances in surrogate modeling applied to architectural and energy-efficient building design, the reader is referred to Westermann and Evins (2019).

It is seen that in most reviewed cases the figures obtained through the surrogate models concern a building or complex as a whole, with little consideration to figures of individual building parts and/or areas or spaces within the building. Daylight performance, for instance, is considered for a building as a whole, with only a few studies concerned with the quality of daylighting within individual spaces and locations. Even though useful for general design performance evaluation, such abstract figures are not useful for evaluating the performance of specific spaces of the building. In addition, it is seen through the above studies that the input to the surrogate models consists of design-specific or building type-specific global descriptors, such as shape characteristics, percentage of glazing, etc. The use of descriptors usually leads to abstraction so that more detailed, localized information regarding different areas of the building cannot be derived through a model-based purely on global descriptors. This in turn has a significant impact if the model is to be used in decision making, as it is often that the decision-maker need to obtain specific information on the performance of a part of a building design. Even if a strategy of separate models for individual building parts or spaces is considered, a radical design change of change in design requirements during the conceptual design process may necessitate fitting surrogate models anew, which of course is a tedious process, unfit to the rapid pace that conceptual design progresses. Such considerations offer a starting point for research on surrogate models that would eventually be more readily applicable to the conceptual design stage.

§ 2.8.2 Surrogate-Assisted Evolutionary Computation and Applications in Architecture

Surrogate-Assisted Evolutionary Computation (SAEC) is a research field that makes use of surrogate models to model computationally complex objective functions, with the aim of reducing the computational requirements to solve challenging optimization and design problems. Essentially, SAEC combines the advances in two fields, that of Surrogate Modeling and that of Evolutionary Computation. Several approaches adopt an adaptive strategy that is based on indicators of model accuracy and prediction confidence. These indicators are used to guide whether the evaluation of subsequent solution performance will be performed by the surrogate model or by the actual objective function. For a review of such adaptive algorithms, see Jin (2005) and especially section 3.1.3 therein.

Aydın et al. (2015) propose an Artificial Neural Network-based surrogate model to estimate the energy consumption and daylight autonomy of L plan-shaped office buildings, using inputs of footprint area, number of levels, fenestration, shading, U-values of building elements, and HVAC system selection. The derived model is an ANN with a single hidden layer with five nodes, trained using 5000 training iterations, and L2 regularisation factor of 0.0001. The model demonstrates an R^2 value of 0.958 for the Daylight Autonomy approximation, and 0.922 for the Energy Consumption approximation. In turn, paper authors utilize the derived surrogate model in performing a bi-objective optimization using the NSGA-II algorithm (Deb et al. 2002) with a population of 500 and achieve convergence to Pareto front after 30 generations. Finally, they report an exponential fit to the non-dominated solution distribution correlating the two objectives.

Kirimtat et al. (2019) report on the performance of irregular-shaped shading devices that are designed through parametric modeling. Initially, the paper authors discuss the derivation of a linear regression surrogate model for approximating UDI (Useful Daylight Illuminance) (Nabil and Mardaljevic 2005) and subsequent model validation. Subsequently, they make use of the model in addition to EnergyPlus simulation in optimizing the shape of the shading devices so as to minimize combined (heating and cooling) energy consumption and maximize UDI. Paper authors compare the performance of two population-based multi-objective optimizers, namely NSGA-II and self-adaptive continuous genetic algorithm with differential evolution, namely JcGA-DE, with the latter performing better in terms of hypervolume indicator. Overall, they report a 14% reduction in total energy consumption results while maintaining UDI above 50%.

§ 2.9 Discussion

This chapter presented a concise overview of a number of relevant fields in Computational Intelligence, namely Multi-Objective Evolutionary Computation, Multi-Objective Decision Making, Machine Learning, and related technologies, in relation to the state of art relevant to the research questions and initial research direction of this thesis. Namely, the focus was on one hand on machine learning technologies that aim to reduce the computational cost of performance evaluation in the context of optimization, and on the other hand, on technologies to facilitate decision making through incorporating decision-maker preferences in the decision-making process.

More specific to the architecture discipline, this chapter presented a brief overview of the state of art in the application of computational intelligence-based decision support tools to architectural design. Such application, while not plentiful, are identifiable in literature. Several studies focus on the intelligent aspect, making use of single- or multi-objective computational optimization to tackle design problems. In addition, there are studies that combine the intelligent part of optimization with a cognitive part, where a surrogate model is used to alleviate computational complexity during the design process.

Despite the fact that studies, exist that combine intelligent with cognitive approaches, it is claimed that further intelligent-cognitive integration is possible with the aim of augmenting the decision support capabilities of intelligent-cognitive systems. The direction that this thesis is taking, as such, is that of building on existing approaches of intelligent decision support, and introducing novel cognitive components towards achieving the aim outlined above.

In this direction, and taking into account the state of art as presented in this chapter, it is possible to identify opportunities for development that may address the research questions initially posed in 1, as follows:

- Through formulating machine-learning-based surrogate models for use in approximating building simulation results in a way that is flexible enough to be incorporated in the early stages of conceptual design, where drastic design changes as part of the design process are commonplace.

- Through considering the relative lack of approaches addressing decision making with a focus on second-order preferences, by establishing a novel approach for post-Pareto decision support that places emphasis on the role of decision variable values as representatives of desirable concrete design features.

The aforementioned research directions are further elaborated in subsequent chapters where the research methodology is substantiated and the individual model components elaborated.

3 Background Investigation

§ 3.1 Introduction

The primary aim of this chapter is to present the background investigation that has served to establish the research premises for putting forward the problem statement and research questions proposed by this thesis. The investigation presented in this chapter, together with the literature review presented previously, form the foundations of this thesis. However, in contrast to the literature review, the investigation presented herein resembles a research-by-design process, where the experience of design technologies in practice forms the main source of conclusions being drawn.

The chapter consists of two main sections. The first section comprises a published journal article that outlines the application of an intelligent decision support system, as well as the development of supporting tools and techniques to a real-world design process of a state-of-the-art facade design. Drawing on this application, a series of observations related to the potential of computational intelligence as decision support for complex design tasks are outlined. Considering the conclusions of the first section, urgent issues pertaining to design applications of computational intelligence and considering user requirements are established. It is noted here that the chronological placement of the research outlined in this section is around the middle of the research timeline. By that time, there were already other cases that supported the premise of this thesis, however, due to the importance of this particular case study and its strong connection to a real-world case study, it is outlined extensively herein.

The second section comprises an analysis of published works that the author has performed in collaboration with MSc students during the course of design studios taught at Yaşar University, with the main aim being the teaching of advanced computational intelligence-based design approaches. The main aim of this section is to identify challenges that are being faced in the works of the students, in order to pinpoint opportunities for evolving intelligent and cognitive tools to better serve their design decision support goal.

The main points from the investigation and their connection with the research questions and problem statement are summarized and shortly discussed at the end of the chapter.

§ 3.2 Design Complexity in Practice

Introductory Note

In the present section, research is presented wherein an investigation is conducted as to the application of a Computational Intelligence Decision Support approach to a real-life complex design problem. The problem at hand concerns the design of a shading device for a large facade in a public university building in the Netherlands. The proposed approach is not tied to the specific problem but is applicable to a range of facade design problems. This section introduces the relation between design complexity and sustainability requirements of modern buildings, through the lens of the complexity proponents discussed in Chapter 1, and especially discussing the issues of combinatorial explosion and complex non-linear relations between object properties and performance.

FIGURE 3.1 The specific aspects of methodology that this chapter focuses on.

In the context of this thesis, the research reported hereafter highlights the following relevant points:

- On one hand, the applicability of Evolutionary Computation to an emerging kind of design problems whose main characteristic is complexity and where decision making without the help of computation is otherwise a process that may easily overwhelm the decision-maker

- On the other hand, it aims to establish the foundation for the work that will be the focal point of this thesis, through pinpointing the requirements of the decision-maker wherein the EC-based decision support framework is determined to be in need of extensions in order to address them effectively.

The research reported in this section has been published under the following title:

> I. Chatzikonstantinou M. Turrin, C. Cubukcuoglu, A. Kirimtat and S. Sariyildiz, "A Comprehensive Optimization Approach for Modular Facades: The Case of PULSE Sunshading" International Journal of Design Sciences and Technology, 23: 2, 2019.

The following acknowledgement is included in the aforementioned publication:

> The authors wish to acknowledge the team from Ector Hoogstad Architecten, in particular Joost Ector, Lennaert van Capelleveen, Laurence van Benthem, Daniel Diez-Ausias, and Rena Logara for facilitat-

ing the project and leading the architectural design process. David Maimone contributed to the preliminary daylight analysis. The 3D printing research was carried out by/with the leadership of Paul de Ruiter. The post-optimization parametric modeling of detailed modules was carried out by Milou Teeling as the main researcher; Pirouz Nourian helped to define the mathematical models behind the geometry. Rob Nijsse and his team, especially Peter Eigenraam, designed the structure and determined the parametric constraints to be incorporated within the digital model. Mark van Erk contributed to involving manufacturing aspects and preparing the geometry for 3D-printing. Leapfrog provided 3D-printing support.

§ 3.2.1 Introduction

It is a common understanding that architectural design is characterized by complexity (Chatzikonstantinou and Sariyildiz 2017; Chatzikonstantinou et al. 2019). Architectural design is expected to solve an architectural design problem comprising a set of requirements and constraints, by creating something new (a new building or built item). Increasingly, this is achieved through complex geometries, which on the one hand enable achieving better performance, however on the other hand add further complexity to decision making. Efficiently exploring possible solutions among all possible design alternatives is a challenging task, especially in the early stage of the design process. The architectural design problem could be also defined as a multi-objective optimization problem since it is characterized by several conflicting objectives and is also subject to challenging constraints. Computational intelligence-based decision support tools can play an important role in managing complexity and present promising alternatives in design.

Within the domain of architectural design, facades are a greatly relevant design topic. Nowadays, building facades are required to respond to a multitude of design criteria. A few of the most important ones are ensuring a comfortable climate indoors and promoting energy conservation. In this respect, shading systems play a crucial role. For instance, in the European Union buildings are responsible for nearly 40% of the total final energy use and 36% of the total emissions of the EU Member States (of the European Union 2010). Thus the European policies aim to improve energy efficiency to accentuate energy guarantee and climate change (Carvalho 2012) and aim to reduce the green gas emissions at least to 20% levels until 2050 (of the European Union 2010). In both cases, facade systems are crucial. To provide daylight and more external view, architects and engineers design facades with large, glazed portions in the buildings, yet a risk of creating high heating and cooling loads in these buildings should be considered (Poirazis et al. 2008; Hien et al. 2005). Therefore the use of shading devices is one of the most significant precautions to prevent overheating during cooling periods. In order to provide energy efficiency in the buildings, there are various shading device types such as overhangs (Tavil and Lee 2006), external roller shades (Tzempelikos and Athienitis 2007), Venetian blinds (Simmler and Binder 2008) and internal shading (Florides et al. 2000). In (Kirimtat et al. 2016b), the shading device types used in the building sector were reviewed in detail and a description of the performance aspects of these shading devices by introducing different simulation tools was also given. These performance aspects are generally linked with daylight comfort levels, visual comfort, and low energy consumption.

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

It is not uncommon for contemporary buildings to present complex design requirements concerning daylighting. Complexity in this case stems from the diverse design requirements corresponding to different spaces within the building. A large scale public building may comprise a multitude of spaces of different functions, capacities and locations within the building. To ensure that a suitable distribution of daylight is assigned to each of the spaces is a challenging design task. Careful planning needs to be exercised even for spaces with similar requirements and functions, as other properties such as their location and configuration have an effect on the interior distribution of daylight throughout the operating period of the building. It is a goal, therefore, to apply the proposed method to complex real-world designs whose requirements concerning daylight are directly in line with the way of thinking outlined above. Therefore, the goal is to establish a model that can provide a concise but accurate figure of whether the daylight distribution guaranteed by a facade is adequate concerning building requirements.

In very broad terms, a designer wishes to ensure that all spaces within a building receive at least the minimum amount of daylight required for the function associated with each space, for the maximum amount of time possible. This constitutes a good use of daylight which promotes conservation of energy and is associated with the well-being of building tenants (Andersen 2015; Mardaljevic et al. 2009). On the other hand, extreme amounts of daylighting is generally avoided as it is associated with undesirable visual or thermal discomfort (Nabil and Mardaljevic 2005; Mardaljevic et al. 2011). A desirable level of daylighting thus lies in a range that is dependent on the function of the space. Sun-shading elements in the facade contribute mainly to this end, mediating the extremes of sunlight intake while ensuring the minimums are met for the longest time possible. As the sun position and climate are subject to constant change, daylight distribution for a fixed site is subject to perpetual temporal fluctuations. It is important, therefore, to consider temporal, as well as spatial, distribution of daylight in assessing a space.

The introduction of new manufacturing techniques enable the design to depart from traditional concerns of standardization, and embrace a condition where fine-grained component variability is desirable, though more complex. Besides, the use of accurate tools for estimating facade behavior allow a better prediction of the resulting performances. However, this implies also the understanding of the highly non-linear relationships between design decisions and resulting performances.

Each of the design aspects outlined above introduce additional design complexity that leads to challenges throughout the design decision making process in general, while in the case of facade design additional design aspects that will be outlined throughout the rest of the chapter intervene and increase complexity. Intending to address these issues, this study presents a method for addressing complex design problems with application to facade design. In addition, this study acknowledges and adopts the general approach introduced in (Sariyildiz 2012) comprising "form generation", "performance evaluation" and "optimization", available in Figure 3.2. The proposed method comprises innovative techniques for form generation and performance evaluation, and couples those with advanced multi-objective computational optimization algorithms namely the Hyper volume Estimation (HypE) algorithm. The proposed method is applied and validated on a real-world complex facade design problem.

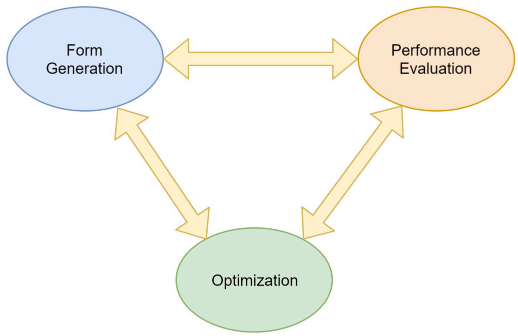


FIGURE 3.2 The loop of the Performance Driven Conceptual Design as conceptualized by Sariyildiz (2012). Performance-based Computational Design is at the center of research of the Chair of Design Informatics (TOI/DI) at the Delft University of Technology.

§ 3.2.2 Proposed Method

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

§ 3.2.2.1 Form Generation

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

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

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

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

To investigate potential strategies for dimensionality reduction, aesthetic properties of architectural facade designs are considered. It may be empirically observed that the vast majority of real-world facade design cases exhibit patterns that may be exploited to reduce search space. Such patterns are often the result of stylistic or aesthetic preferences and are established as part of the overall facade concept. Through considering these patterns, it is possible to stipulate that at any given time, only a very small subset of possible design alternatives is of interest to the decision-maker, even before having any knowledge regarding facade performance. An example of aesthetic preference that can be seen in many recent architectural design examples, is facade designs where the composition of element parameters gradually varies along the facade plane. This seems as a preferable design direction for many real-world design applications. Some recent architectural examples of this type of facades are demonstrated in figure 3.3.

FIGURE 3.3 Recent examples of facades that follow a module-based approach. a. Al Bahar Towers, AEDAS, Image Credit: AEDAS; b. Nanjing International Youth Culture Centre, Zaha Hadid Architects, Image Credit: Khoo Guo Jie; c. Nantong Urban Planning Museum, Henn Architekten, Image Credit: Bartosz Kolonko/HENN

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

A variety of approaches for simplification of design problems has been proposed in literature, the majority of which is statistical and rely on techniques such as Design of Experiments (DOE), sensitivity analysis, clustering approaches etc. to identify the influence individual design variables have on design performance, before proceeding to intelligent optimization. It should be noted that the technique outlined so far in this section, and elaborated in the next section, is to be differentiated from statistical dimensionality reduction techniques, and the main points of differentiation are as follows:

- The proposed technique aims to provide a lower dimensional control scheme of a high-dimensional parametric object,
- the proposed technique is not statistical in nature,
- the proposed technique does not consider relations between decision variables and objective functions/constraints,
- the proposed technique is specific to designs that can be analyzed as n-dimensional arrangements of parametrically defined elementary units, and,
- the proposed technique is much less complex, comprising few elementary relations and applicable using elementary geometric tools.

In fact, statistical analysis and dimensionality reduction approaches, such as those described by Yang et al. (2018) can be a natural next step following the approach proposed herein, and offering further complexity reduction through identification of the most influential decision variables in relation to objective functions and constraints.

MANAGING COMPLEXITY THROUGH INDUCING LOCALIZED MODULE TRANSITIONS To alleviate combinatorial complexity due to the factors discussed in the previous section and focus on a more relevant subset of the search space, this section identifies constraints that may be applied to the decision variable distribution of the facade elements. In particular, and as already stipulated, smooth formal transitions between neighboring elements throughout the search space are considered, while maintaining the expressiveness of the model to allow facade design professionals expressive power. In this section, a model where the decision variable corresponding to elements' properties becomes a dependent variable that varies in accordance to the element's proximity to a set of control nodes spatially distributed along the facade area is proposed. Similarly to the facade elements' definition, the control nodes are defined by $w = \{V_w, P_w\}, w \in W$. $V_w \in R^n$. is a decision variable value vector, with each of its values corresponding to one facade element parameter. Each node is additionally characterized by a vector $P_w \in R^2$, which denotes their position on the facade plane. The control nodes act to"affect" the parameter composition of each of the facade's elements, with a magnitude that varies according to some function of the Euclidean distance between an element and a node. As an example one may consider that the effect of a node on an element varies inversely proportional to the Euclidean distance between them. In this case the following equation holds:

$$c(e, w) = \frac{1}{|P_e - P_w|} \tag{3.1}$$

Thus the effect that a node has on an element is maximized the closer the element is to the node.

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

$$V_e = \frac{\sum_{w \in W} c(e,w) V_w}{\sum_{w \in W} c(e,w)} \tag{3.2}$$

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

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

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

FACADE DESIGN EXAMPLE As mentioned at the beginning of the section, the technique presented above is generally applicable to any facade design that comprises regular patterns of individual modules. As an example of a simplified parametric model, a Grasshopper definition is presented in the figure 3.4.a, which makes use of a total of three control nodes and 18 parameters in total to adjust the properties of a facade comprising 66 facade elements, with four parameters each, for a total of 264 parameters. This definition translates to facade available in figure 3.4.b, and demonstrates a few alternative arrangements of modules corresponding to varying attributes.

The control magnitude metric used in this example is the biased inverse of the Eu-a.

b.

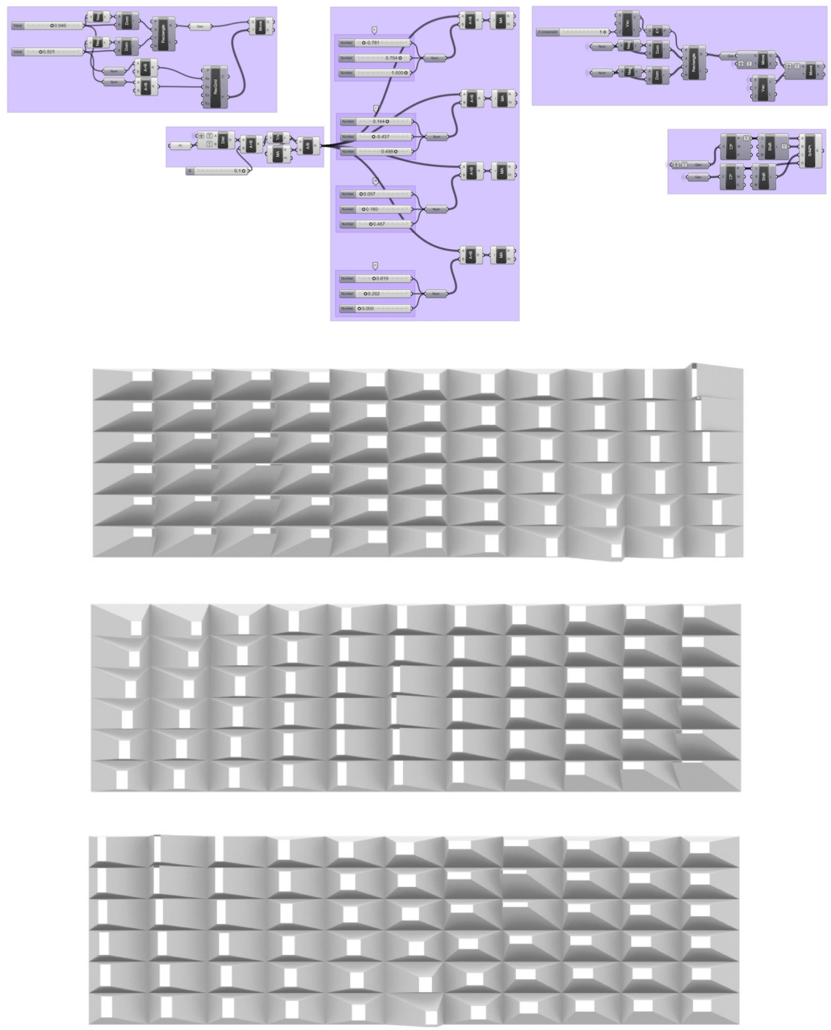


FIGURE 3.4 (a) An exemplary parametric definition demonstrating the method presented in section 3., that allows a facade comprising 264 parameters in total to be varied using three control nodes and a total of 18 parameters, (b) three example facade configurations.

clidean distance, which is analytically expressed as follows:

$$c(P_a, P_b = \frac{1}{\sqrt{(P_{x,a} - P_{x,b})^2 + (P_{y,a} - P_{y,b})^2}} \tag{3.3}$$

Replacing equation 3.3 into 3.2 thus gives us the ultimate value function for each of the facade modules' properties as follows:

$$V_e = \frac{\sum_{w \in W} \frac{1}{\sqrt{(P_{x,e} - P_{x,w})^2 + (P_{y,e} - P_{y,w})^2}} V_w}{\sum_{w \in W} \frac{1}{\sqrt{(P_{x,e} - P_{x,w})^2 + (P_{y,e} - P_{y,w})^2}}} \tag{3.4}$$

§ 3.2.2.2 Daylight Indicators and Modeling

As has been stipulated previously, control of daylighting is a fundamental function of a facade, and especially its shading system. As part of the present investigation, daylight control has been introduced as a main objective of optimization for the shading device that is to be designed. To this end, daylight indicators are used instead of raw daylight levels, as indicators give a good summary value of the daylighting conditions throughout the year, at hours that are of interest for the function of the building. In particular, the widely adopted Useful Daylight Illuminance (UDI) (Nabil and Mardaljevic 2005) metric is used as a base evaluation metric for building a comprehensive daylight evaluation scheme. The definition of UDI begins by defining illuminance ranges concerning the level of comfort associated with them (Nabil and Mardaljevic 2005):

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

A two-level hierarchal model is considered, which is analyzed as follows: In the lowest level, an accurate daylighting simulation offers information regarding the distribution of daylight within a single space, for each relevant space of the building. Given these results, the highest level comprises an aggregation scheme that combines individual results into a single figure, which is subsequently used in computational optimization as an objective.

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

$$UDI(p,t,g) = \begin{cases} 0, \text{if} L(p,t,g) < 100 \\ \frac{L(p,t,g)-100}{400}, \text{if} 100 \leq L(p,t,g) < 500 \\ 1, \text{if} 500 \leq L(p,t,g) < 2000 \\ 0, \text{if} 2000 \leq L(p,t,g) \end{cases} \tag{3.5}$$

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

$$UDI_q(p,g) = \int^y UDI(p,t,g)dt \tag{3.6}$$

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

$$UDI_{a,h}(p,g) = \sum_{t=0}^{y} UDI(p,t,g) \tag{3.7}$$

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

- Obtain an aggregate figure of the daylight performance for multiple points within a single or within different indoor spaces, and,

- Be able to specify alternative thresholds for minimum illuminance in the UDI formula.

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

$$UDI(p,t,g,m_l,m_u) = \begin{cases} 0, \text{if} L(p,t,g) < m_l \\ \frac{L(p,t,g)-m_l}{m_u-m_l}, \text{if} m_l \leq L(p,t,g) < m_u \\ 1, \text{if} m_u \leq L(p,t,g) < 2000 \\ 0, \text{if} 2000 \leq L(p,t,g) \end{cases} \tag{3.8}$$

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

The second extension builds on the previous one by allowing the integration of multiple measurements in different spaces each with its own requirements in daylighting levels. The extension considers a set of spaces S, each of which includes a set of measurement points P_S. A set of requirements R contains a tuple of required illuminance levels indexed by elements in S. Under these assumptions, the formula is defined as follows:

$$sUDI(S,R) = \frac{1}{\sum_{s \in S} |P_S|} \sum_{s \in S} \sum_{p \in P_S} aUDI_{a,h}(p,g,m_{l,s},m_{u,s}), m_{l,s}, m_{u,s} \in R_S \tag{3.9}$$

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

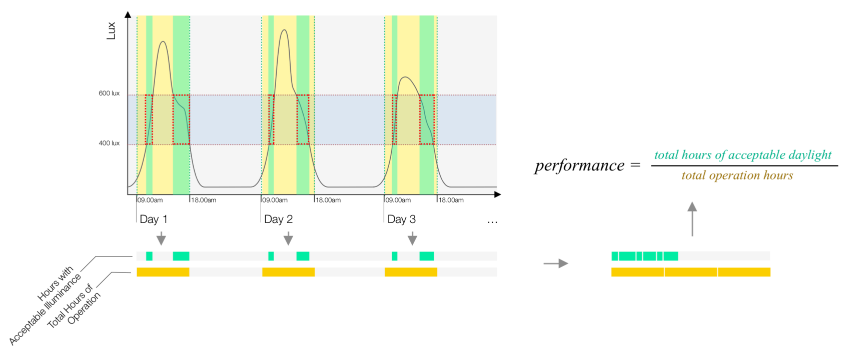


FIGURE 3.5 Visual diagram of the UDI calculation for daylight performance.

§ 3.2.2.3 Computational Complexity

The daylighting evaluation outlined above requires accurate indoor illuminance distribution figures which can be obtained using simulation. One of the most widespread daylighting computation software is the RADIANCE tool (Ward 1994). RADIANCE is an advanced ray-tracing software that can accurately determine the illuminance values at the required indoors measurement points, for different times of the year and outdoor skylight distributions. This study utilizes software that allows the use of RADIANCE from within a Parametric Modeling environment, namely the DIVA software (Jakubiec and Reinhart 2011). The use of simulation enables the accuracy of the proposed method, however it contributes significantly to the computational complexity of the proposed method. Concerning the use of simulation there are, in fact, several factors that contribute to computational complexity:

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

In order to alleviate issues related to computational complexity, a parallelization scheme is used that is compatible with both the simulation software at use and the population based optimization algorithm that will be outlined hereafter.

The proposed scheme consists of two levels of parallelized computation:

- The first is offered by the RADIANCE program and concerns the use of multiple processors in the same computer, to accelerate daylighting computations. As the daylighting computations are by far the most computationally intensive task in the proposed method, use of multiple processors translates into a computational gain that is nearly proportional to the number of processors at use in a single machine.
- The second layer concerns the use of multiple machines to distribute the computation of individual solutions within a population. A simple queueing scheme allows for the use of heterogeneous infrastructure where each machine may receive one or more tasks depending on its capabilities and the computational complexity of each task. A compute cluster size of up to the population size of the tasks for each population can be used for parallelization.

A diagram of the proposed scheme is available in figure 3.6.

§ 3.2.2.4 Multi-Objective Optimization

In order to address the multi-objective optimization problem at hand, Multi-Objective Evolutionary Algorithms (MOEAs) are employed. This class of algorithms has been extensively covered in section 2.5.1. In particular the Hypervol-

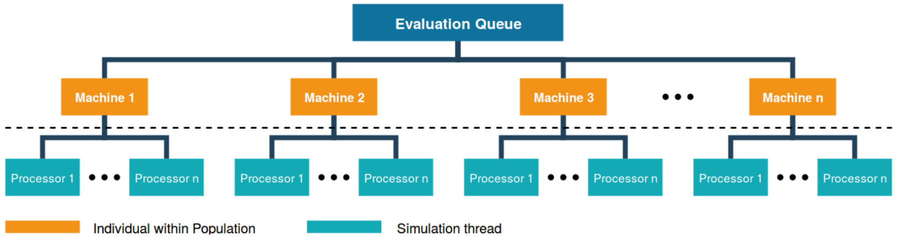


FIGURE 3.6 Hierarchical organization of available compute infrastructure: Each individual in a population is assigned to a machine where the relevant simulation is performed on multiple threads.

ume Estimation Algorithm (HypE) (Bader and Zitzler 2011) is selected as a competitive indicator-based MOEA.

§ 3.2.3 Case Study: The PULSE Project

In order to provide validation for the proposed method, a real-world architectural facade design problem is chosen.

§ 3.2.3.1 Overview

PULSE is the name of the newest addition to the university campus of the Delft University of Technology, an education building that serves as a central place bringing students and lecturers together to make contacts, collaborate, acquire and share knowledge and develop themselves. The Western facade of the building features a striking large glass area, which is protected by innovative shading elements. The design of said elements has been the focus of an extensive research effort between the Chair of Design Informatics (TOI/DI), Department of Architectural Engineering and Technology of the Faculty of Architecture of Delft University of Technology, Ector Hoogstad Architects, the architectural firm leading the design of the PULSE building, and researchers Cemre Çubukçuoğlu and Ayça Kırımtat from Yaşar University in Izmir, Turkey. PULSE is the first energy-neutral building on the TU Delft campus, and as such, the demand for an efficient facade that promotes energy conservation and generates a comfortable indoor climate has been high on the design agenda. At the same time, it was a requirement for the facade to employ a unique aesthetic that may easily be used to identify the building.

§ 3.2.3.2 Daylighting Requirements

The PULSE building includes several indoor areas that are adjacent to the facade in question. Each of these spaces has different requirements concerning acceptable illuminance ranges. These are presented in figure 3.7. For each indoor space in question, a grid of measurement points is established in simulation. The grid has a fixed size of 1m. Values from each measurement point are combined in a single objective function by applying the method outlined in section 3.

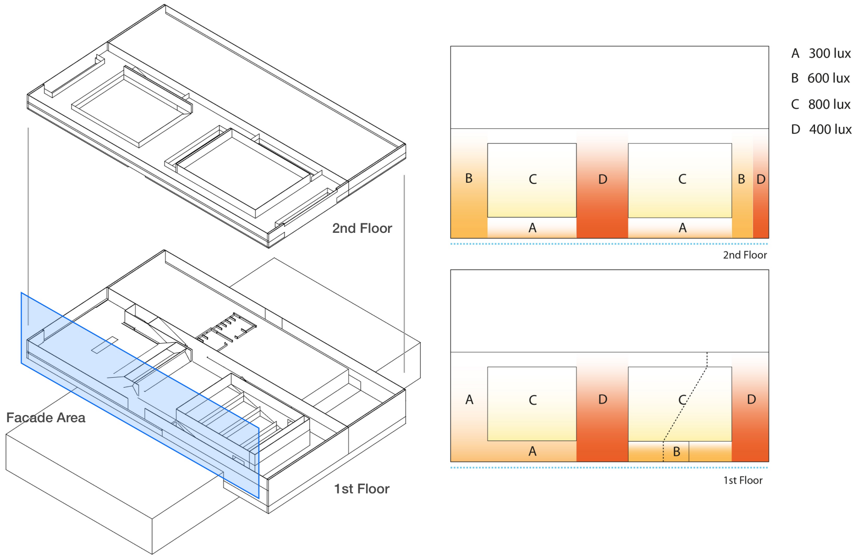


FIGURE 3.7 Location of interior spaces in relation to the facade (dotted green line), and minimum lighting requirements. Image and design by Ector Hoogstad Architecten & TU Delft/Chair Design Informatics.

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

§ 3.2.3.3 Shading Element Design

The form of the shading element has an abstract wave shape as inspiration. A visual pattern of waves is formed when the elements are in arrangement on the facade. A 3D printed prototype of the element form is available in figure 3.8. The main form of the element is constructed by sweeping a profile curve along the curved axis, with different profile curves along various axis points. The profile of the element is thus wider at the center, where it offers most of the potential for mediating direct sunlight. Each element offers three connection points to neighboring elements: Two on each edge of the “wave”, and one at the center of the element. The connection pattern is edge-to-center, with two elements connecting to a third elements’ center. The elements include hollow paths along their diagonal, which are run by steel reinforcement cables under tension. The purpose of the cables is to increase the stiffness of the shading device along the surface so that it can better withstand lateral loads (e.g. wind load). The configuration of the elements along with the reinforcement system is available in figure 3.8.

FIGURE 3.8 Physical prototype of a single shading element. Image and design by Ector Hoogstad Architecten & TU Delft/Chair Design Informatics.

§ 3.2.3.4 Rapid Prototyping and Material Technologies

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

$$u(X) = A_{tot} = \sum_{e \in E} a(g_s(V_e)) \tag{3.10}$$

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

§ 3.2.3.5 Parametric Definition of Shading Device

The PULSE facade parametric definition has been developed with the aim of testing and optimizing the element parameters of the facade shading device, by application of the method outlined in the previous section. The shading device is a rectangular region that occupies the front of the Western glazed area of the PULSE building. The arrangement of elements is fixed. There are a total of 3800 individual elements arranged in a diamond-shaped grid that measures 76 elements in each row and 50 elements in each column. The angles for each side of the diamond are 45 and 30 degrees accordingly. A schematic view of the shading elements in combination with the supporting wire arrangement is available in figure 3.9.

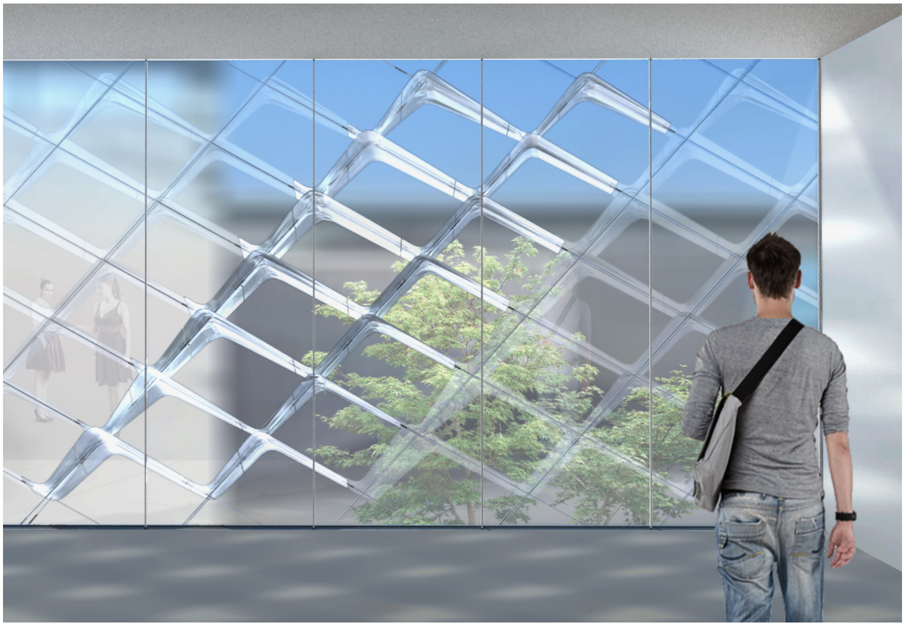


FIGURE 3.9 Diagonal arrangement of shading elements on facade. Image and design by Ector Hoogstad Architecten & TU Delft/Chair Design Informatics.

The form of each individual shading element is controlled by three parameters: Two parameters control the shading element's angle, one along each of the two steel wire directions, and one parameter controls the width along the element centerline. A visualization of the element's parameters is available in figure 3.10.

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

A regularly located grid of 21 control nodes covers the surface of the shading device in order to control the shading elements configuration. The control nodes utilize a biased inverse-distance-proportional control aggregation function with constant falloff, like equation 3.4. A separate problem instance that included variable falloff modifiers as decision variables has been tested, however, it was deemed that

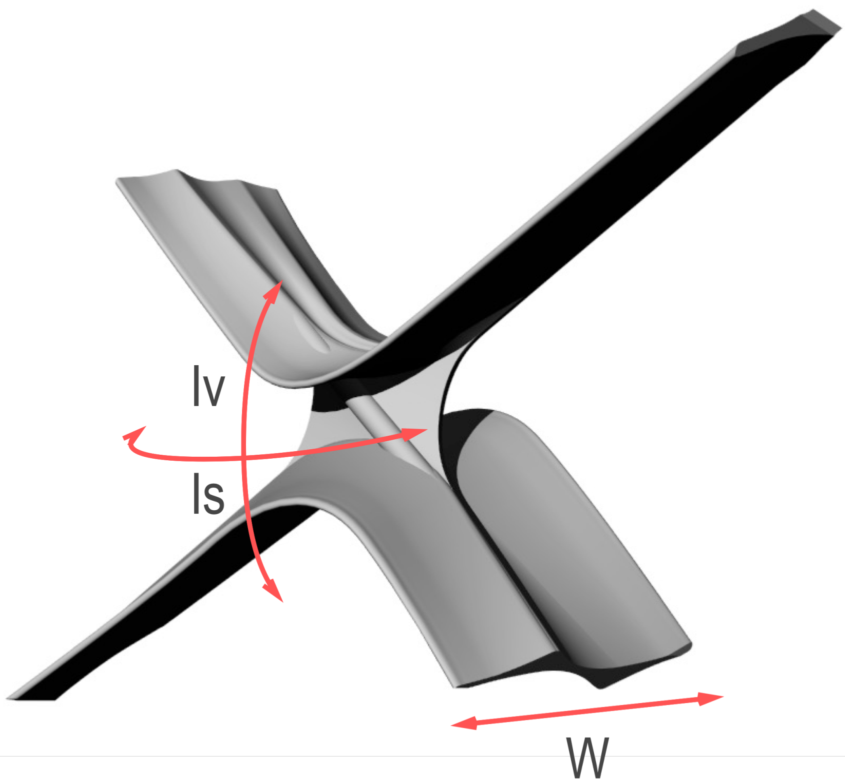


FIGURE 3.10 Cross-section of a single facade element, where decision variables effects are demonstrated. Element design by Ector Hoogstad Architecten & TU Delft/Chair Design Informatics.

it did not offer advantages that would justify the increase in search space complexity. There are seven control nodes in each row of the control grid, and three in each column. Each control node controls separately the three parameters that correspond to a single element's configuration. This corresponds with a search space of 63 dimensions in total. It is interesting to note that had each shading element have had its own parameters as decision variables in the problem definition, the dimensionality of the search space would be 11250, which would make a challenging to navigate the search space. The configuration of control nodes is available in figure 3.11.

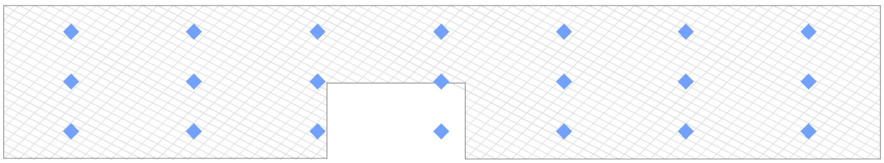


FIGURE 3.11 Location of control nodes for the PULSE facade (TU Delft/Chair Design Informatics).

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

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

§ 3.2.3.6 Problem Definition

Under the assumptions outlined above, a real-coded, bi-objective unconstrained optimization problem is formulated, which aims to be addressed using evolutionary computation and in particular, the HypE algorithm outlined in section 3.4. The decision variables together with their indexing and variable bounds are available in table 3.1. The optimization problem definition is as follows:

Minimize

$$\begin{aligned} &1 - sUDI(S, R, g(X)) \\ &u(X) \end{aligned} \tag{3.11}$$

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

§ 3.2.3.7 Experimental Set-up

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

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

The above variations introduced unexpected delays in objective function evaluations. As such, computation time became the most significant constraining factor in the optimization trials. It was eventually identified that an optimization run of 50 generations with a population of 100 individuals could be completed within a single weekend on the available computing cluster, and as such these values were chosen. In particular and in both trials, the required simulation computations were performed in a heterogeneous cluster of machines using the parallel computation scheme outlined previously. The cluster comprised 25 machines of varying processing power and availability that was mainly during weekends. To maintain project schedule, it was decided that each trial would be carried out within one weekend – allowing for two additional weekends prior to trials to perform test runs. The running time for each simulation was near five minutes, as such an optimization run of 50 generations of 100 individuals would have a minimum duration of 18 hours. However, due to unexpected phenomena such as machine shutdowns and data loss over the remote connection, the actual duration was slightly more than 24 hours, allowing a time window enough for a single run per weekend. The algorithm parameters are available in table 3.1.

TABLE 3.1 Parameters of the Radiance simulations

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

§ 3.2.3.8 Results and Discussion

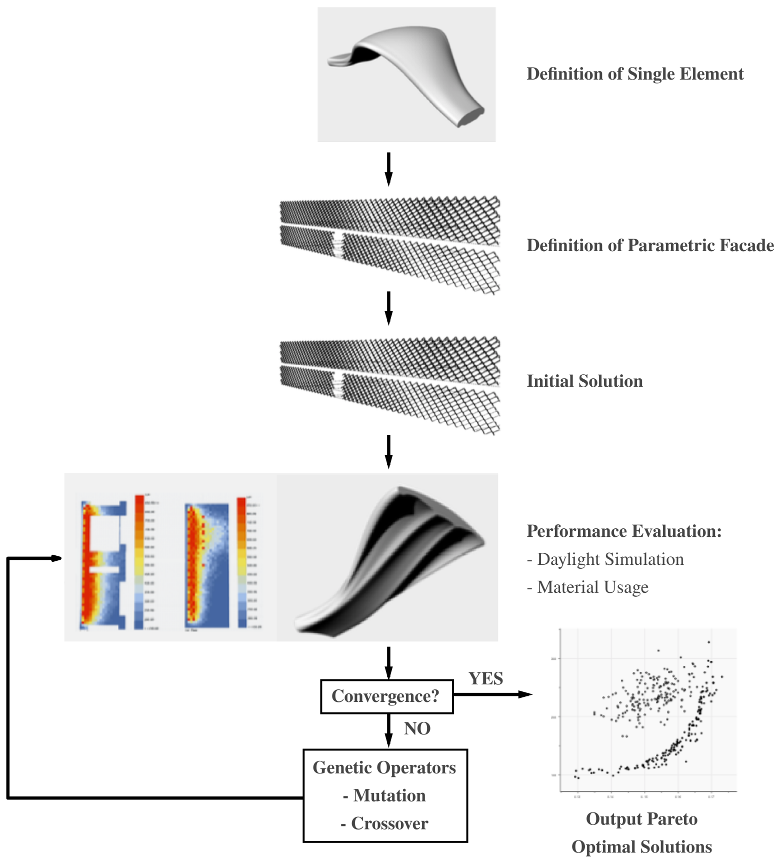


FIGURE 3.12 Overview of the performance optimization process as applied in the PULSE case study (TU Delft/Chair Design Informatics).

Figure 3.12 presents an overview of the performance optimization method as applied in the PULSE case. Two extended trials using the proposed method were performed during the PULSE project. The first was performed at an intermediate design point, where the precise constraints related to manufacturing and structural aspects were not fully known by project partners. The second trial was performed at the end of the preliminary design stage, where such aspects were known to a detailed degree.

The objective function space of the algorithm population pertaining to generations 1 and 50 of the first trial is presented in figure 3.13. As may be observed in this figure, the final population comprises mostly non-dominated solutions, however, it seems that the algorithm did not fully converge and convergence may be achieved if the algorithm is allowed to run further. Still, looking at the results at hand it is possible to see that the optimized designs offer significant material savings (up to 67% for the one end of the Pareto front) and overall better compliance to the daylight requirements of roughly 2% on average.

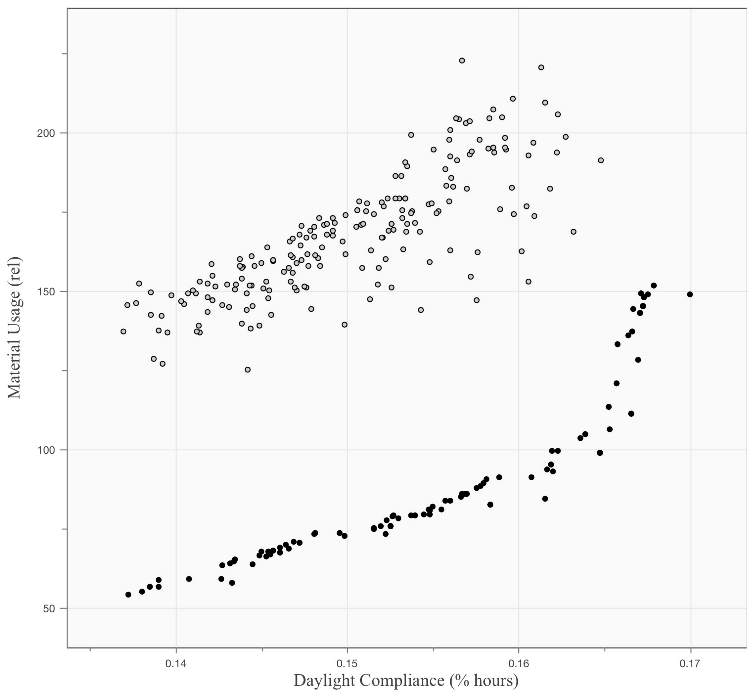


FIGURE 3.13 Objective function space visualization for individuals in the first generation (grey) and the final generation (black), first trial (TU Delft/Chair Design Informatics).

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

Objective function charts pertaining to generations 1 and 50 of the second trial are available in figure 3.14. As in the first trial, the 50th generation is not fully converged and further generations may be able to improve optimality. As seen in the figure, there is a 5% improvement on average in the use of material in comparison to the initial population, and a 1% improvement in terms of daylight requirements compliance. Figure 3.15 presents six Pareto optimal designs corresponding to the colored points in that figure. As can be observed, areas of the facade where less daylight is required overall are denser on solutions with more material use. The opposite is also true, areas with more daylight requirements are generally less occluded by the shading device. Solutions that demonstrate minimal material use do not show significant variations in occlusion, however, the orientation of the shading elements is still affected to either allow or block daylight as required.

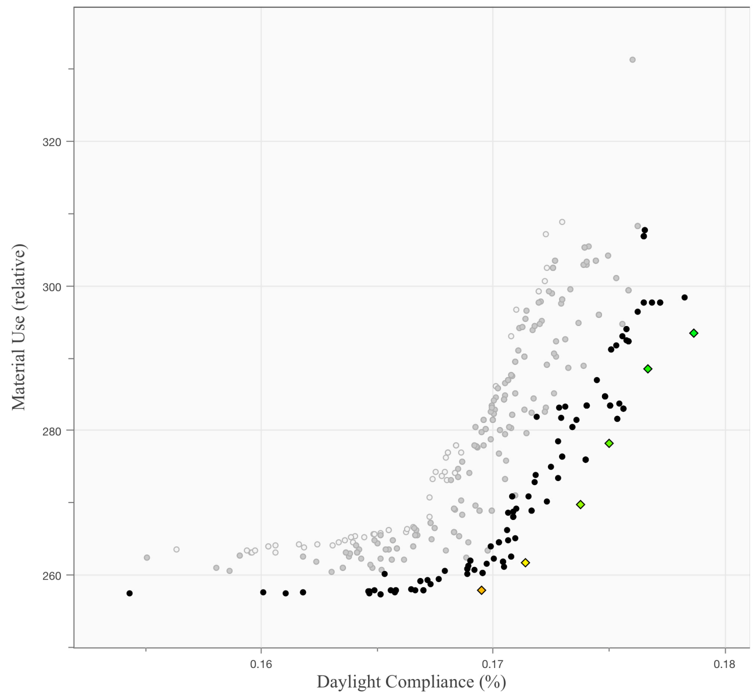


FIGURE 3.14 Objective function space visualization for individuals in the first generation (grey) and the final generation (black), final trial (TU Delft/Chair Design Informatics).

The proposed optimization approach results in a set of Pareto-optimal solutions to the multi-objective facade design problem, which has been also the case in the PULSE application. Following optimization, the process of identifying the most suitable out of the presented solution has taken place. Selection among Pareto-optimal solutions may happen either on the basis of considering the tradeoff be-

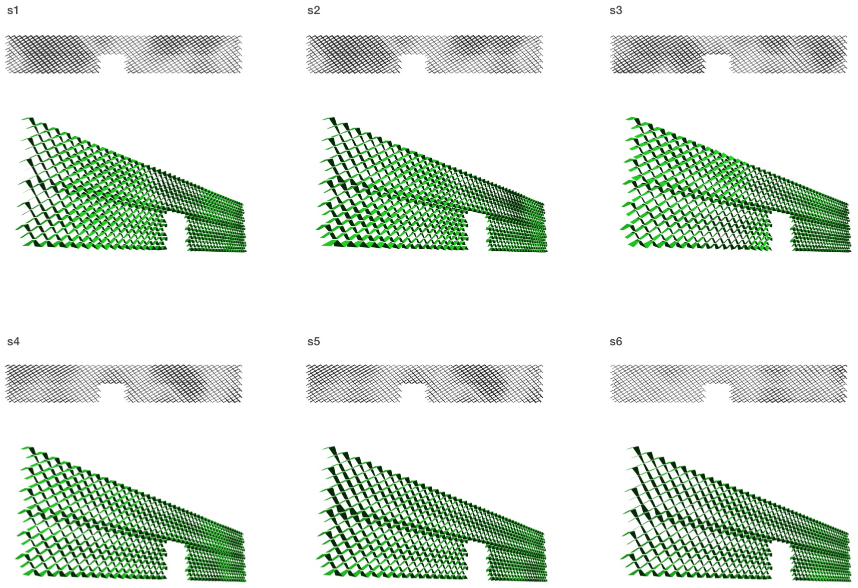


FIGURE 3.15 Visualization of facade configurations post optimization, samples according to the distribution in figure 3.15.

tween objectives or considering additional preferences that have not been explicitly treated in the course of optimization. In the case of PULSE, decision-makers went through an iterative process to examine each of the resulting solutions and decide on the most suitable one, where both tradeoffs between objectives as well as preferences concerning the formal properties of the design were considered. More specifically, some of the designs that had better daylighting performance were also preferred due to the variation they presented in terms of element transitions. However, the same designs were generally on the higher end of the range of total facade material cost. It is noted here that while this is one approach to post-optimality decision making, other approaches that consider soft objectives and preferences also exist. Addressing soft objectives in the context of computational decision support is a challenging task that has been extensively researched and comprises diverse strategies, such as those presented in Takagi (2001), Meignan et al. (2015) and Chatzikonstantinou and Sariyildiz (2017); Ciftcioglu and Bittermann (2015b). One future direction for the present work is to research potential methods for augmenting cognitive decision support during the post-optimality phase, to better address preferences and satisfy soft objectives beyond those specified before optimization.

§ 3.2.3.9 Discussion

This study presented a novel approach in computational decision support focusing on supporting the design of complex component-based facades and shading devices where components are dissimilar and individually manufactured. Such prob-

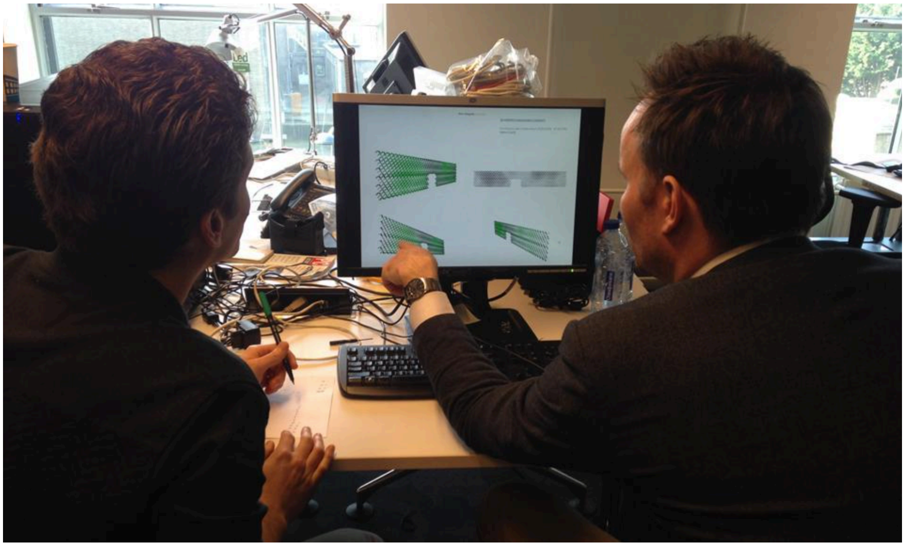


FIGURE 3.16 Project stakeholders visually inspecting solutions post optimization for selection (TU Delft/Chair Design Informatics).

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

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

§ 3.3 Design Research and Teaching

§ 3.3.1 Introduction

This is the second section of chapter 3, which has as the main objective to present an analysis of a series of scientific contributions that have been published by MSc students as part of computational design studios that they participated, with the author as an advisor to the work. The significance of this section is to provide complementary background information that, together with the findings presented in section one above, can support a justification of the starting point of the research presented in this thesis. Specifically, the brief analysis of the works that follow, serves to indicate, on one hand, the potential applications of computational decision support systems in problems commonly encountered by students in advanced design studio settings, and on the other hand, to pinpoint potential shortcomings that the applied methodologies may suffer from, and identify opportunities for improvement. The latter is performed in a separate discussion section at the end of the chapter.

§ 3.3.2 Analysis of Published Contributions

A brief outlook of each of the selected contributions is presented first, to briefly introduce their approach.

Kirimtat et al. (2016a) focus on the design of shading devices for residential building through a computational optimization approach. The paper discusses the design in the form of an optimization problem formulation where there are two objectives. The first objective concerns the minimization of total energy consumption and the second is the maximization of natural daylighting, through the Useful Daylight Illuminance (UDI) indicator. The particular type of shading devices that are studied are the horizontal louvers. As such parameters to the problem are the size, inclination and density of the louvers. The multi-objective problem is addressed by employing MOEAs, namely NSGA-II and jDEMO. Evaluation of solutions is done through the use of Radiance, for daylighting, and EnergyPlus, for energy calculations. The Pareto front results together with indicative solutions are presented in figure 3.17.

Yufka et al. (2017) discuss the problem of dimensioning a series of skylight modules located over an indoor atrium in an education building. The design objectives as formulated are to maximize incident daylighting throughout the working hours and minimize construction cost of the skylight assemblies. A flexible dimensioning scheme is derived, where it is possible to control the top and bottom dimensions of each skylight individually, thus yielding potentially interesting formal results in the ceiling of the space in question. Through this problem definition, a total of 21 decision variables and two objective functions are stipulated. Paper authors present comparative results by evaluating two evolutionary algorithms, a variant of Differential Evolution and a Genetic Algorithm. Figure 3.18 presents the derived Pareto front and a few picked solutions.

Ünlü et al. (2017) propose an evolutionary computation approach applied to the design of an urban public shelter structure, located in Izmir Turkey. The study

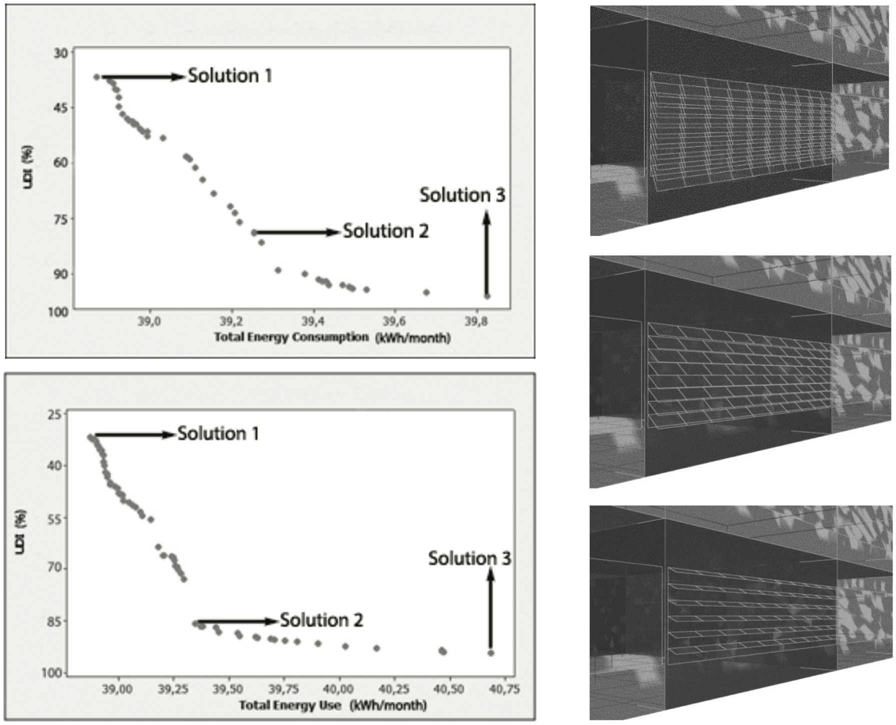


FIGURE 3.17 Resulting Pareto front distributions in objective function space, and three indicative solutions Kirimtat et al. (2016a)

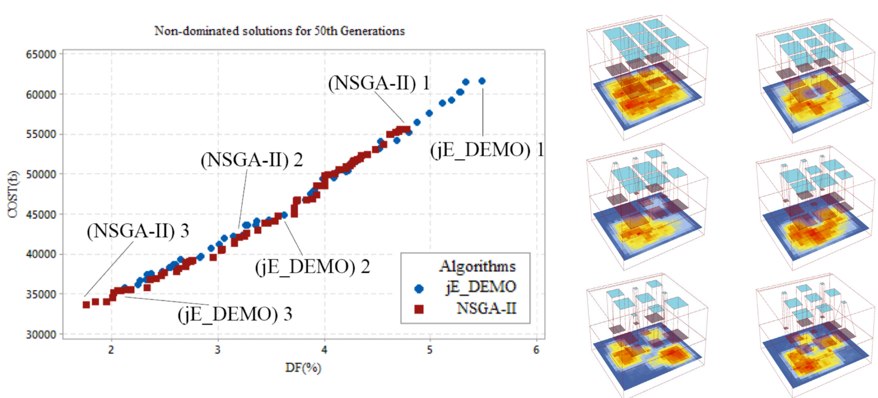


FIGURE 3.18 Resulting Pareto front distributions in objective function space for two algorithms, and six indicative solutions, three per algorithm Yufka et al. (2017)

considers the dimensioning of a unique type of structural supports that branch to better support the wide roof above them. The objectives defined in he study concern the minimization of structural displacement in various load cases, and the minimization of member sizes, which suggests a view towards minimizing the material cost of the structure. Authors utilize NSGA-II to derive a Pareto front to the bi-objective design problem.

Ugurlu et al. (2015) focus on a unique field of architectural research, namely that of the design of floating settlements. Floating settlements are relevant and innovative solutions for dealing with new challenges in the development of cities and settlements. However, their design poses a lot of considerations and technical challenges, a fact that contributes significantly to design complexity. To alleviate complexity issues and support decision making in design, authors turn to CI techniques and namely MOEAs. Authors consider the design of floating settlements at an urban scale in a coastal region near Izmir, Turkey. The problem is formulated as one of locating functions within an allowable area of sea, with the goal of satisfying objectives of accessibility and visual privacy. The location of each function forms a decision variable, and there are also constraints related to allowable sea depth and proximity to existing coastal settlements. Authors present comparative results of two different MOEAs, namely NSGA-II and multi-objective DE. Indicative results are demonstrated in figure 3.19.

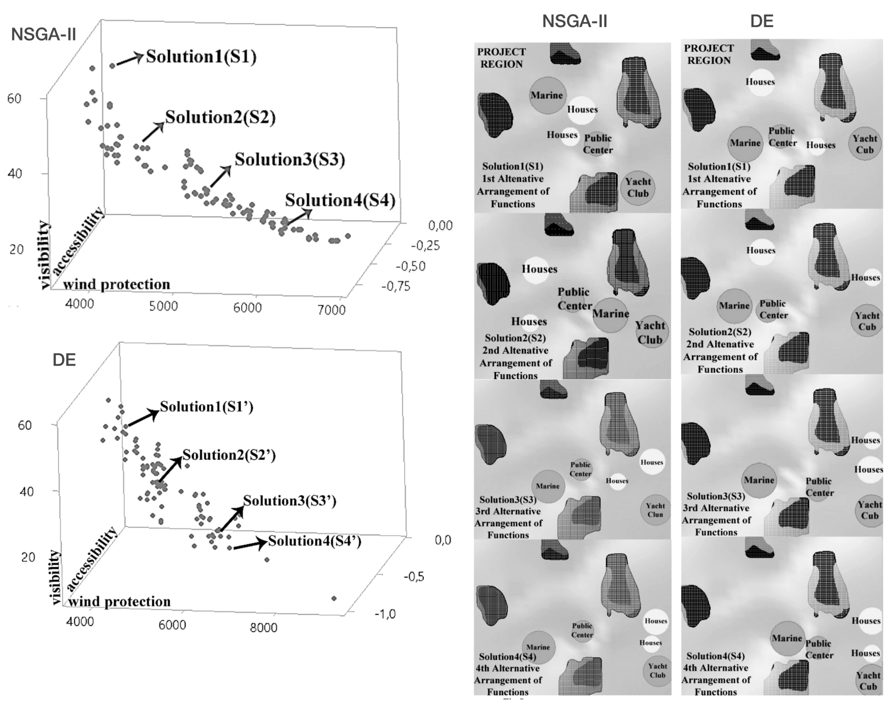
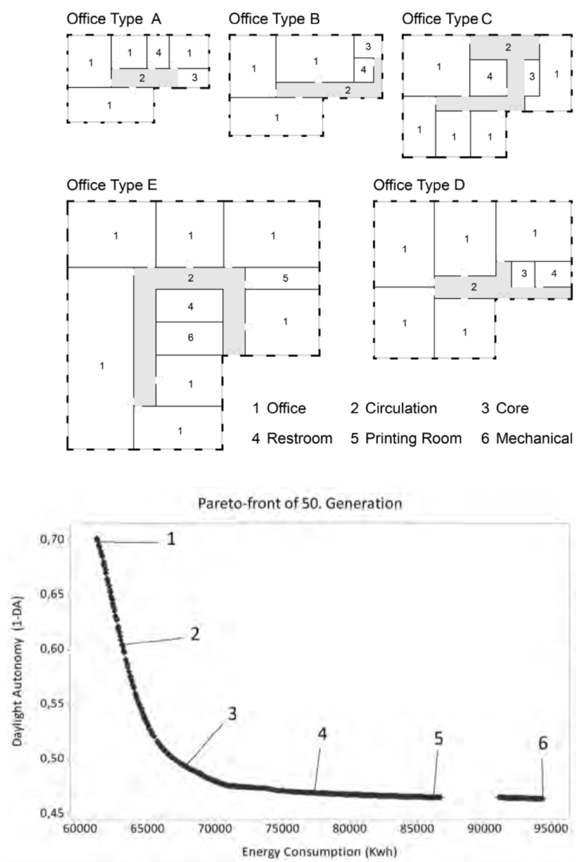


FIGURE 3.19 Resulting Pareto front distributions in objective function space, and indicative solutions Ugurlu et al. (2015)

Finally, Aydın et al. (2015) propose an intelligent-cognitive approach to sustainable design, through the optimization of a surrogate model-assisted performance of an office building in terms of energy consumption and daylight autonomy. The paper authors generate a database of designs based on a series of typical office floorplans (figure 3.20), variations of which are subsequently simulated to derive performance figures for each. The parameters considered are Fenestration ratio, Overhang projection factor, U-value of external walls, U-value of the roof, U-value of windows, Number of floors, Footprint area, and HVAC type. The design parameter and performance pairs are used to fit an artificial neural network (ANN) model for each office type, for daylighting, and for energy consumption. As a final step in the proposed method, the paper authors formulate a bi-objective problem and perform optimization using an MOEA, namely NSGA-II, yielding a Pareto front of office variations.



	1	2	3
X1	0.20	0.46	0.70
X2	0.00	0.36	0.70
X6	3	3	3
X8	2	2	2
Y1	61228.9	63159.1	67310.0
Y2	0.70	0.60	0.49

	4	5	6
X1	0.70	0.70	0.70
X2	0.70	0.70	0.70
X6	5	5	5
X8	2	2	6
Y1	79096.9	85881.2	94304.1
Y2	0.47	0.46	0.46

FIGURE 3.20 Office types considered and resulting Pareto front distribution (Aydın et al. 2015)

In table 3.2, a summary of the outlined contributions is presented.

TABLE 3.2 Summary of Presented Contributions and their Characteristics

Study	Algorithm	Topic	Objectives
Kirimtat et al. (2016a)	NSGA-II Deb et al. (2002), DEMO w/ ens. approachRobič and Filipič (2005); Tasgetiren et al. (2010)	Sunshading Device	Energy Consumption, UDI
Yufka et al. (2017)	NSGA-II Deb et al. (2002), DEMO w/ ens. approachRobič and Filipič (2005); Tasgetiren et al. (2010)	Daylighting Cupolas	Daylight Distribution, Cost
Ünlü et al. (2017)	NSGA-II Deb et al. (2002)	Shelter Structure	Displacement, Cost
Ugurlu et al. (2015)	NSGA-II Deb et al. (2002), DEMO w/ ens. approachRobič and Filipič (2005); Tasgetiren et al. (2010)	Urban Configuration of Floating Settlement	Visual Privacy, Accessibility
Aydın et al. (2015)	NSGA-II Deb et al. (2002)	Facade Dimensioning & Material Selection	Energy Consumption, Daylight

§ 3.4 Discussion

It is clear from the above publications that the focus, with the exception of Aydın et al. (2015) is on intelligent optimization of designs. As the presented works are carried out in the context of a post-graduate studio environment, there is a conspicuous educational value of introducing students to advanced intelligent decision support. On the other hand, it is worthwhile to consider the benefit that integration of intelligence with cognitive approaches may bring to the table; in particular, it is seen that two of the most important shortcomings commonly present in the aforementioned works could be addressed, namely: The excessive computational complexity associated with detailed energy simulations, leading to lengthy processing times, and the lack of systematic post-Pareto decision making approaches, that go beyond the simple choice of alternatives among the ones sampled from the Pareto front.

Concerning the latter, it is seen in the above works that post-Pareto selection is done through a strategy of selecting solutions that are approximately equidistant on the Pareto front, to demonstrate the full range of design alternatives that the multi-objective approach guarantees.

The above condition is suggestive of the fact that, at least as far as architectural design is concerned, there is a tacit principle in post-Pareto decision making that is indeed concerned with the composition of decision variables characterizing each solution. Even though this may seem obvious in everyday design practice, it is an important observation when it comes to justifying the approach taken for supporting post-Pareto design decisions.

Nonetheless, even though sampling from the non-dominated solutions found may be a viable approach in some cases, in others it is clear that it is too limited to reveal the full spectrum of potential formal expression suggested by the problem definition. As an example in Yufka et al. (2017) it is seen that, even though solutions that balance objectives are abundant within the population, they are still not enough to reveal potentially interesting formal combinations of the skylight modules. One can thus wonder if the set of discovered near-optimal solutions could be used in a cognitive strategy that could learn and generalize principles and patterns found therein, to augment the decision-maker's choice when exercising their preferences in a post-Pareto manner.

§ 3.5 Conclusion

This chapter presented a series of applications of intelligent computational decision support, in particular evolutionary computation, to a series of design problems that have been published throughout and in parallel to this research. The publications that have been reviewed demonstrate the application of intelligent methods and techniques to challenging design problems that demonstrate their potential. At the same time, limitations of such methods are made evident throughout the chapter. Such limitations have been pinpointed and revealed to establish the research premises for putting forward the problem statement and research questions proposed by this thesis, and better frame the proposed approaches that will be discussed in the following chapters.

4 Model Development

§ 4.1 Introduction

As already described in previous chapters, the proposed approach aims to address two crucial aspects in computational decision support, for architectural applications, namely: 1. Integrating the treatment of the soft design aspects, and in particular aspects in the domain of concrete design attributes, and 2. Managing computational burden due to computational complexity that defines accurate computational simulation models used in performance-based architecture practice.

To address these needed improvements, the proposed method allows to i. derive surrogate models that can drastically reduce computational cost in the early stages of design and ii. enable post-Pareto decision making based on preferences on concrete design attributes, while maintaining near-optimality concerning design objectives. The former is achieved through performing fitting and subsequent inference of appropriate machine learning models. The latter is achieved by associative machine learning models that inductively learn relationships between design features characterizing highly performing designs. The proposed method comprises a pre-optimization phase, where a model approximating the problem state-space is derived, an optimization phase where multi-objective optimization is performed, and a post-optimization phase where the preference model is derived and inference is performed.

The proposed approach forms a comprehensive Computational Intelligence-based decision support system for early-stage architectural design. In this sense, the proposed approach incorporates methods already employed in the field of Computational Intelligence and applications to architecture and augments their capabilities with novel developments aiming to address the research goals as set forward in this thesis.

Figure 4.1 presents an overview of the proposed decision support approach. This in contrast to figure 4.2, where an existing optimization-supported approach is presented.

§ 4.2 Parametric Model

The main role of the use of a parametric model is to encode the knowledge on the design problem at the early stage of design. In the parametric modeling paradigm, this knowledge is made explicit through the definition of constraints and relationships between the properties of the design object. In the context of an optimization problem, a-priori knowledge on the problem can be applied using parametric

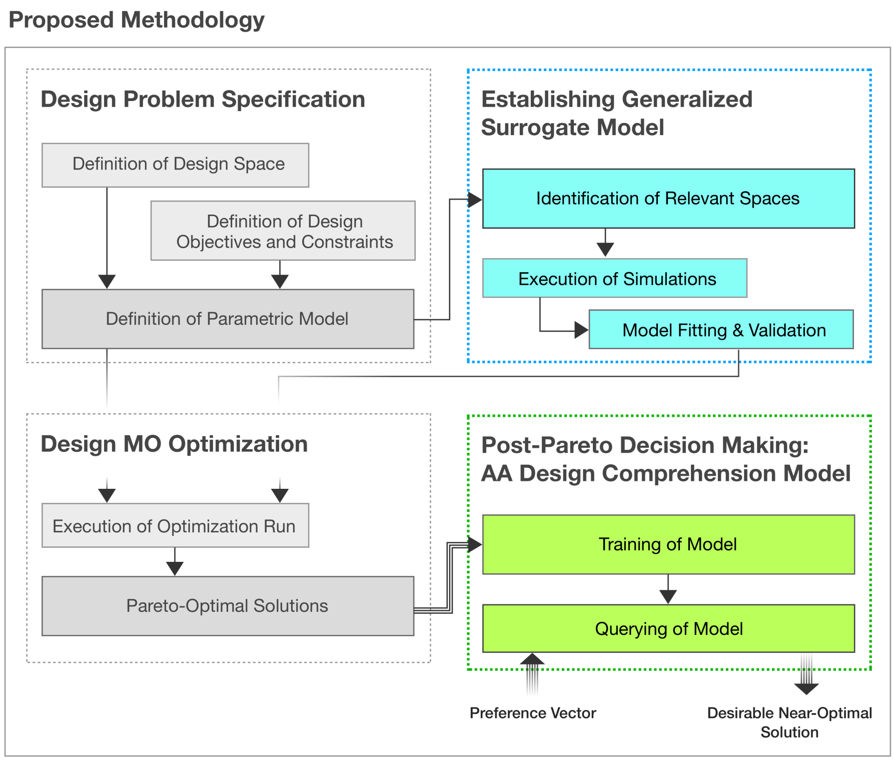


FIGURE 4.1 Overview of the proposed comprehensive Computational Intelligence-based design decision support approach.

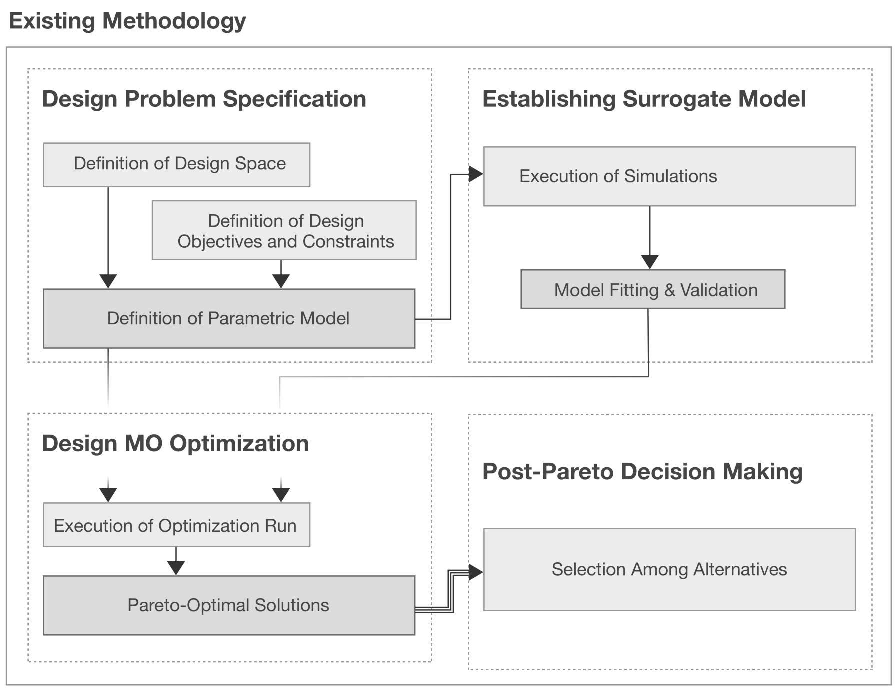


FIGURE 4.2 Overview of an optimization-based decision support approach.

modeling techniques to determine a mathematical problem definition, using geometric and numerical operations. The following aspects related to the design problem at hand are defined as part of a parametric model:

1. Definition of the quantitative design space, through the definition of design decision variables, including their type (i.e. continuous, discrete, categorical, or binary) and range constraints. The design space is the set of all possible combinations of model decision variable values, within the defined bounds.

2. Definition of relations between decision variables and objectives, through the definition of the relevant objective functions. This entails multiple sub-steps, as will be elaborated on right next. It is also noteworthy that in modern design practice most relevant objective functions are usually not available in closed form, rather it entails an iterative process of simulation using a model of the relevant physics domain (e.g. daylighting or thermal simulation), which is itself a computationally costly process.

3. Definition of relations between decision variables and constraints, similar to point 2.

4. Definition of any problem parameters that are not part of the optimization (i.e. are not decision variables), that serve to make the model adapt to design scenario variations.

In practice, a parametric model seldom defines purely mathematical expressions to achieve the points mentioned above. Rather, the use of advanced geometric generation, geometric analysis tools, and interfaces to external analysis (simulation) software is used. Reflecting this composition, a typical parametric model in an architectural design application can be broken down into a series of steps, each of which is necessary to fully define the problem objective functions and constraints. A usual sequence of steps found in a parametric design model can be summarized as follows:

1. Generation of problem-specific abstracted geometric forms

2. Establishing of problem-specific geometric analysis tools

3. Establishing of the connection with external analysis software

4. Establishing of the quantitative performance figures through mathematical combination of the analysis results

The parametric model occupies a central role of the orchestrator of the various processes involved, integrating them in an automated workflow that may be automatically executed from start to end as required.

§ 4.3 Multi-Objective Evolutionary Optimization

In the proposed approach the Multi-Objective Evolutionary Optimization occupies a central position as it is the intelligent mechanism through which discovery of Pareto-optimal solutions is guaranteed. The Multi-Objective Evolutionary Algorithm acts in the decision variable space defined by the parametric model and aims to identify best-tradeoff solutions that optimize objective functions defined as part of the parametric model. As an application in this thesis, the Non-Dominated Sorting Genetic Algorithm-II (Deb et al. 2002) is used, the functioning of which has been elaborated in chapter 2.

§ 4.3.1 Proposed Modular Surrogate Modeling Approach

The main aim of a surrogate model as integrated in the proposed approach is to address the computational complexity of modeling building performance simulations, in order to facilitate application in the early conceptual design stage. The aim of using a surrogate model is to approximate the value of an objective function defined as part of the design problem. As it is often the case that objective functions entail in their computation computationally complex simulations, the surrogate model aims at machine-learning-based approximation of the simulation results.

A common characteristic of simulation studies in architecture is that they refer to quantities represented by spatial distributions. In particular, these distributions refer to the indoors spaces of the building design at hand, representing quantities such as daylight, temperature, humidity, energy expenditure etc. Or, it is often the case that said indoors distributions concern a synthetic metric such as is often the case in daylight comfort studies, where metrics such as Daylight Factor (DF), Useful Daylight Illuminance (UDI), or Daylight Glare Probability (DGP) are represented by their indoors distributions. Even though aggregation of such distributions is often reported as a means of gaining an overall performance figure for a specific design, a decision-maker often needs the detailed information that is represented by the distribution to conclude as to individual spaces within a building or even individual arrangements within a space. A simple example is the positioning and orientation of a set of office desks in space to minimize glare.

Drawing from the above statements, the surrogate model proposed herein aims to be applicable in modeling quantities that are represented by distributions in indoor spaces. To this end, a specific type of surrogate model is proposed that has the following two properties:

- Its input is defined by a variable set that parametrically describe an abstract, flexible space that is designed to represent a wide range of possible spatial configurations and location conditions within a project (or even among several projects), and,

- its input includes a relative 2D point definition that corresponds to the point within the proposed space to be sampled.

The input variables of the model are selected in such a way that the model can approximate distribution in a variety of spaces subject to limitations on size, shape, and location of openings. In particular, the model that is proposed in detail in the following chapter applies to rectangular spaces of varying dimensions and window positions in one or two adjacent walls. However, considering different or increased requirements of a specific project it is possible to augment the input variables of such a surrogate model.

Multiple spaces in a single building may be modeled by multiple model inferences with different input values. In other words, instead of having a single model that computes the ultimate performance figure of a specific building design, the proposed model offers the potential of inferring performance figures for spaces within a building separately, and combine them in a way that is satisfactory to the decision-maker. Model inference takes a fraction of a second, as such even a large number of inferences is negligible in terms of computational cost, compared to simulation. As a result, complete interior arrangements of complex buildings may be modeled without a practical increase in model or simulation running time.

Besides, due to the flexibility of the model and the fact that it makes minimal assumptions regarding spatial features, there is great potential for model re-use even if radical changes occur in the building layout, by appropriately adjusting the values of the input variables. The overall method for deriving the model is presented in figure 4.3.

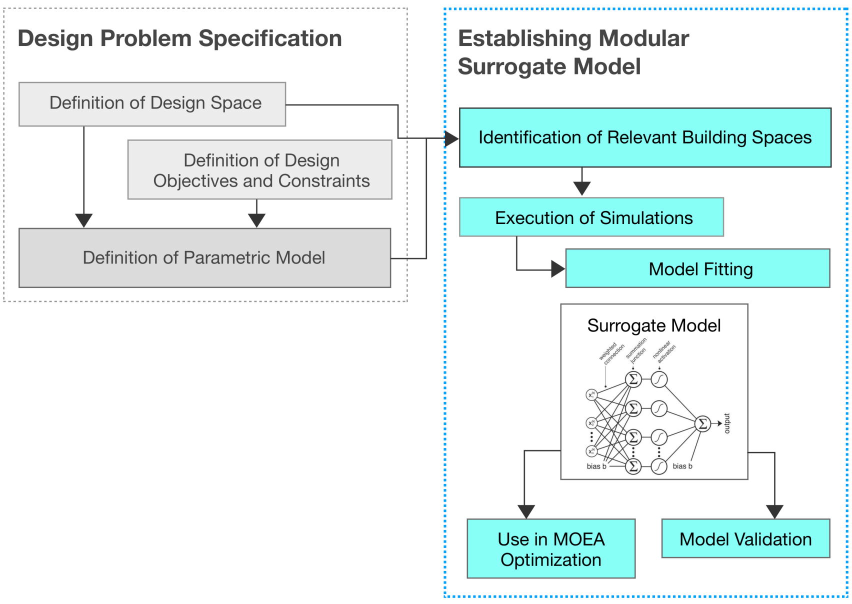


FIGURE 4.3 Proposed Modular Surrogate Model

§ 4.3.2 Application to Parametric Design

In the context of a real-world design task, the interest of course is in the application of the proposed model as part of a parametric building definition that can output detailed figures as to the quantities of interest, for multiple points and/or spaces. In practice, if the proposed model is considered as a module within a parametric definition, the steps required for model integration are as follows:

1. Identify all indoor spaces that are to be modeled,
2. translate concrete building and spatial properties into model-compatible input variables,
3. indicate required sampling locations and quantities
4. retrieve model outputs for specified locations and process as necessary

Through the above process, it is possible to accommodate major changes in design, by altering the indoor spaces and their attributes, while the model remains the same. This is in contrast to an "end-to-end" surrogate model, i.e. one that accepts design parameters as inputs and outputs aggregate figures, where re-fitting of the model would be necessary upon a major design change.

Due to the nature of the proposed surrogate modeling approach, it is expected that increased computational complexity is experienced compared to the case of an "end-to-end" model. This is understandable since several iterations of model inference need to be performed, one for each sampling point. However, given that most models perform inference that is many orders of magnitude faster than actual simulation, performance gains of even complex projects with 100s of sampling points are expected to be significant.

§ 4.3.3 Proposed Post-Pareto Preference Approach

It is worth pointing out that real-world design problems usually entail decision variable spaces of much higher dimensionality than the corresponding objective function space. On the contrary, the dimensionality of the decision variable space is usually much higher. In such a configuration, solutions that seem to evenly occupy a surface in the low-dimensional objective function space may be very sparsely located in the high-dimensional decision variable space. As such, it is evident that continuity in terms of object properties is not guaranteed to occur, and one may expect some physical features that might be desirable not to appear as part of the solutions identified by the stochastic search.

§ 4.3.4 Auto-associative connectionist models

From a structural viewpoint, auto-associative connectionist models are those whose inputs and outputs are the same, that is, they belong to the same domain. This is in contrast to, e.g., hetero-associative networks, where model inputs and outputs belong to different domains. From a functional viewpoint, an auto-associative network learns the latent relationships found in data during training. Upon excitation with a random input vector, the model exercises constraint satisfaction on the input data, based on the learned latent relationships. In other words, the model settles into the most likely interpretation of the input, based on the knowledge it has learned (McClelland et al. 2010). The relationships learned during the training of the model thus become so-called "weak" constraints for the input distribution (Maia and Cleeremans 2005). Here it is important to distinguish “weak” constraints, from the hard constraints commonly encountered in optimization problems. The precise difference is that, while weak constraints do incur a cost when violated, it is tenable to come across plausible solutions, even if some of the soft constraints are violated to some degree. This is in contrast to hard constraints where even an infinitesimal violation renders the corresponding solution infeasible in the context of the design problem addressed.

The property of constraint satisfaction has been extensively discussed in the past, and in various settings, such as machine learning (Maia and Cleeremans 2005; Vincent et al. 2008) language modeling (Prince and Smolensky 1997; Liou et al. 2008) and neuroscience (Sirois 2004; Maia and Cleeremans 2005), among others. In many studies, it has been shown that auto-associative models were able to extract efficient encodings of their environment. It has also been suggested that the constraint satisfaction function that auto-associative networks perform has been an important correlate for the function of the brain, and especially memory, e.g. see (Sirois 2004; Maia and Cleeremans 2005; McClelland et al. 1995; Kumaran and McClelland 2012), among others. It is especially important to point out the pattern-completion ability of the auto-associative networks, which stems from their constraint satisfaction property and corroborates with the auto-associative memory in human cognition.

Feed-forward and other types of connectionist models used in supervised learning may be used as auto-associators. The supervised learning task is then converted into an unsupervised learning task. This is achieved generally by forcing the network to learn a series of examples, where for each example the inputs and target outputs are the same. This type of model is called an autoencoder. An autoencoder takes its name from the fact that it learns an encoding corresponding to the distribution of its input. The objective of the autoencoder training thus is for the model to reconstruct its inputs:

$$\min_{\theta} ||X - f(X, \theta)||^2 \tag{4.1}$$

Notably, degenerate models learning the identity function are trivial to obtain given the above objective function. To prevent this, there are several training strategies proposed in the literature. Those are briefly summarized hereby.

One simple strategy when dealing with a Feed-Forward Network is to reduce the number of hidden nodes to less than that of the inputs. This enforces a compressed representation of the input at the hidden layer since the size of the layer is not large enough to be able to represent all the possible input value combinations. Another similar strategy makes use of an equal or larger number of nodes at the hidden layer but enforces a sparsity constraint during model training. Sparse encodings are those in which only a small fraction of hidden layer neurons are activated upon excitation of the model with each example. Thus, the loss function is modified suitably to account for the sparse encoding.

Another approach to training autoencoders is the introduction of a regularization parameter. Regularization has been used and considered efficient in preventing learning the identity function. In this case, the objective function becomes:

$$\min_{\theta} ||X - f(X,\theta)||^2 + \lambda \sum_{i} \theta_i^2 \tag{4.2}$$

In the above formula, the last term corresponds to an L2 regularization term, which is equivalent to the weighted squared sum of model weights.

Finally, another strategy is to train the autoencoder by partially corrupting the input data, while keeping the output data as is. This strategy enforces a more challenging reconstruction task to be learned, thus excluding the possibility for the identity mapping to be learned. In the reconstruction task, the objective function changes as follows:

$$\min_{\theta} ||\tilde{X} - f(X,\theta)||^2 \tag{4.3}$$

In the above, $\tilde{X}$ denotes a vector containing a corrupted version of the target value, X, obtained by altering some of the attributes of input examples. This training method produces models termed denoising autoencoders, from their ability to rectify noisy input. It has been applied to the training of feed-forward networks with many hidden layers (Vincent et al. 2010) and especially in the training of Deep Learning models.

§ 4.3.5 Auto-associative models in decision support and optimization

Several types of auto-associative networks have been used in optimization tasks. In a series of studies, auto-associative networks have been used to guide stochastic search. Authors of said studies have applied auto-associative networks known as Restricted Boltzmann Machines to combinatorial optimization problems (Tang et al. 2010; Probst 2015; Churchill et al. 2016), as well as autoencoders to real value and multi-objective problems (Prince and Smolensky 1997). The common aim in these studies is to take advantage of the constraint-satisfaction properties of auto-associative models to guide the stochastic search, utilizing them in a way analogous to the recombination and mutation operators in a genetic algorithm.

While the approach is similar to the one presented here, the objectives are different; in this section, the main objective is to use the knowledge embodied in the auto-associative model to guide decision-maker preferences post-optimization, to ensure near-optimality of preferable solutions. Thus, the model training is also modified and happens by considering the non-dominated solutions after the stochastic search has been finalized.

In another series of studies, Ciftcioglu and Bittermann have used RBF networks to treat second-order preferences in an engineering (Ciftcioglu and Bittermann 2015b) and an architectural problem (Ciftcioglu and Bittermann 2015a) involving soft objectives. The RBF network has been trained auto-associatively using non-dominated solutions identified through stochastic search. It is noted that while the study in question has objectives very similar to the present one, the present research is differentiated in the following points:

- The theoretical foundation of the auto-associative learning task differs in that emphasis is placed on the constraint satisfaction property of auto-associative models. This helps us expand the application of the proposed method to other types of models, such as Feed-Forward Networks trained by Backpropagation, and to the use of training techniques, such as input corruption (Vincent et al. 2010), to improve model generalization
- In this study quantitative model performance validation metrics are introduced
- In this study the performance of the auto-associative model is validated using an architectural design problem involving daylight comfort and energy-related objectives, thus demonstrating potential application to sustainable design

§ 4.3.6 Outline of the Approach

Successful designs are well-performing concerning design objectives, but also possess desirable physical features. The latter is an issue not directly addressed by computational optimization. Desirable physical features, albeit important for design, are not guaranteed to be present in the set of non-dominated solutions discovered by optimization.

In particular, the main aim of the approach proposed herein is to enable "attribute-first" post-Pareto decision making that considers preferences in the decision variable space as the driving components of decision making. This is in contrast to existing post-Pareto optimality analysis approaches as outlined above. At the center of the proposed approach is an auto-associative neural network whose main role is to approximate the empirical distribution of decision variable values derived from the Pareto-optimal solutions resulting from multi-objective optimization. The model is auto-associative: the model input is a vector of the same dimension as the model output, and each input-output pair has the same semantic. In other words, the model accepts a design solution, expressed as a decision variable value combination, as input, and produces a transformed combination of the decision variables in the design space, as output.

What is the significance of this transformation? Let us begin explaining it by considering that the model input vector encodes the decision-maker design preference, expressed through selected decision variable values. It is important to stress that decision variables are associated with the physical attributes of the design solution. As such, by establishing a vector in design space, a decision-maker is essentially stating their preference in terms of object attributes. It is uncertain to what degree a decision-maker can comprehensively consider the performance of the design corresponding to their choice of decision variable values, due to the complexity of the problem at hand. As such, the selected design may or may not be near the Pareto front. If the selected design is not near the Pareto front, i.e. it is sub-optimal, there is a significant problem arising as the decision-maker preference seems to conflict with design performance.

If the preferred design is sub-optimal, and there is a significant conflict between the preferred decision variable values and any combination of optimal or near-optimal decision variable values, then there is little to do. The decision-maker needs to review their preferences so that they are in line with design performance. On the other hand, if the adjusted solution is already near-optimal, then there is no action necessary. There is also a third possibility, however, namely that the preferred design, as is, is sub-optimal, but it is possible to improve its performance with the limited transformation of decision variable vector so that the transformed vector is not unlike the original, but the corresponding performance is significantly improved.

This is the main premise behind the proposed auto-associative approach: The model input is transformed based on the model knowledge in such a way that the model output vector encodes a near solution, in decision variable space, to the preferred input vector, while having the property that it belongs to the set of Pareto-optimal solutions. In other words, the system, based on the learned knowledge matter, can respond so that features and combinations thereof that negatively affect design performance are eliminated, to the degree possible within the bounds of the problem definition.

In reality, the input to the model is not an arbitrary vector in the design space, rather it is a near-optimal solution that has been altered by the decision-maker to better fit their preferences. As such, in practice, it is almost always the case that an informed and accurate adjustment of decision variable values has the potential for significant performance increase.

The overall scheme of the proposed method is available in Fig. 4.4. On the left side of the figure (step 1 & 2), the intelligent search process, implemented through multi-objective stochastic search, is outlined. The result of this process is a finite set of non-dominated solutions. This set is used to fit the auto-associative model through neural network training (step 3). In the inference phase (step 4), a preference vector is an input to the resulting model, and the model response is retrieved as required.

§ 4.4 Integration in the Design Process

§ 4.4.1 Proposed Workflow

The proposed approach, as outlined above, is most suitable to be implemented as a decision support system in the early stages of the design process. Owing to the importance of the parametric model definition, it is generally desirable that the design process has advanced enough so that the design intention is clearly expressed in the parametric model.

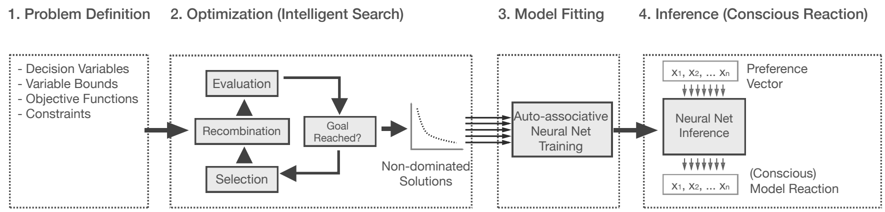


FIGURE 4.4 Overview of the proposed auto-associative preference treatment method. Steps 1 and 2 constitute the intelligent search for optimal instances. In step 3 instances are used to train the auto-associative model. In step 4 the trained model receives the preference vector as input, and responds with a decision variable vector corresponding to a solution that ensures design performance and desirability, to the extent possible by the problem definition.

The proposed approach comprises a series of software tools that work together to execute the desired task. To enable efficient decision making and avoid cognitive fatigue, a high-level interface is proposed that obscures the underlying technical complexity of the proposed techniques. This interface is found outside the typical parametric design environments common to architectural practice nowadays. The main reason is that even though parametric design tools are becoming more and more commonplace nowadays, their complexity is still intimidating for many design professionals, and poses the threat of undermining the attention of the user.

With this in mind, the proposed workflow comprises the following discrete stages:

1. A technical expert, under the guidance of the decision-maker, prepares a parametric model corresponding to the design intention, performance considerations, and design constraints, including setting up the necessary hardware and software infrastructure for carrying out the proposed approach.

2. A technical expert prepares an initial surrogate model. This process comprises several steps, indicatively appropriate sampling of the decision variable space, statistical analysis to establish distributions and correlations, optional refinement of sampling according to analysis, fitting of the model, and validation of model performance.

3. The optimization process is carried out and Pareto-optimal solutions are obtained. At this stage, the update of the surrogate model may take place per the validation of results. In this case, unless the surrogate model is adaptive, repetition of the optimization process may be necessary.

4. A technical expert derives an auto-associative model based on the Pareto-optimal solutions obtained in the previous step.

5. Under the guidance of the expert, the decision-maker can focus on the design space regions of interest according to their preferences, through the use of the auto-associative model.

The role of the technical expert in the above workflow is to ensure that technical procedures are applied correctly and to identify and amend potential issues throughout the process. This is mostly necessary as the approach proposed in this thesis is not at a high TRL at the moment. As future steps, further technical development of the workflow and tools involved therein should take place to increase TRL, which will also result in minimization of the requirement for human experts and further automation of the overall workflow.

§ 4.4.2 Software Architecture and Implementation Details

The proposed approach is implemented as an integrated application suite that includes all the necessary components for performing surrogate model fitting, multi-objective evolutionary optimization, and finally auto-associative model fitting. Besides, the suite includes an interface that allows the user to vary the values of decision variables and discover the response of the auto-associative model in real-time. From a technical standpoint, the development view of the architecture is split into two major parts: On one side, a parametric design environment is used to define the design problem in terms of geometric generation and analysis components. Moreover, the parametric design environment offers interfaces to the various simulation tools used, such as e.g. Radiance for daylight simulations, EnergyPlus for climate and energy simulations, etc. Finally, the parametric setup includes a simple API that serves to enable altering design decision variables and obtaining objective function and constraint values. On the other side sits an interface application to Computational Intelligence algorithms outlined in this thesis, namely the Evolutionary Computation algorithm, the Surrogate Model, and the Auto-Associative model. These communicate with the parametric design environment via the defined API and otherwise perform tasks using internal data. Part of the interface application is a Human-Machine Interface (HMI) that allows the decision-maker to interact with the program and receive to the point summary views of the process.

In line with what has been outlined in this chapter, an important aspect of software implementation is the choice of the parametric environment. Due to the familiarity of the author with a particular parametric design tool, namely the Grasshopper parametric design tool, it has been chosen as the platform for this thesis. The choice has been purely due to the author being accustomed to this particular tool. It is important to point out that the proposed approach and individual components therein should be trivially adaptable to other parametric design software.

A development view of the software architecture is available in figure 4.5. Elaborate treatment of the software architecture of the proposed approach is elaborated in detail in a relevant publication by the author (Chatzikonstantinou 2016).

§ 4.5 Conclusion

This chapter served to present the proposed cognitive approach in detail, elaborating on each of the individual components and associated methods therein. The proposed approach comprises two main cognitive components, namely: An adap-

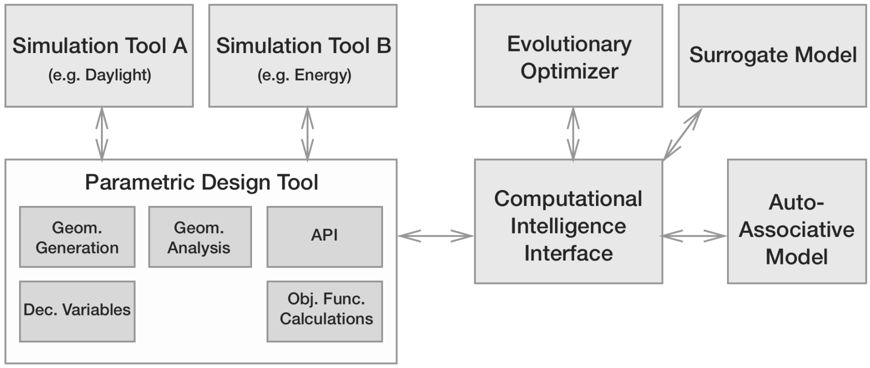


FIGURE 4.5 Development view of the software architecture of the framework proposed by thesis

tive and modular surrogate modeling method that enables managing computational burden due to computational complexity that defines accurate computational simulation models used in performance-based architecture practice, and a cognitive method for the treatment of soft design aspects, and in particular preferences in the domain of concrete design attributes. The proposed approach forms a comprehensive Computational Intelligence-based decision support system for early-stage architectural design. In this sense, the proposed approach incorporates methods already employed in the field of Computational Intelligence (namely, evolutionary multiobjective computation) as well as tools commonly found in advanced architectural practice such as Parametric Modeling, and augments their capabilities intending to improve decision support in architectural design.

5 Case Studies

Introductory Note

In this chapter two published case studies are presented, each of which aims to highlight the application of one of the two components of the proposed approach to architectural design cases borrowed from real-life design scenarios.

The first case study aims to validate the proposed surrogate modeling method. It does so through a series of individual investigations namely i. an extended algorithmic comparison and parameter search thereof, ii. a comparison of results between the algorithms and the actual simulation results, and, iii. an actual small-scale case study demonstrating the use of the surrogate model as a decision support tool in the arrangement of an indoor space of an office building.

Through the above, two main aspects of the proposed method aim to be validated. Firstly, the hypothesis that machine learning algorithms offer models that able to encode the knowledge embedded in simulations of parametric models, as defined in the case studies, and to the degree that would be satisfactory for use in the preliminary architectural design stage. This includes a comparison of a few different algorithms, as well as parameter search to identify the best performing parameter combination. Secondly, it is aimed to validate the usefulness of the proposed method in a design context, through qualitatively evaluating its applicability in a small-scale design study of office interior.

The research reported in this case study has been published as part of the following paper:

> I. Chatzikonstantinou and S. Sariyildiz, "Approximation of simulation-derived visual comfort indicators in office spaces: a comparative study in machine learning," Architectural Science Review, no. August 2015, pp. 1–16, Aug. 2015.

The second case study aims to validate the proposed post-Pareto decision support method using an auto-associative model. Here, two aspects aim to be validated: The first concerns algorithm performance; regarding this aspect, a first step is to define the notion of performance in the context of the task at hand, which is performed through the introduction of novel performance metrics. Secondly the actual evaluation and comparison of two different machine learning algorithms underlying the proposed method and resulting model, and in terms of the proposed metrics, is presented. The second aspect concerns validating the applicability of the proposed method in an actual design study. In this case, a scenario is derived for an office building situated in an urban area, where the facade openings and shading devices are designed in an integrated manner. The aim is thus to qualitatively validate the extent to which the proposed method can satisfy preferences while adhering to design goal satisfaction.

For this case study, a multi-objective optimization is performed with the objectives of improving indoors daylight distribution and minimizing energy losses, whereby a population of Pareto-optimal solutions is identified. Subsequently, the auto-associative model is trained on that population, and performance is evaluated. Part of the study focuses on the derivation of novel metrics to evaluate model performance, as the task that the model supports is unique and no such metrics exist up till now. Moreover, a comparison between two different algorithms is performed, Feed-Forward Networks and Radial Basis Function Networks. Finally, algorithm outputs are presented in terms of performance as well as a visual comparison for the shading device designs.

The research reported in this case study has been published as part of the following paper:

> I. Chatzikonstantinou and I. S. Sariyildiz, "Addressing design preferences via auto-associative connectionist models: Application in sustainable architectural Façade design," Automation in Construction, vol. 83, no. August, pp. 108–120, 2017.

§ 5.1 Case Study I: Surrogate Approximation of Interior Daylight Distribution

The first case study aims to evaluate the proposed surrogate modeling approach in approximating the interior daylighting distribution of a single office space set in an urban setting. The case study primarily aims at determining the accuracy of the surrogate models that are derived through the proposed method. Besides, the case study presents a comparison of three models derived using different machine learning methods. Finally, a model parameter estimation study and an application of the resulting models to a decision making problem concerning the interior arrangement of said single office space optimizing visual comfort are presented.

§ 5.1.1 Algorithm Selection

As part of this case study, three machine-learning techniques are being compared: feed-forward networks (FFNs) trained by backpropagation, support vector machines (SVMs), and random forests (RFs). Besides, k-nearest neighbors (kNNs) are included as a performance comparison. FFNs are one of the most widespread machine-learning algorithms. RFs are a widely adopted algorithm, with multiple applications in regression, for example (Fanelli et al. 2011; Denil et al. 2014). Besides, SVMs have been frequently used in function approximation tasks in the literature (Jin 2005). Finally, kNN is added for performance comparison.

§ 5.1.2 Algorithmic Implementations

The machine-learning experiments outlined in this section have all been carried out using tools available as part of the R statistical programming language (Bunn and Korpela 2015). In particular, the following packages have been used:

- nnet Venables and Ripley (1994)
- kernlab Karatzoglou et al. (2004)
- knn Venables and Ripley (1994)
- randomForest Liaw and Wiener (2002)

In addition, the package "caret" (Kuhn 2015) has been extensively used for performing cross-validations and parameter grid search.

§ 5.1.3 Approximation of Visual Comfort Indicators

Visual comfort of interiors is a complex topic, due to the various parameters that need to be taken into account. Several different factors contribute to a visually comfortable working environment. Ruck identifies four main performance factors relating to visual comfort: illuminance, glare, distribution, and direction (Ruck 2000). For the scope of this study, the first two are investigated: illuminance and glare. The Daylight Autonomy (DA) metric (Reinhart and Walkenhorst 2001) is chosen for illuminance, and the Daylight Glare Probability (DGP) metric (Wienold and Christoffersen 2005) is chosen for glare.

Daylight Autonomy (DA) has been one of the first of a series of climate-based, annual daylight metrics, which have been introduced in the past few decades. DA, in its current interpretation, has been introduced by Reinhart and Walkenhorst (Reinhart and Walkenhorst 2001). In their study, the authors define DA as a physical quantity that denotes the fraction of a considered time interval during which a minimum illuminance level can be maintained by daylight alone (Reinhart and Walkenhorst 2001). In our case, 300 lux has been considered the minimum suitable illuminance level for office work (IESNA 2000). Furthermore, the time interval that corresponds to standard weekly working hours in an office environment, that is, 9 am to 5 pm, is considered. In publications following that of Reinhart and Walkenhorst, a manual blind control model that predicts the status of movable shading devices at all time steps in the year further refined the concept of DA (Reinhart et al. 2006). In this study, those refinements are not considered.

Daylight Glare Probability (DGP) is an indicator developed by Wienold and Christoffersen, which indicates the probability that a person would experience the effects of glare from a specific viewpoint in the interior space (Wienold and Christoffersen 2005). DGP is dependent on two factors: glare due to scene brightness, and glare due to scene contrast. These two are summarized in the calculation of DGP as follows:

$$
\begin{aligned}
DGP = & 5.87 \cdot 10^{-5} \cdot E_v + 9.18 \cdot 10^{-2} \\
& \cdot log(1 + \sum_i \frac{L_{s,i}^2 \cdot \omega_{s,j}}{E_v^{1.87} \cdot P_i^2}) + 0.16
\end{aligned}
\tag{5.1}
$$

In the above equation, E_v is the vertical illuminance at eye level in lux and depends on the orientation of the plane perpendicular to the direction of gaze. L_s is the luminance of the source in cd/m2, ω_s is the solid angle of the source in sr and P is the Guth position index.

A raytracing-based approach using Radiance, and the Evalglare tool (Wienold 2013) is employed to identify potential glare sources and accurately calculate the DGP. Initially, radiance is used to generate a high dynamic range, wide-angle image of the interior of the office, from a specific viewpoint. This image is then inputted to the evalglare tool, which is responsible for calculating DGP. It should be noted that the image produced by radiance is an intermediate step only used for determining DGP, and is not used further for this study.

TABLE 5.1 Independent variables of the office model

	Variable	Unit	Range
Room Meas.	Office Width	m	[3,7]
	Office Length	m	[3,7]
	Office Height	m	[2.5,3.5]
Room Orient.		rad	[0,2π]
Wall A	Window X-Pos	%	[0, 100]
	Window Width	%	[0, 100]
	Window Height	m	[1.2, 2.1]
Wall B	Window X-Pos	%	[0, 100]
	Window Width	%	[0, 100]
	Window Height	m	[1.2, 2.1]
Meas. Point	X-Pos	%	[0, 100]
	L-Pos	%	[0, 100]
	Viewing Dir.	rad	[0,2π]
Time	Time of Day	h	[9, 18]
	Time of Year (days to 21st June)	days	[0, 182]

§ 5.1.4 Parametric Office Model

A computational model of an office has been developed using parametric design techniques. The orientation and dimensions of the room, as well as dimensions of openings, are the parameters of the model. The model can represent offices ranging from three by three meters up to seven by seven meters, with windows of variable positions and sizes, on one or two adjacent walls. Thus, the model covers the most common cases of row and corner offices. An overview of the parameters and their units and ranges is given in Table 5.1. A diagram showing an instance of the model together with parameters is presented in Figure 5.1. The office model has been set in a simplified virtual urban environment, with building volumes enclosing the office volume at a distance of 30 m on all sides, which is presented in Figure 5.2.

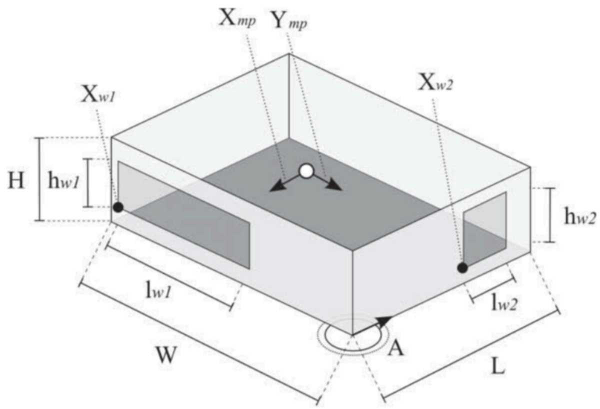


FIGURE 5.1 Parametric model of the office showing parameters and corresponding dimensions.

For the modeling of surfaces and exterior openings, standard materials included in the radiance materials database have been used. Namely, for the modeling of the floor, 'Generic Floor 20% Reflectance' was used; for walls, "Generic Interior Wall 50% Reflectance"; for ceiling, "Generic Ceiling 80% Reflectance" and for the openings, the "EC-Clear" type of glazing. While, for the scope of this research, properties of materials are not included as independent variables, it is intended to include them in future research.

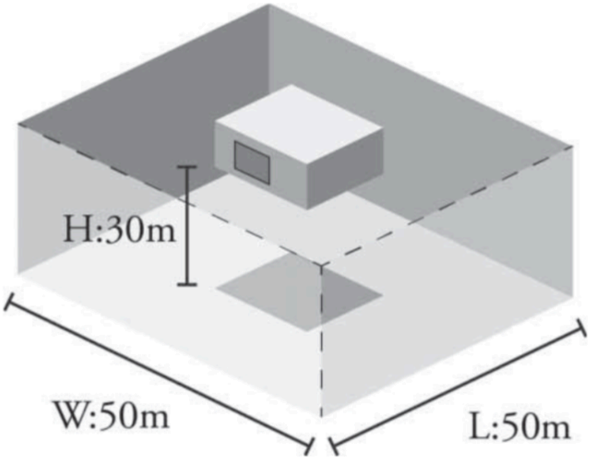


FIGURE 5.2 Placement of the office module within a virtual urban context.

Two similar versions of the model were generated, each specific to the calculation of the two different metrics, DA and DGP. The calculation of DA is performed annually, and requires location data since it makes use of illuminance figures. The DGP calculation requires both location and temporal data to be specified. For both cases, the location of Izmir, a city on the East coast of Turkey, coordinates: 38°26 N 27°09 E, has been selected. The time of day and time of year are independent values in the case of DGP, resulting in the dimensionality of the DGP dataset being higher than that of the DA dataset.

Since the focus of this study is on office environments, it is reasonable to consider that knowledge about visual comfort at working position is most relevant. As such, DA measurements were performed on the working plane. This has been considered as a horizontal plane set at 0.75 m over the ground. Concerning glare, measurements were performed from viewpoints located at a height of 1.22 m, which approximately corresponds to the average eye level for a person working at a computer terminal. Figures about the eye level and working plane positions were obtained by Neufert (Neufert and Neufert 2002). A visual representation of the working position while using the table surface is provided in Figure 5.3. The corresponding position while using a computer is given in Figure 5.4. Measurement configuration for DA is available in Figure 5.5 and for DGP in Figure 5.6. Besides, the latter presents results of the radiance simulation (b, c), as well the areas of the image that are primary causes of glare, as determined by the evalglare tool (d).

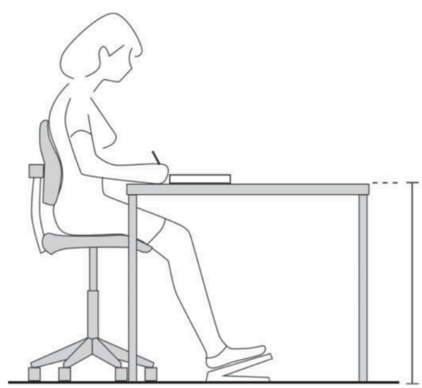


FIGURE 5.3 Working position utilizing working surface for reading and writing tasks. Adapted from (Neufert and Neufert 2002)

Measurement points for the DA analysis were distributed along a one by one-meter grid. Subsequently, each point was perturbed by a random distance of up to 0.5 m. This was decided to better ensure that generalization is sufficient for a wider variety of indoor measurement points. As such, a semi-random measurement grid was derived, which was used for the calculation of DA values.

The light simulations were carried out using the Radiance program (Ward 1994), version 4.2.a-win32, using high-quality settings. Radiance is a stochastic ray tracing light simulator that has been extensively validated and is suitable for use in architectural simulations. The glare calculations were carried out using evalglare version 1.11. Two interface programs, termed DIVA and Honeybee, were used to

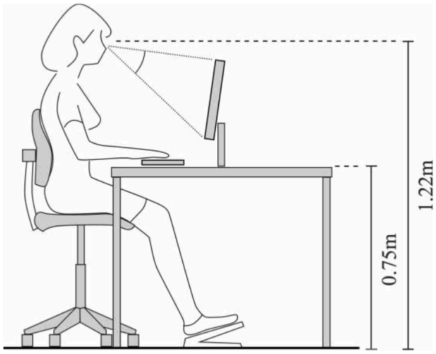


FIGURE 5.4 Working position utilizing a computer terminal. Adapted from (Neufert and Neufert 2002)

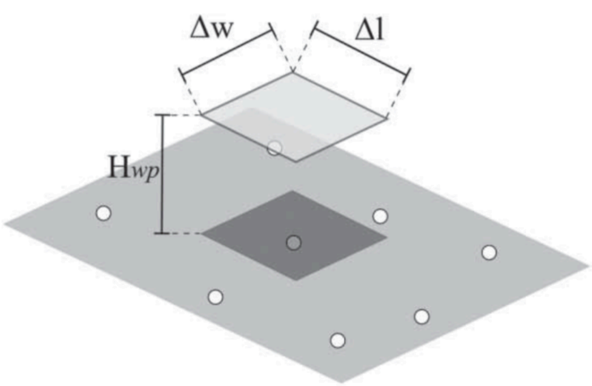


FIGURE 5.5 Measuring arrangement for daylight autonomy in radiance, showing the infinitesimal horizontal measurement surface.

allow easy use of Radiance through the Rhinoceros CAD platform. The values of the settings used are available in Table 5.2. A screenshot of the measurement set-up in the Rhinoceros program can be seen in Figure 5.7.

TABLE 5.2 Parameters of the Radiance simulations

Parameter	DA Sim Value	DGP Sim Value
Ambient Bounces (ab)	3	3
Ambient Resolution (ab)	800	800
Ambient Accuracy (aa)	0.03	0.02
Ambient Divisions (ad)	1500	2000
Ambient Supersamples (as)	192	256

The simulations described above frame the approximation problem sufficiently. This is a problem of approximating a function with 12 and 15 independent variables, for DA and DGP respectively, and a single dependent variable in each case. The functions are highly non-linear and, in the case of DGP, highly sensitive to factors such as the orientation of space and viewpoint, as well as discontinuous in some cases. For the case of DGP, it is thus reasonable to expect a lower model fidelity than that of DA.

§ 5.1.5 Data Preparation

Two datasets were produced from simulations, according to the procedure described above. The first one contains the results of DA simulations and comprises 12 independent variables, one dependent variable, corresponding to DA, and 2000 samples. The second dataset contains the results of DGP simulations and comprises 15 independent variables, one dependent variable, corresponding to DGP, and 3000 samples. The datasets will be herein referred to as DA dataset and DGP dataset, respectively. Summaries of the dependent variables in the generated datasets are available in Table 5.3. Dependent variables in both datasets exhibit skewed distributions. In particular, the dependent variable in the DA dataset exhibits a negative skewness. It exhibits a minimum of 0.0, a maximum of 97.0, a mean of 73.9, and a standard deviation of 31.06. The dependent variable of the DGP dataset exhibits positive skewness. It has a minimum value of 0.002, a maximum of 1.0, a mean of 0.262, and a standard deviation of 0.148.

To investigate the effect of skewness on the learning performance of the models, training and validation runs were performed also for a separate series of datasets, where dependent variables have been transformed to achieve a distribution closer to normal. The transformations were different for the DA dataset, and the two DGP datasets. For the DA dataset, with negative skewness, a reflected logarithm-based transformation was applied:

$$X_T = -log(-X_R + C_1) + C_2 \tag{5.2}$$

In the above equation, C1 is selected so that the minimum value of $-X_R + C_1$ is equal to 1.0, and C_2 so that the minimum value of X_T is equal to 1.0.

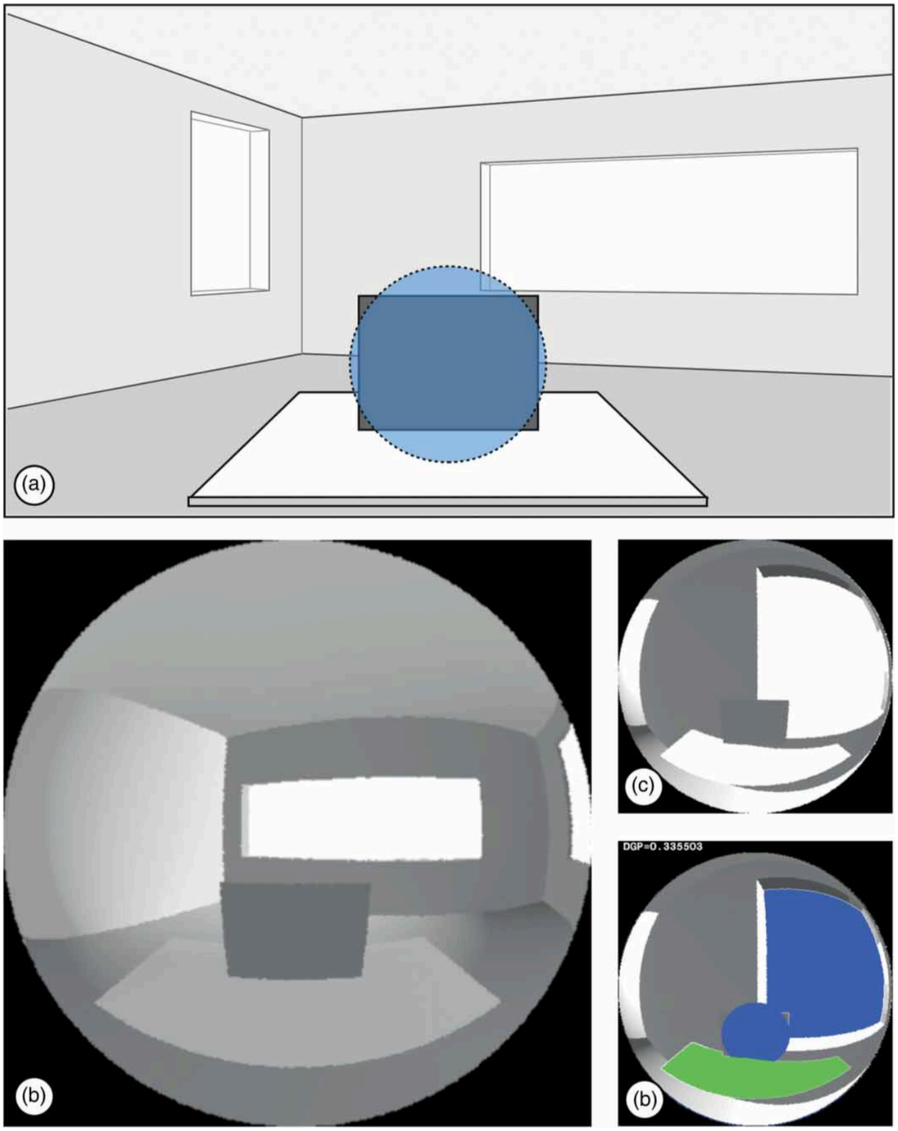


FIGURE 5.6 Measuring arrangement for daylight glare probability, showing the scene set-up with the area of interest (blue circle, a), the output from a fish-eye rendering in radiance (b, c) and the evaluation of glare sources by evalglare (d).

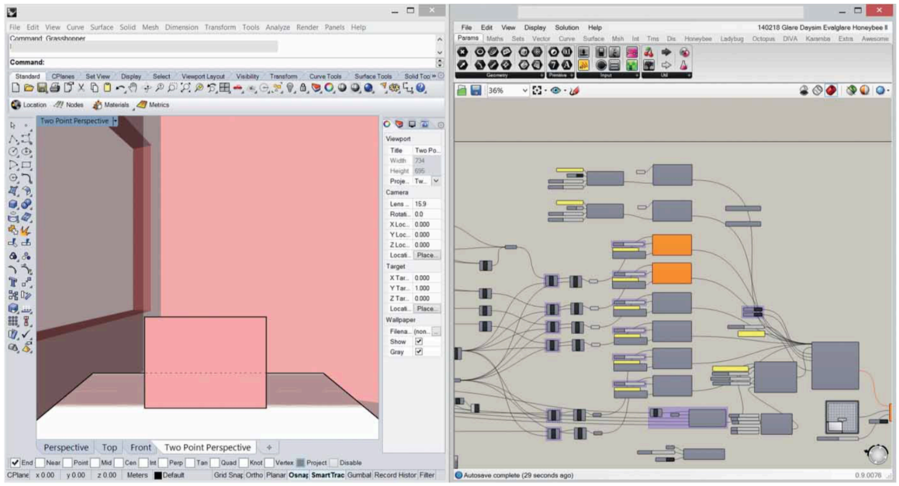


FIGURE 5.7 Simulation set-up in the Grasshopper parametric environment.

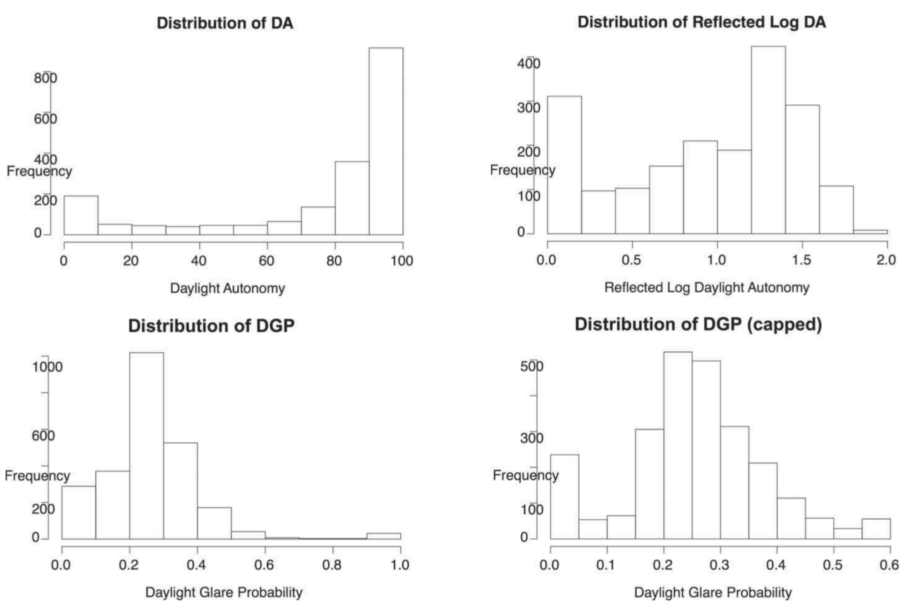


FIGURE 5.8 Histograms of the original and transformed DA and DGP datasets.

TABLE 5.3 Summary of the dependent variables of the two datasets

	Attrib	Samples	Min	1st Q	Median	Mean	3rd Q	Max	SD	Skewness
DA	13	2000	0.00	70.00	90.00	73.92	94.00	97.00	31.06	-1.4712
DGP	16	3000	0.0029	0.195	0.2538	0.262	0.325	1.00	0.148	1.5118

In the case of the DGP dataset, values above a DGP of 0.6 were truncated to 0.6. This led to distribution much closer to normal. The rationale for this transformation was based on two observations, namely i. very few DGP values exceeded 0.6, and ii. any value above that threshold can be said to be generally unsatisfactory, and as such differentiation between values is not strictly necessary.

In all cases, it was found that the transformations were beneficial to the performance of the models. In the following discussion, results based on the transformed datasets are considered. Figure 5.8 presents histograms of dependent variables for the original and transformed datasets.

§ 5.1.6 Model Configuration

§ 5.1.6.1 Objective Functions

The evaluation of the methods' prediction accuracy was based on two statistics, namely the Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i}(y_i - f_i)^2} \tag{5.3}$$

and the Coefficient of Determination R^2:

$$R^2 = 1 - \frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{5.4}$$

where N is the number of test predictions, y_i is the observed value and f_i is the predicted value. The R-squared statistic offers an understanding of the amount of total variance in the dataset that may be explained by the predictive model. In all cases, the derivation of prediction performance figures for each model has been based on 10-fold cross-validation.

§ 5.1.6.2 Determination of Model Parameters

For each of the models considered, an investigation in establishing suitable hyperparameters has been conducted. In this section, a brief mention of each model's hyperparameters, as well as the results of the investigation is discussed. This investigation made use of a grid search along a few crucial parameters of each model. Where additional parameters beyond the ones considered existed, they were kept at the default values offered by their respective implementations.

The crucial parameters of the FFN structure are the activation function, the number of hidden layers, and the size of each hidden layer. Besides, in regularized networks, the regularization parameter, Lambda, is of great importance. For this investigation, a variable number of hidden nodes, as well as different values for the regularization parameter Lambda were considered. The most crucial parameter to determining RFs models is the number of tree estimators that are grown as part of the training process. This variable is varied ranging from a value of five, up to 200. SVMs are defined mainly by the C parameter, and, in the case of radial basis function (RBF)-based SVM, as in our case, the width of the kernel plays a significant role as well. For this model, a 2D grid search for the above parameters is performed. Finally, a defining parameter in the case of the kNN model is that of k, the number of neighbors to consider.

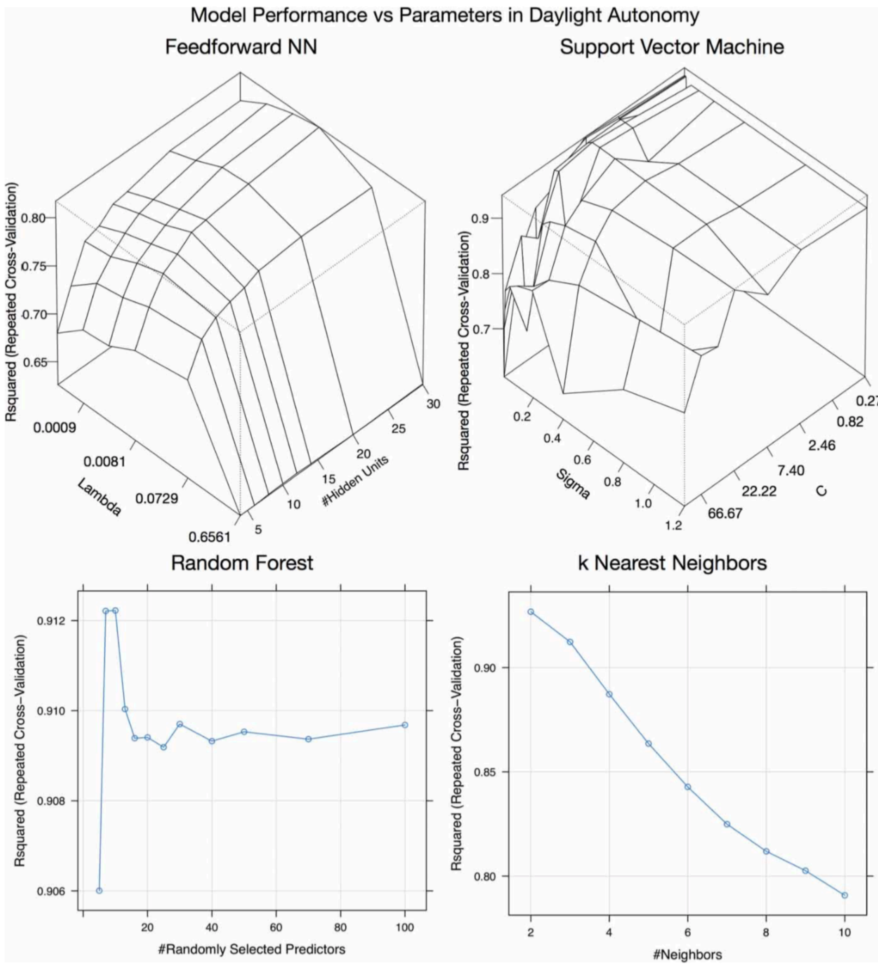


FIGURE 5.9 Approximation performance for different hyperparameter values, DA dataset.

Results of the hyperparameter grid search are available in Figures 5.9 and 5.10. Table 5.4 presents a summary of the optimal configurations identified for each model. The following is observed: (i) the relative insensitivity of the performance of the RFs predictor to the number of regressors, (ii) on the contrary, the sensi-

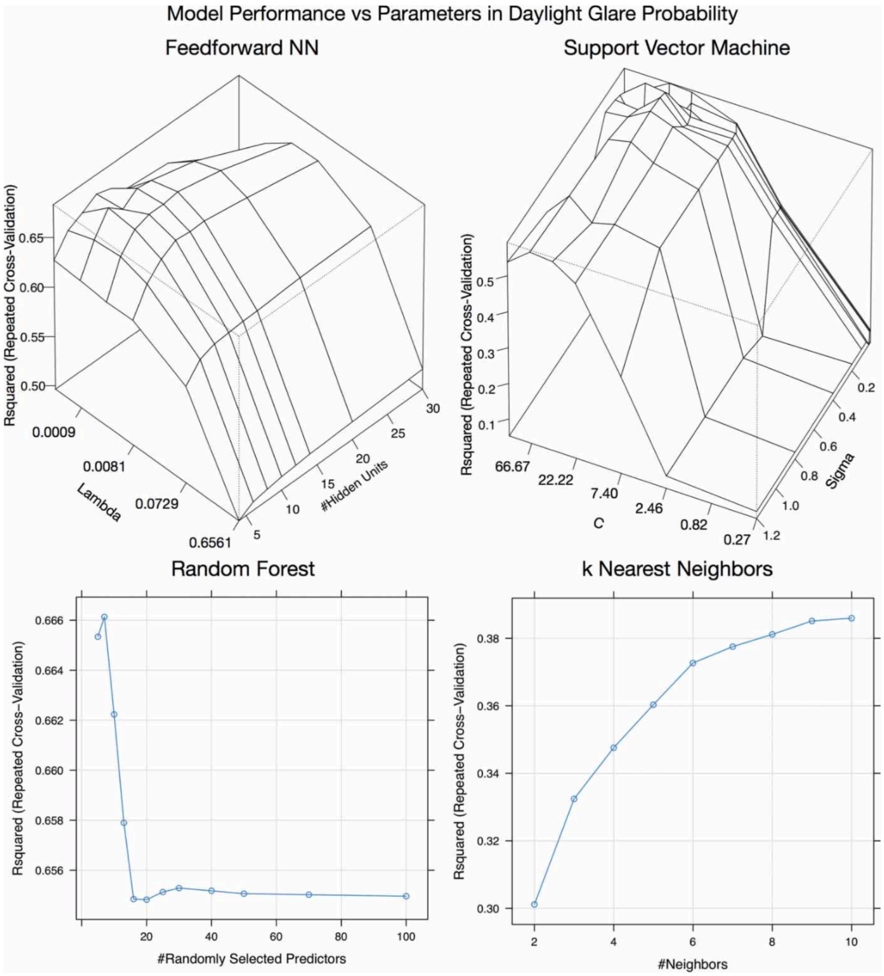


FIGURE 5.10 Approximation performance for different hyperparameter values, DGP dataset.

tivity of the FFN and SVM to the regularization parameter Lambda, and the cost parameter respectively and (iii) the antithetical influence on the kNN predictor, concerning the two datasets, of the number of neighbors, k.

TABLE 5.4 Optimal parameter configurations for the learning models

	SVM-RBF		FFN		RF	kNN
Optimal Value	C	Sigma	λ	k	#regressor	k
DA	66.7	0.1	0.027	30	10	10
DGP	66.7	0.02	0.027	14	10	2

§ 5.1.6.3 Model Bias and Variance

The Learning Curves method is employed to evaluate the models with respect to bias and variance. Learning curves represent the generalization performance of the model as a function of the size of the training set (Perlich 2010). Learning curves plot the change in training and cross-validation error versus the increase in training set size. When trained on small training sets, it is expected that estimators (even high-bias ones) will be able to provide good approximations on the training set but perform poorly on cross-validation. As the training set increases, the prediction error on the training set increases, but the cross-validation error decreases. The difference between training and cross-validation error at full training dataset size provides an indicator of the expected benefit if more training data are added, which is closely related to the variance of the estimator.

Figure 5.11 depicts the Learning Curves for the case of the DGP dataset. It is observed that the models perform similarly, with training and cross-validation error of the RF estimator converging to a slightly lower RMSE, and that of SVM-RBF to a slightly higher, while the kNN estimator demonstrates significantly larger cross-validation error. Learning curves for the DA dataset indicate a similar situation, although in that case, the difference between training and cross-validation prediction is higher, indicating that adding more samples could have a beneficial effect. However, given the excellent cross-validation performance of the models in the case of the DA dataset, the choice was not to extend the dataset further. Given these results, it is reasonable to argue that no further benefit may be acquired by the extension of the datasets.

§ 5.1.7 Results and Discussion

§ 5.1.7.1 Approximation Performance

Table 5.5 presents a summary of model performance. In approximating DA, it can be seen that all models achieve good generalization performance. In terms of the R2 metric, FFN achieves a cross-validation value of 0.812; SVM-RBF, a value of 0.941; RF, a value of 0.912 and kNN, a value of 0.927. The best-performing

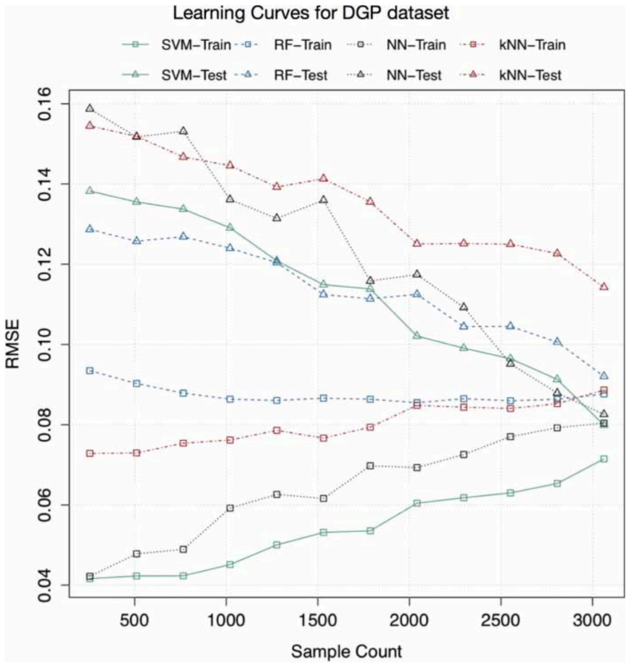


FIGURE 5.11 Learning curves for optimal model configuration, DGP dataset.

model is SVM-RBF, while RF exhibits an error that is significantly greater than the others.

TABLE 5.5 Optimal parameter configurations for the learning models

	RMSE (SD)		R^2(SD)	
Method	logDA	DGP	logDA	DGP
FFN	0.329(0.009)	0.071(0.004)	0.812(0.023)	0.682(0.044)
RF	0.164(0.015)	0.074(0.004)	0.912(0.018)	0.662(0.039)
SVM-RBF	0.131(0.012)	0.080(0.005)	0.941(0.011)	0.591(0.046)
kNN	0.147(0.019)	0.099(0.004)	0.927(0.021)	0.385(0.051)

Figure 5.12 depicts a visual comparison of two radiance simulations with different settings and a prediction made by the SVM-RBF predictor, for the DA metric. Two scenarios were investigated. In the first scenario, an office of 5 by 6 m, facing southeast, with windows in the southwest and northwest sides is considered. The approximation captures the main features of the high-quality DA simulation, but fails to capture some details, mainly located in the corners of the room. In the second scenario, an office of 4 by 5 m and a single window in the west wall is considered. In this scenario, the approximation produces an elongated distribution, which, in the southmost part of the office, is deviating from the simulated values.

In approximating DGP, the performance of the models drops significantly. In terms of the R2 metric, FFN achieves a cross-validation value of 0.682; SVM-RBF, a

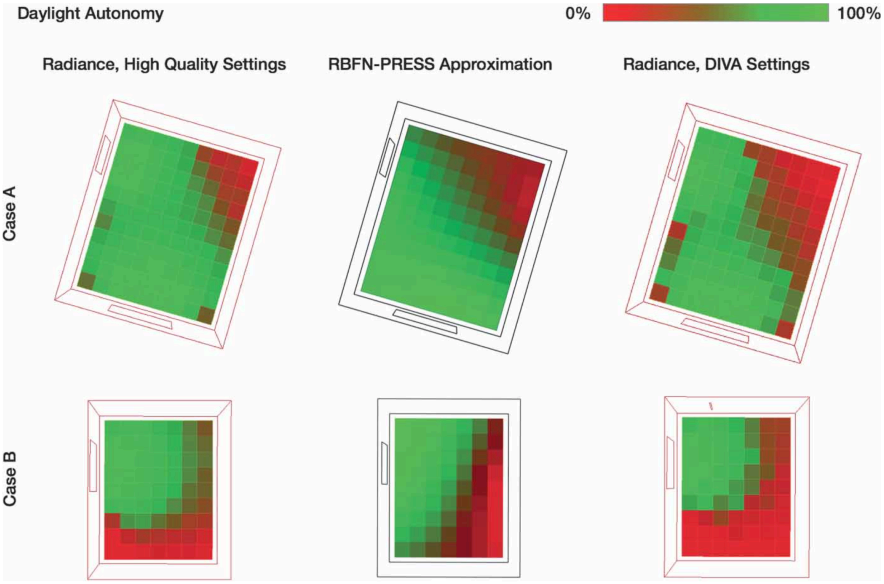


FIGURE 5.12 Comparison of simulation-derived and predicted results for daylight autonomy, for two different office settings. Left: radiance results, HQ settings, center: SVM-RBF approximation, right: radiance results, DIVA standard settings..

value of 0.591; RF, a value of 0.662 and kNN, a value of 0.385. The reason for the drop in generalization performance may be attributed to the increase in complexity that the calculation of DGP entails. In contrast to the smooth distribution of interior daylight, glare is affected by multiple factors, both indoors and outdoors, whose effect changes rapidly as the viewing angle and the properties of the space change, possibly introducing discontinuous areas in the DGP function as well. These properties of the DGP dataset render it harder to approximate. Furthermore, the increase in the dimensionality of the dataset, from 12 to 15 features, should be pointed out. Especially since RBF and SVMs are being used, this may partially account for the drop in their performance.

§ 5.1.7.2 Computational Complexity

All approximation models included in this study have a prediction performance, that is, orders of magnitude faster than the radiance simulation. Achieving such performance is, in fact, the main intention behind surrogate modeling. However, most importantly, model training times are also less time-consuming than the simulation themselves. In this respect, time cost varies among models. The shortest training time was achieved by the kNN, as expected, and the longest by the RFs trainer. All training and prediction time measurements were performed on an Intel Core i7 machine, with 16 GB of RAM. Table 6 presents a summary of simulation, model training, and prediction times.

TABLE 5.6 Optimal parameter configurations for the learning models

	RMSE (SD)		R^2(SD)	
Method	logDA	DGP	logDA	DGP
FFN	0.329(0.009)	0.071(0.004)	0.812(0.023)	0.682(0.044)
RF	0.164(0.015)	0.074(0.004)	0.912(0.018)	0.662(0.039)
SVM-RBF	0.131(0.012)	0.080(0.005)	0.941(0.011)	0.591(0.046)
kNN	0.147(0.019)	0.099(0.004)	0.927(0.021)	0.385(0.051)

§ 5.1.8 Application in a Design Scenario

It is important to stress that the goal of employing machine-learning models in the design process should be the improvement in decision-making in the early stages of the design (Wilkinson et al. 2012). To highlight the potential contribution of how approximation methods may prove beneficial to building design, an application to improve the early design decision-making process will be outlined. Let us consider the following design problem: an office space module is to be designed for a new building, and the window shape, placement, and dimensions need to be specified. It is considered that the positions of desks within the office are not strictly determined; on the other hand, they may vary according to the function of the space, the arrangement, and also through time. Given these assumptions, the goal is to identify the dimensions of the window that would provide the optimal lighting comfort conditions for as much of the interior space of the office as possible. In other words, the aim is to identify a window shape that can guarantee sufficient daylight, with the least glare possible. A quick evaluation of the DA and DGP values for a multitude of different points within the office, as well as different configurations, would be beneficial in such a task.

Figure 5.13 presents an overview of the daylight and glare conditions, for different window dimensions. The values in the plots correspond to a score calculated by combining the two different values, DA and DGP, as follows:

$$score = 2 - max(0.2, DGP) - min(0.8, DA) \tag{5.5}$$

The above formula penalizes the measurement points that display a DGP above 0.2, as well as those that display a DA below 0.8. Such an evaluation may help the decision-maker in arriving at a more conscious decision concerning the window shape and dimensions. However, due to the great number of simulations that need to be carried out, especially for DGP, deriving such figures is enormously time-consuming. It is thus important to stress that in obtaining overview figures such as the above, approximation through machine learning models in the form proposed in this study offers exceptional flexibility.

Despite the reduction in model fidelity compared to simulation, in the conceptual design stage, the accuracy of estimation need not be the priority, and as such the decision-maker can afford to trade up some accuracy for immense gains in computational complexity and thus time spent in decision making. Besides, employing the proposed approach, the decision-maker may vary other aspects of the design,

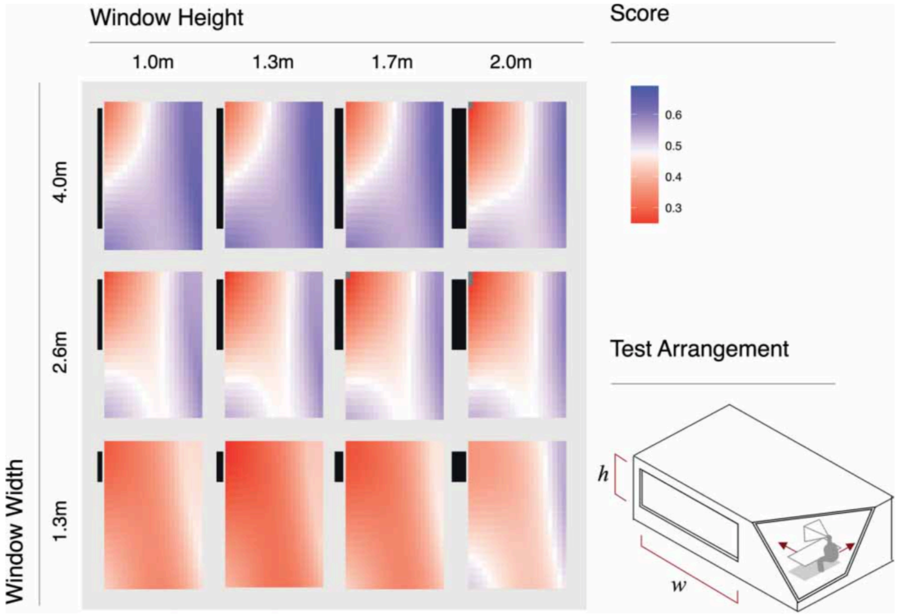


FIGURE 5.13 Variation of indoor lighting conditions in relation to window width and height. Score is calculated based on a combination of DA and DGP.

such as dimensions of the office and viewing direction, and get instant feedback on the conditions corresponding to the new design.

Figure 5.14 presents an alternative investigation into the effect that different window positions have in lighting conditions, for a row of possible desk positions within the office space, and at a fixed distance from the window. The first axis corresponds to the possible desk positions. The second axis corresponds to different window sizes. By examining those charts, it can be seen that placement of the desk in such a way that the window is next to it but not in front of it provides a satisfactory DGP while maintaining DA at acceptable levels. The blue dashed line in the chart outlines the series of most suitable window-desk position configurations.

At this stage, obtaining the results as demonstrated above requires involvement with specialized software that the decision-maker may not have access to or the necessary experience to make use of. This is because the approximation method outlined has not yet undergone any integration with a design environment. However, a product based on the proposed approximation method should be able to be trivially integrated with, e.g., parametric design environments such as grasshopper or dynamo. Integration could happen in the form of a plain input-output node in the parametric graph, which would replace the original simulation node.

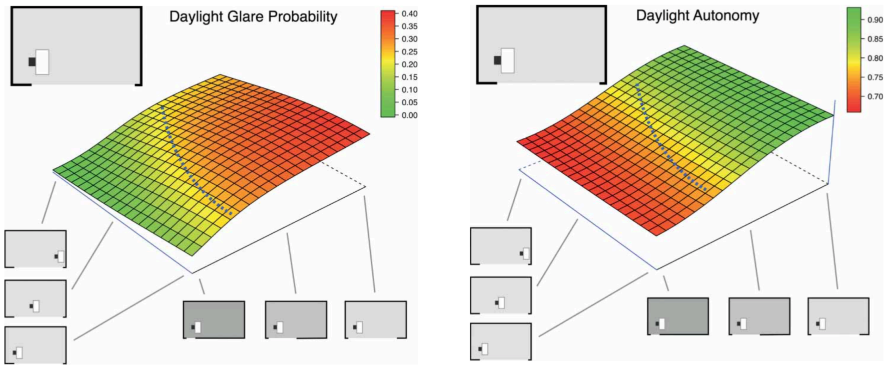


FIGURE 5.14 Variation of DGP (left) and DA (right) in relation to window size and working position.

§ 5.2 Case Study II: Post-Pareto Treatment of Second-Order Criteria

The second case study presents an application of the proposed auto-associative model for post-Pareto preference treatment. The application concerns the design of the shading devices of an office block situated in an urban environment, through multi-objective optimization of interior daylight distribution and unit cost. As part of the case study, novel developed performance metrics for evaluating the performance of auto-associative models for preference treatment are presented. Finally, the case study presents a comparison of the performance of two different machine learning models, namely a Feed-Forward Network and a Radial-Basis Function Network, according to developed metrics.

§ 5.2.1 Design Task

The design of building façades is a topic that is at the forefront of contemporary architectural design. The façade, as a building system and component, affects its performance in numerous ways. Firstly, it contributes to maintaining an indoor climate, by regulating heat exchange with the environment. It controls daylight penetration and protects against excessive solar gains. It often is combined with the structure of the building and needs to resist various environmental loads, such as wind, impact, earthquake, etc. Finally, it endows the building with its essential architectural identity, establishes the relationship of the building with its context, and is mainly responsible for the visual comfort of the building's inhabitants. From the above it is easily understood that façades go far beyond being a pretty dress for a building; however, at the same time, design preferences are commonly found to be concentrating on the composition of the façade, since it forms the layer that is most characteristic of the perceptual aspects of the building.

In this study, the performance of the façade system of a typical office building situated within an urban context is considered, as is visible in Fig. 5.15. The location of the office is in the city of Izmir, in Turkey, which is characterized by a temperate Mediterranean climate. The performance of the façade is defined along two aspects, energy performance, and daylight comfort. Thus, the façade is considered as a thermal barrier, whose efficiency needs to be maximized and at the same time, as a moderator of the solar radiation, both in terms of its thermal as well as visual effects. A façade with rectangular windows at regular intervals and a shading device in front of each window is considered. The position and sizes of the windows are variable, as are the sizes and positions of the shading device elements. A complete list of the decision variables, together with their correspondence in physical quantities is available in Table 1. Fig. 5.16 presents a correspondence between decision variables and physical features.

FIGURE 5.15 Photo-realistic representation of the fenestration and shading device considered in this study. Right: Representation of the façade in an urban context.

A bi-objective problem is considered, with the first objective being that of maximizing indoors daylight availability, and the second one is that of minimizing energy consumption of the building. Regarding the first objective, the Daylight Autonomy metric (Reinhart and Walkenhorst 2001; Reinhart et al. 2006) is used to evaluate the performance of the façade. Daylight Autonomy (DA) is a climate-based metric, which corresponds to the annual percentage of hours that a measurement point located indoors achieves a minimum threshold of illuminance, just through the use of natural daylight. The choice of the measurement location is usually that of a workstation, with a vertical position slightly above the working plane. The annual hours for which DA is calculated are calculated as the weekly office working hours, 9 am–5 pm. To calculate DA, the Radiance software (Ward 1994), a validated lighting simulator based on the ray-tracing technique, is used.

The second objective regards the energy expenditure of the hypothesized office building. This objective includes the energy spent for heating, cooling, ventilation, lighting, and indoor equipment usage. Heat losses occur by thermal transfer through the building envelope. To calculate energy expenditure, the EnergyPlus software, a validated simulation engine developed by the US Department of Energy (Crawley and Lawrie 2000), is used. The exterior walls and windows contribute to a different degree to heat transfer; windows contribute much more than walls, due to the high U-value of glazing systems. As such, façades with large, glazed surfaces are generally associated with higher energy usage, although this may vary with material composition and window to wall ratio. Besides, heat gain through solar irradiation contributes to indoor temperature rise.

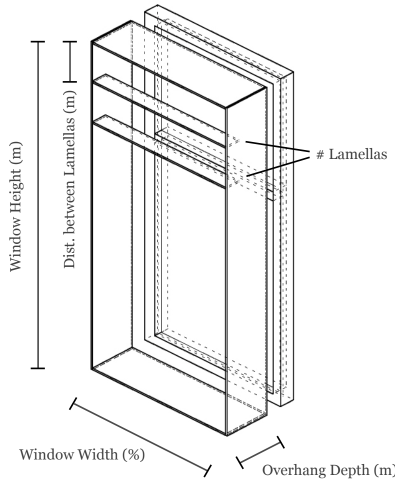


FIGURE 5.16 Correspondence between decision variables and design features of the fenestration and shading

All in all, the composition of the façade, placement, and ratio of the openings, as well as the size and form of the exterior shading devices, are building features that have a profound effect on building energy consumption. The two objectives considered conflict with each other. The improvement in indoor daylighting conditions, in many cases, proves to be detrimental to energy consumption. This is because, as glazed surfaces increase, the heat transfer through the envelope increases, and so does the heat gain through solar irradiation. That being said, a fine synergy between window positioning and sizing, as well as shading device placement and formation, should be enough to obtain solutions that achieve the best tradeoff between energy expenditure and daylighting.

The satisfaction of the two objectives to the best extent possible imposes non-trivial relationships between decision variables, for the computational identification of which there is no option but to employ costly non-linear stochastic optimization processes. At the same time, the decision variables correspond to design properties that largely determine the final image of the building. As such, it is expected that the decision-maker will express preferences on the decision variables, whose importance may vary depending on the variable. Thus, we arrive at a typical design problem case of the general problem description, as outlined earlier in this chapter. To effectively treat the problem at hand, the proposed method is applied, as will be described immediately.

§ 5.2.2 Derivation of Façade auto-associative model

A multi-objective GA, namely NSGA-II (Deb et al. 2002) has been applied to obtain the best tradeoffs to the problem. The optimization was performed using parameters of 100 population members, Simulated Binary Crossover rate of 0.95, and Polynomial Mutation rate of 0.05. The optimization ran for 30 generations, after which it was observed that convergence to the Pareto front was achieved.

Fig. 5.17 presents the initial generation of randomized individuals and the achieved Pareto front after 30 generations.

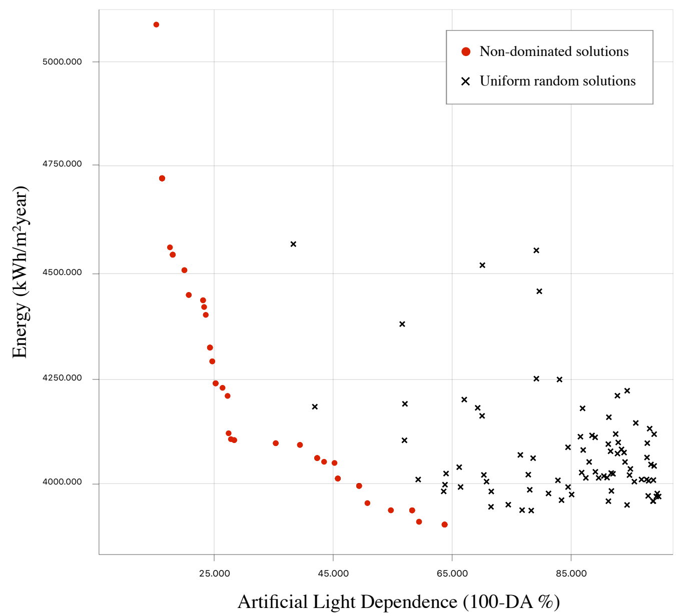


FIGURE 5.17 Diagram of the Objective Function space, demonstrating performance of a. initial (random) population (black crosses), and b. Non-dominated solutions, as identified after stochastic search (red circles).

Decision variable compositions of the 100 non-dominated individuals are used to train predictive models, in auto-associative mode, and compare their performance. The non-dominated solution set is presented both at the input and as the target output. Following the training procedure, the obtained predictive model is activated using randomized decision variable vectors, and record the model response each time. Subsequently, the vectors of the model response are used to perform new simulations and record the solution's performance. Finally, the performance of each of the two sets, input and output, together with the non-dominated solutions recorded from the optimization, is plotted in charts of the objective function space.

Two types of models are chosen for this study: a regular Feed-Forward Neural Network, trained using Backpropagation (FFN), and a Radial Basis Function Network (RBFN), (Moody and Darken 1989) trained using the Orthogonal Least Squares (OLS) algorithm.

Feed-Forward Networks are connectionist models that comprise a set of artificial neurons, organized into one or more layers. Each artificial neuron receives a weighted summation of the previous layer outputs and applies a non-linearity to produce its output. The process is repeated for each layer. The first layer receives the input, and the final one produces the output. A common non-linearity is the sigmoid:

$$S(x) = \frac{1}{1 + e^{-x}} \tag{5.6}$$

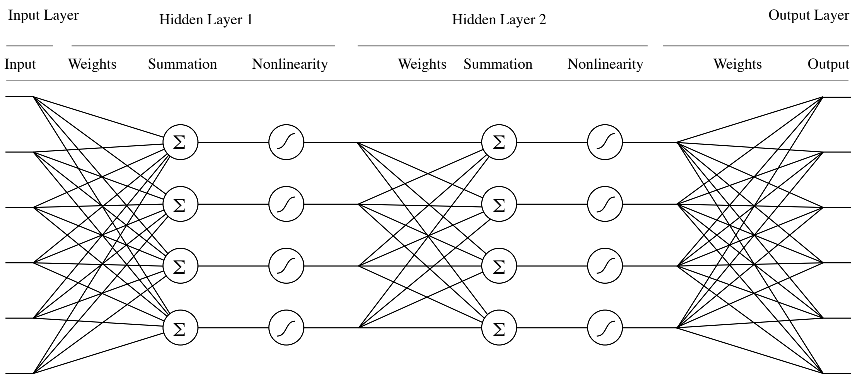


FIGURE 5.18 Auto-associative feed-forward network with two hidden layers.

The internal knowledge representation of the network is stored in its weights. Determining the values of the weights, also known as "training" the network, is performed by gradient descent, and the gradients for each weight are determined by back-propagating errors from the supervised outputs (Rumelhart et al. 1985). An auto-associative FFN with two hidden layers is shown in Fig. 5.18. The auto-associative network is trained by partially corrupting its input, as described in Section 3.2. The corruption process alters each attribute of the input dataset with a probability p, by adding a number according to a Normal distribution with variance and mean linked to the attribute:

$$\tilde{X}_i = \begin{cases} \text{P} & X_i + c, c \sim \mathcal{N}(\mu_i, \sigma_i^2), \\ \text{otherwise} & X_i \end{cases} \tag{5.7}$$

In the above function, and 2 denote the mean and variance of the respective attribute.

The structure of an RBF Network consists of an Input Layer, a Hidden Layer, and an Output Layer. Each of the three layers has a distinct function. The N-dimensional input signal arrives in the input layer. The hidden layer consists of a variable number of units, or neurons, which offer a localized response to the input signal, based on its Euclidean distance from each regressor center. The response of the output layer of the network is formed by a linear combination of the hidden layer neuron responses. In Fig. 5.19, a schematic representation of the RBF network structure is available. The output of the network can be summarized as

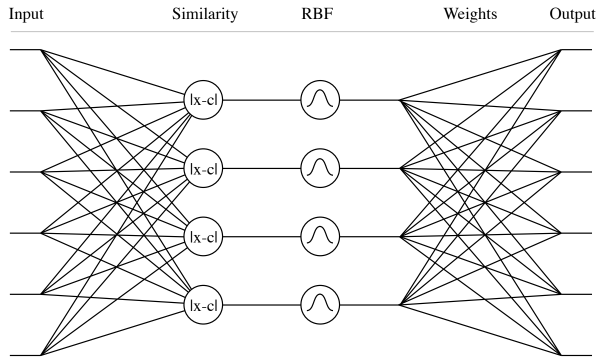


FIGURE 5.19 Auto-associative RBF Network.

follows:

$$f_r(x) = \lambda_0 + \sum_{i}^{n_r} \lambda_i \phi(||x - b_i||) \tag{5.8}$$

In the above formula, b denotes the neuron center, the basis function and the linear weight attributed to the function. Hidden layer nodes in RBF Networks may use various activation functions. A common choice is the Gaussian:

$$f(x) = e^{-\frac{(x-b)^2}{2e^2}} \tag{5.9}$$

In the above formula, c denotes the bandwidth of the kernel. In these tests, the OLS training algorithm (Chen et al. 1991, 1992) and multi-output RBF networks (Chen 1995; Chen et al. 1996) are employed. Besides, a parameter search is performed by varying the kernel function bandwidth, to evaluate its effect on the performance of the model. The Error Tolerance parameter of the network was empirically set to 0.005. It should be noted here that, due to the nature of the learning task in OLS (which trades off accuracy for model parsimony), the network was able to learn an efficient encoding of the input data (non-dominated solutions), without altering the training method, such as in the case of the FFN. Off-the-shelf software is used in these parametric model definitions, optimization, and model training and activation. For parametric modeling, the Rhinoceros CAD platform is used. For optimization and neural network training, the CIDEA platform (Chatzikonstantinou 2016) is used.

§ 5.2.3 Assessing model performance

The main task of the auto-associative model, as outlined in this study, is the rectification of a preference vector that appears at its input, so that the output becomes a nearby vector that has the property of being on or close by the Pareto front. Given this task, one may inquire as to the potential methods of evaluating algorithm performance, concerning the task at hand. The main criterion by which to evaluate the algorithm performance is naturally the quality of the solutions produced, concerning design objectives. A model that is capable of producing solutions closer to the Pareto front may be considered well-performing in the comprehension task. It is thus possible to make use of a measure of the proximity of a resulting solution to the Pareto front, to evaluate algorithm performance. The Generational Distance (GD) (Van Veldhuizen and Lamont 1998), is a measure of precisely this quantity, and as such may prove advantageous in evaluating model performance. GD is defined as a measure of the distance between a tested Pareto front, and the theoretical Pareto front for a specific problem. Here, this definition is modified, since information regarding the theoretical Pareto front in most real-world design problems does not exist. Rather the interest is in approximating the GD between the finite set of non-dominated solutions discovered by stochastic search, and the solutions that form the response of the model. The proposed GD approximation is as follows:

$$GD = \sqrt{\frac{\sum_i \min_j(|S_i - P_j|)}{n}} \tag{5.10}$$

In the above equation, S indicates a response solution, and P a member of the non-dominated set. Our approximation assumes that there is at least one non-dominated solution close by the response. This is a reasonable approximation if it is considered that the number of objectives is low, and the non-dominated solutions are evenly spread, a requirement easily achieved by modern distance-preserving stochastic algorithms. Based on this definition, and to evaluate model performance, the following procedure is employed:

1. Identify the empirical front through stochastic search
2. Train an auto-associative model on the non-dominated solutions resulting from the search
3. Generate a series of n random decision variable vectors, within the bounds defined by each variable
4. Excite the model using the random vectors, and record the output
5. Calculate the GD metric for each of the output vectors, and derive the mean value, $\overline{GD}$

$\overline{GD}$ may then be used as a comparison metric to evaluate the relative performance of different models, within the context of a single design problem. In addition to the absolute value of the GD metric, a useful quantity is the ratio of the GD value of the response of the model, divided by the corresponding value of its input, GD. Conceptually, this quantity indicates the improvement in performance that the model imbues in its input. Based on this, the Coefficient of Pareto Restitution

(CPaR), is derived and defined as follows:

$$CPaR = 1 - \frac{GD_{response}}{GD_{distorted}} \tag{5.11}$$

Through the above formula, a model performance figure is obtained that is similar in scale to the well-established R-Square metric in regression; a CPaR value of one would denote a model that can rectify the Pareto solutions from any given one perfectly. A value of zero would denote a model that does not offer any improvement over the original (input) solution. Negative values denote transformations that lead to solutions that are worse in terms of preference satisfaction than the original. Given that, for a negative value to occur, the output decision variable vector should be different than the input, solutions that correspond to negative CPaR value are generally unfavorable. Fig. 5.20 depicts a visual explanation of GD and $CPaR$ indicators.

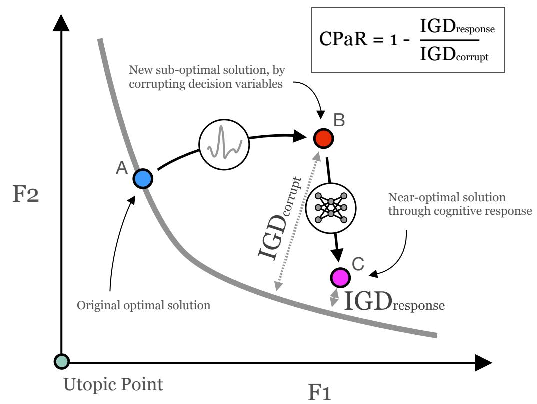


FIGURE 5.20 Visual depiction of the GD and $CPaR$ calculation process. Without loss of generality, a bi-objective problem is considered, where the distance of point B to the Pareto front gives the GD of the random/corrupted solution. The distance of point B gives the GD value of the response. Their ratio is used to derive $CPaR$.

In addition to the performance of the output solution, its similarity to the preference vector is also a point of interest. This may be easily measured by considering the Euclidean distance between the two vectors, input, and output, at the decision variable space. The comparison should happen after each value has been normalized to the value bounds defined by the problem at hand, to avoid issues of individual decision variables dominating the results. This indicator is termed the Normalized Distance between Solutions (NDS), and defined as:

$$NDS = \frac{|C_i - R_i|}{n} \tag{5.12}$$

In the above equation, C indicates a vector corresponding to a corrupted or random solution, and R indicates a vector corresponding to the response of the model.

Fig. 5.21 depicts a visual explanation of the NDS indicator.

It is also worth looking at the architectural features of the solutions resulting from the model response. For this reason, two experiments are performed: In the first one, the model is presented with random preference vectors, and the output is logged. Subsequently, both input and output are inspected and compared.

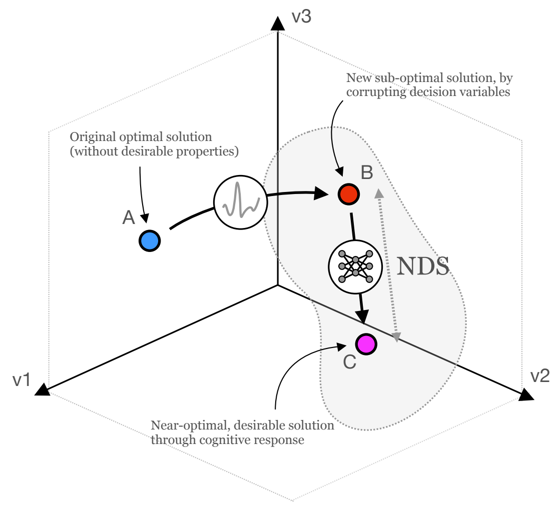


FIGURE 5.21 Visual depiction of the measurement of NDS in the (normalized) Decision Variable space. Point B corresponds to the random/corrupted solution. Point C corresponds to the response. The Euclidean distance between them gives NDS.

Even though such a scenario may provide a viable figure for the performance of the network, the proposed approach will rarely be useful in this situation. Our goal, after all, is not to produce a model that will be a replacement for generic optimization algorithms. Instead, it would be more informative to investigate the reaction of the model to perturbations of solutions close to the Pareto front, which would in any case more closely resemble real-world design investigations. For this reason, another investigation is performed, this time by starting from a solution on the Pareto front, perturbing its parameter values, exciting the model with the perturbed solution, and recording the output. Subsequently, all three solutions are instantiated, and a visual inspection is performed.

§ 5.2.4 Discussion

Parameters of both types of models (FFN and RBFN) are varied, and their performance is assessed according to the aforementioned metrics, GD, CPaR, and NDS. Tables 2 and 3 present a summary of each model with different parameters, namely c (hidden layer size) for FFN and (kernel bandwidth) for RBFN. Figs. 5.22 and 5.23 summarize the results of the comparison. In the first figure, performance indicators CPaR and NDS for different FFN hidden layer sizes are shown. In the second figure, two characteristics of the resulting RBFNs are superimposed,

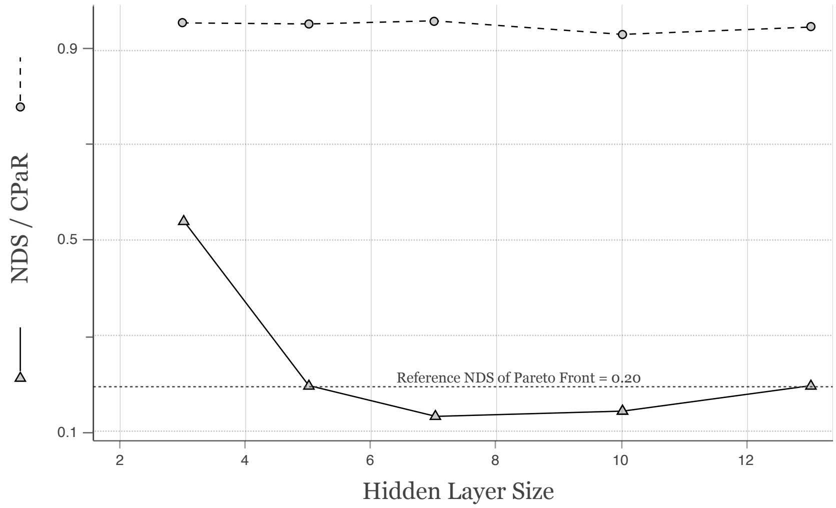


FIGURE 5.22 Performance comparison of different FFN models, according to the performance measures discussed.

namely kernel bandwidth and the number of selected regressors, as well as the performance indicators CPaR and NDS.

The indicators have been calculated as per the process described previously. Namely, a calculation was performed by considering a set of solutions obtained by uniformly sampling the decision variable space. These solutions become the input to the auto-associative models, and subsequently, the response is recorded and used to calculate the values of the indicators. Concerning the result, all models indicate exceptional performance, being able to almost fully restore the preference vector to a position very close to the Pareto front. With this in mind, it can be concluded that the models have identified successfully the latent relationships present in the set of non-dominated solutions.

The NDS indicator has been calculated by partially corrupting the decision variable values of the non-dominated solutions identified by the stochastic search. These corrupted inputs were subsequently introduced to the auto-associative model as preference vectors. The output of the model was recorded and used to calculate the indicator. Concerning the results, all except three FFN and two RBF networks indicate performance that is better than choosing a nearby Pareto solution, verifying the value of the proposed method. In particular, it is worth noting that among the solutions resulting from the model's reaction, there are several non-dominated ones, and a few that stand out from others in the Pareto front.

Figs. 5.24 and 5.25 present the model response to the randomized preference vector, for different hidden layer values, in case of FFN, and bandwidth values, in case of RBF network. The results are superimposed over the two solution sets of Fig. 5.17, uniform random and Pareto. The computational time for deriving model

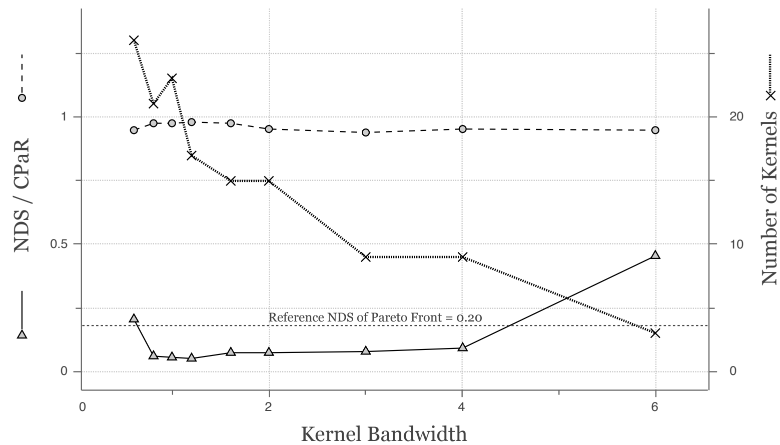


FIGURE 5.23 Performance comparison of different RBF models in terms of performance measures discussed.

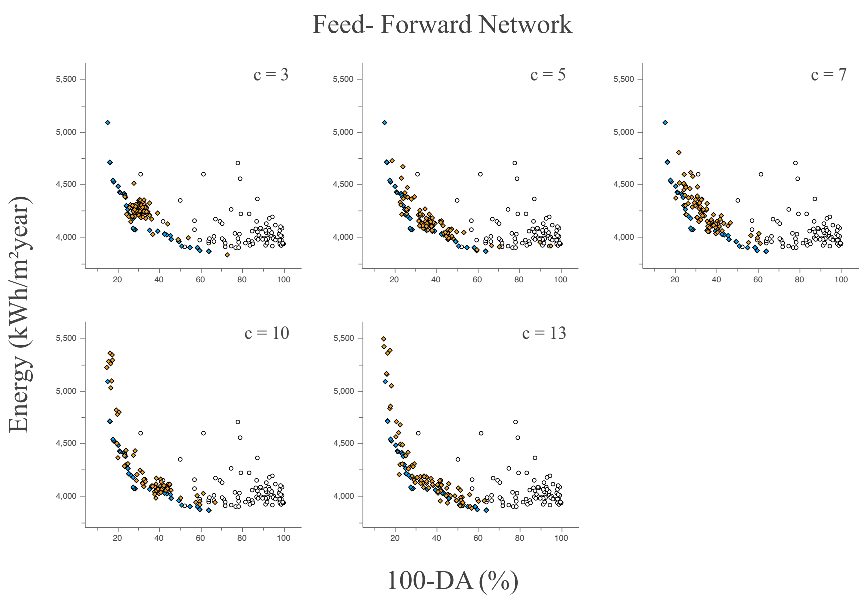


FIGURE 5.24 Performance of Feed-Forward Network for different hidden layer sizes. It is clear that more complex models are able to rectify the Pareto front better. Empty circles: Random solutions. Blue diamonds: Pareto solutions. Yellow diamonds: Auto-associative model response.

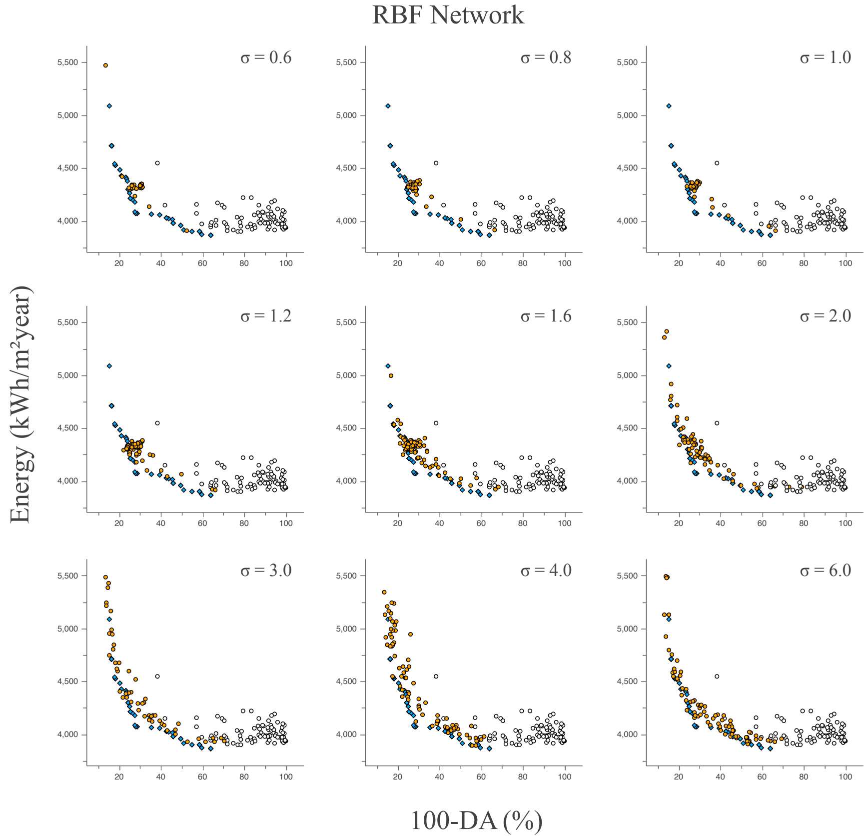


FIGURE 5.25 Performance of RBF network for different kernel bandwidths. Empty circles: Random solutions. Blue diamonds: Pareto solutions. Yellow circles: Auto-associative model response.

responses for both types of auto-associative models is imperceptible, and as such not discussed here. The models are suitable for real-time use. Training of the models takes less than a minute on average.

Concerning the architectural characteristics, it is observable that they are always following what would be expected, for the façades' performance. For instance, solutions with very good Daylight Autonomy performance demonstrate large openings, with minimal overhangs and shading devices on the outside. As expected, these solutions exhibit rather poor energy performance. Even more interesting are the solutions that balance DA and energy performance. It should be noted that solutions in this area initially appeared after a considerable number of generations of the stochastic search had passed. Here, we observe an elaborate balance between the number of shading elements, the dimensions of the overhangs, and the dimensions and proportions of the windows. Overall, we may observe that the main performance tradeoff, as expressed in the decision variable space is, as expected, between the size of the window and the depth of the shading device; the height of the windows is kept to a narrow value range between 2.0 and 2.4 m, and the number of shading elements varies between 2 and 3. The results are available in figure 5.26.

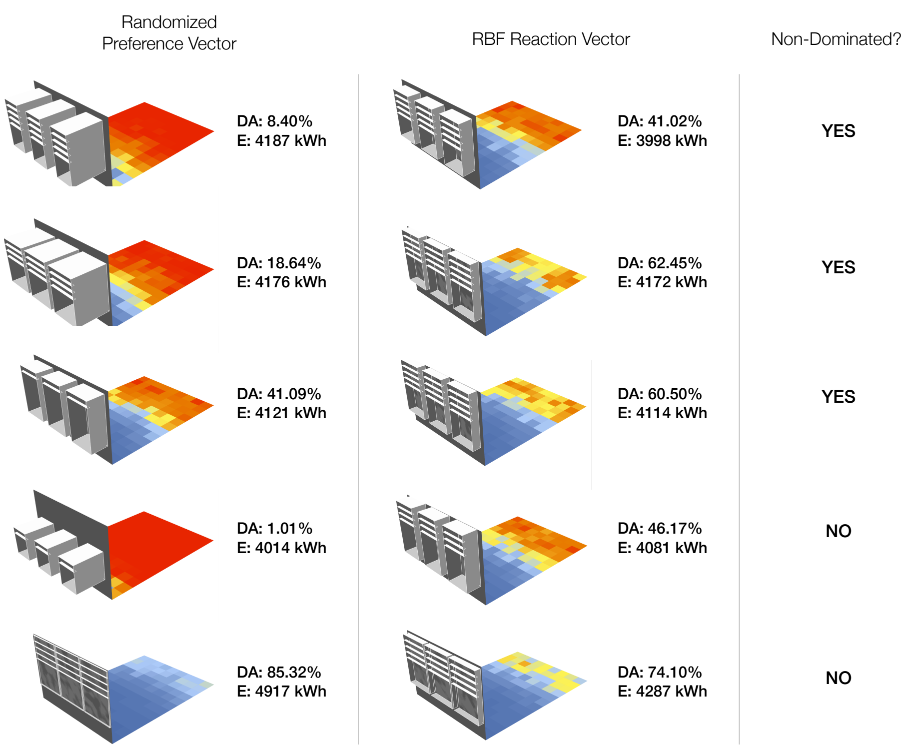


FIGURE 5.26 Solutions as a result of randomized decision variable vectors (left column), and model response (middle column). On the right, it is indicated whether the model response dominates the model input in Objective Function space.

Finally, as an illustration of how the proposed method may be used in practice, the reader is referred to figure 5.27. In this figure, solution A is a solution taken from the non-dominated set. The solution is well-performing, but it does not possess desirable features, which in this case refers to the height of the windows. The decision-maker changes the window height manually by altering the value of the corresponding decision variable. The new solution (solution B) is now sub-optimal. By exciting the auto-associative model, a new solution is achieved (solution C), which has physical features similar to the desirable ones and is also a non-dominated solution. It is worth noting that to derive solution C, the model acts on all decision variable values, adapting them in accordance to the preference vector and the learned knowledge matter.

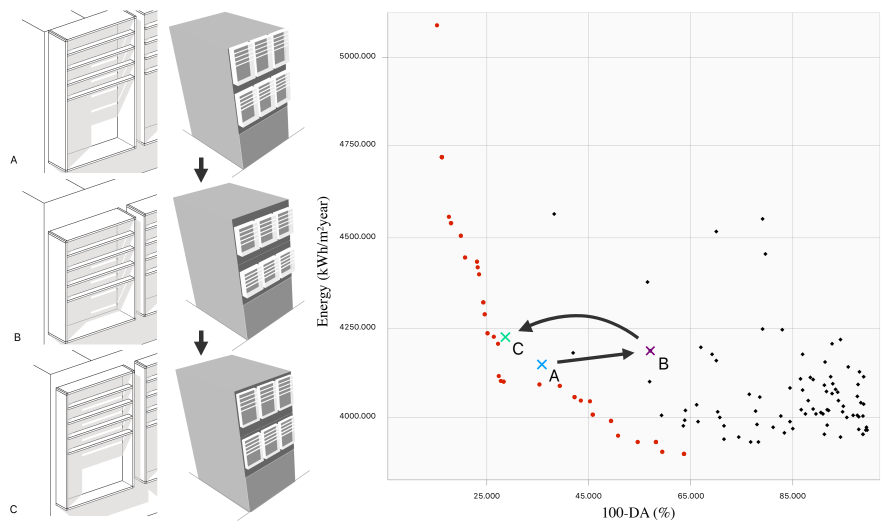


FIGURE 5.27 Process of preference-based decision support by auto-associative network, illustrated on the case study. The decision-maker selects a solution close to the Pareto front, namely A. They exercise their preference by reducing the height of the windows. This leads to solution B, which is clearly sub-optimal. By exercising the auto-associative model (in this case, a FFN), solution C is obtained. This solution is near optimal, and characterized by shorter windows than the original (still taller than the preferred though), as well as shorter shaders.

§ 5.2.4.1 Beyond the Pareto front

In this study, an auto-associative model learns the decision variable distribution of non-dominated solutions in a design problem and uses this knowledge matter to adjust sub-optimal solutions expressing decision-maker preferences, to their near-optimal counterparts. A question arises though: What if the preference vector does not have a nearby correspondence that is near-optimal? In this case, as seen earlier in this section, the algorithm would modify the decision variable composition departing significantly from the preference vector as needed to obtain a near-optimal solution. To a decision-maker expressing strong preferences regarding design features, this would be unacceptable. Thus the question of a model that can limit its action on the preference vector arises. While this issue has not been investigated as part of this research, a proposal is hereby presented for addressing it. It is seen that under normal conditions the knowledge matter, i.e. training data, for the auto-associative model consists of non-dominated solutions. To augment the knowledge matter, solutions that are dominated bur near-optimal may be included. This extended training set is expected to have as a result a model that learns a wider decision variable distribution than that of the non-dominated solutions alone. Therefore, it is expected that the model action on the preference vector overall will be softer, thus better-respecting decision-maker preferences, at the cost of some design performance.

§ 5.2.5 Conclusion

The first case study presented the results of applying the proposed surrogate modeling method in determining visual comfort indicators in office spaces, and the modeling thereof. Two factors contributing to visual comfort were considered, namely DA, an indicator related to the availability of daylight, and DGP, an indicator related to the probability of experiencing glare. As part of the application study, a comparison of the performance of three different machine learning methods underlying the proposed surrogate modeling method was performed, namely: FFNs trained using Backpropagation (FFN), SVMs with RBF kernels (SVM-RBF), and RFs. SVM-RBF and FFN offered the highest prediction accuracy in the DA and DGP datasets, respectively, achieving a coefficient of determination of 0,941 (SVM-RBF, DA) and 0,689 (FFN, DGP).

The validation of model performance has been successfully met by the case study. It was possible to approximate DA with good precision, while for DGP, the approximation reached acceptable but not outstanding performance. All of the studied methods offer a speed of prediction, that is, orders of magnitude faster than the Radiance simulation and the Evalglare calculation itself and very close to real-time performance. The derived models, either as-is or through modifications, may be used to model generic classes of offices in varying building types. Besides, the presented small-scale design study highlighted the potential of the proposed surrogate modeling method to offer near-instant design feedback concerning changing design parameters, allowing for design alternatives to be navigated intuitively and solutions reached quickly.

The second case study focused on applying the proposed auto-associative decision support method in addressing decision-maker preferences concerning an integrated shading device design for an urban office building. This is a lucrative alternative to simply choosing a non-dominated solution in multi-objective optimization. Through this case study, it was first possible to demonstrate the quantitative performance of the proposed method. This was through the introduction of novel performance metrics that can evaluate the potential to satisfy expressed preferences in the decision variable space, and at the same time adherence to design goals. The proposed decision support methods were able to quantitatively demonstrate good performance in both aspects. Secondly, it was possible to qualitatively validate the performance of the proposed method through highlighting several design instances, generated using the proposed method, guiding decision-maker choices and the formal alterations to the design that comes thereby. By using the proposed method, the decision-maker may focus on addressing desirability aspects of design, having the certainty that resulting solutions will be near-optimal in any case.

6 Conclusion

§ 6.1 Introduction

Complexity is an inherent property of architectural design that is born out of the numerous, intricate relationships between design decisions, design goals, and design constraints. As a result of design complexity, identifying optimal design decisions at any time within the design process is a cognitively challenging task. Due to human cognition being constantly challenged because of design complexity, there is a real danger that decisions taken during the design process are sub-optimal, which will end up having a detrimental effect on the satisfaction of design goals by the end design product. Decision-makers, recognizing this condition, have made use of tools to enhance their cognition since the dawn of the act of designing.

Nowadays, the need to reduce the energy consumption of buildings while improving indoor conditions has led to the adoption of a multitude of emerging architectural design requirements that intensify the requirements and constraints that decision-makers face today. Besides, novel capabilities in materials and construction techniques broaden the spectrum of potential solutions to design problems and as such further enlarge the design space. In this setting, the architectural design presents an overwhelming task for human cognition and the need for design decision support systems presents itself as a necessity more than an opportunity.

A prominent class of decision support tools is that which is founded on advancements made in the field of computational intelligence, and more specifically in the fields of computational optimization and machine learning. This thesis' aims are aligned with the research agenda on computational intelligence-based decision support systems with applications in architectural design. It attempts to present a comprehensive decision support framework, where Computational Intelligence (CI) techniques are used not just to provide a means of finding optimal solutions to a design problem, but to do so efficiently and further aid in informed decision making that appropriately treats decision-maker preferences in addition to improving design performance according to set goals and ensuring satisfaction of design constraints.

§ 6.2 Revisiting the Research Questions

This section discusses the major findings of the research, arranged according to the research questions formulated in chapter 1.

How can Computational Intelligence (CI)-based methods and techniques

(including intelligent as well as cognitive methods) better support decision making during architectural design, especially in the early conceptual design stage?

In addressing this research question, the main aim of this thesis has been to propose a comprehensive decision support framework based on CI techniques, which has been extensively elaborated in chapter 4. The proposed DSS is founded on the use of Evolutionary Computation (EC) as an intelligent approach to exploring the design space, which, as a central contribution of this thesis, has been augmented with cognitive capabilities, through a two-fold extension. In particular, Multi-Objective Optimization (MOO) algorithms such as NSGA-II are considered due to their inherent ability to deal with conflicting objectives and non-linear constraints. The comprehensive framework proposed in this thesis aims to make EC-based decision support more agile and adaptive to the rapidly changing environment of the conceptual design process so that the decision-maker can make timely, informed design decisions that take all aspects of design into account. Two particular issues are identified:

- The computational complexity associated with the repeated evaluations of complex functions as required by the EC
- The post-Pareto treatment of decision-maker preference treatment alongside objective and constraint satisfaction.

Towards addressing each of these issues, the following methods based on computational cognition and machine learning are proposed:

- A method for deriving flexible surrogate models that can model generic spatial distributions of values indoors for single spaces, and, iterated, for multiple spaces of varying characteristics.
- A method for deriving auto-associative connectionist models of the distribution of Pareto-optimal solutions in the decision variable space, and thereafter guide the decision-maker on decisions concerning preferences in terms of object properties.

Through the incorporation of the proposed computational cognitive methods into an EC-enabled intelligent model, as elaborated in chapter 4 and applied in chapter 5, a comprehensive and flexible DSS is derived that enhances applicability to the architectural conceptual design stage.

How can cognitive methods augment intelligent decision support tools, in order to lead to better and more agile decision making in design?

It has been a cornerstone of this thesis that intelligent methods that are already in application in architectural design, such as Evolutionary Computation-based optimization methods, can be complemented by computational cognitive methods, to endow them with the ability to more efficiently navigate the design space and support the decision making process. As part of this thesis, there have been two potential contributions of cognitive approaches identified.

The computational complexity of simulations is a real problem in architectural design that is hindering the application of accurate simulation models to timely decision making. Surrogate modeling via machine learning is a well-studied approach towards minimizing computational complexity through the use of machine learning. In this direction, a method for deriving flexible and re-usable surrogate models for building performance based on machine learning has been proposed. In this method, indoor spaces are defined based on their geometric, material and environmental characteristics, and individual surrogate models are applied to each fundamental space. The overall performance is derived considering the contribution of each space to the whole building.

In addition, this thesis proposed a novel method for post-Pareto decision support in problems where object properties form second-order preferences that need to be satisfied as part of the problem. An auto-associative neural network is used to "steer" decision-maker preferences in such a way that design performance is not compromised trying to satisfy a contradicting preference, as such ensuring near-optimality of the solution.

How can methods and techniques borrowed from the field of machine learning contribute to alleviating computational complexity of simulations?

It is established as part of addressing the previous research question that surrogate modeling may contribute to a reduction in computational complexity, however, the flexibility of the derived models is an important issue. As part of the framework proposed in this thesis, a new formulation for a surrogate model is proposed, which is specifically addressed to the building sector and which is applicable to rapidly changing design environments such as the conceptual design stage. The proposed approach uses a common model to predict indoor distributions of the quantity of interest within individual spaces of the building, incorporating indoor position as an independent variable. The characteristics of the building spaces are modeled parametrically to maximize model applicability. Aggregate performance metrics may be easily derived through elementary descriptive statistics on the model output. The proposed approach allows the model to be derived once (or even re-use existing models from other projects) and be re-used even if the quantity, arrangement, or properties of indoor spaces change while maintaining detailed insight of localized performance according to the value of interest. As part of the thesis, an application to the modeling of indoor visual comfort-related metrics has been presented.

At which stage should decision-maker preferences be addressed (before, during, after optimization)?

In relation to a computational optimization-based decision support system, treatment of second-order decision-maker preferences may occur in any of three time points along the process:

- Before the EC optimization (a-priori approaches)
- During the EC optimization (interactive approaches)

- After the EC optimization and derivation of Pareto-optimal set (a-posteriori approaches or post-Pareto preference treatment)

Within the scope of this thesis, post-Pareto decision making is identified as having an advantage over the other approaches, as the point in time following the establishment of the Pareto-optimal set is the point where the most information regarding the design problem at hand is available, and thus decision making at this stage can lead to the most informed decisions. At the same time, though post-Pareto preference treatment is challenging because it entails taking into account the implicit relations among object properties established by the Pareto-optimal set.

How can decision-maker preferences be effectively incorporated alongside design goals in computational multi-objective optimization?

An auto-associative neural network model is proposed as part of this thesis, to assist with the cognitively challenging task of ensuring design goal satisfaction in the face of preferences in terms of object properties, i.e. those found in the decision variable space. The proposed model is considered a post-Pareto decision support approach. The model is auto-associative, in that its inputs and outputs correspond to points in the decision variable space, thus design solutions. The model is initially fit on the dataset comprising Pareto-optimal solutions resulting from the multi-objective intelligent search stage. Following this stage, the decision-maker inputs their preferences to the system by adjusting the decision variables to their preference. The fit model is then used to "guide" the decision-maker by providing "corrections" to the adjustments, which act to keep the model in the optimal region learned by the Pareto-optimal solution composition.

It is claimed that the proposed approach is an effective means of addressing second-order preferences on object properties as i. it offers an easy to grasp and intuitive interface to the decision-maker for expressing preferences, ii. it derives all required knowledge inductively through implicit relations present in a naturally occurring dataset (set of Pareto-optimal solutions), and iii. it is supported by a well-founded exact scientific background which enables consistency and explainability in the resulting model behaviors.

How can the above specifically be applied to current and challenging design problems in architecture?

As part of the thesis, specifically in chapter 5, two case studies, both of which involved real-world design tasks, and in which design instances have been evaluated according to the objectives using state of art building simulation tools. Besides, at the beginning of the research, namely in chapter 3 a complex real-world project has been presented in which evolutionary computation has been identified as the preferable approach to explore the vast design space associated with the design task at hand.

§ 6.3 Concluding Remarks

The applications of Computational Intelligence (CI) in decision support for architectural design are only bound to become more widespread in the near future, owing to developments in method as much as in technique. Such a development is expected to bring plenty of benefits in the design of complex buildings, however, advances in exact scientific methods should be applied in architecture with the idiosyncrasies of the discipline in mind. It is noted that architecture is a blend of science and art, and as such the requirements for an efficient decision support system do not always match those of engineering. The developments presented herein reflect such a regard for the contribution that CI research may have on architectural design, and in particular concerning the role that a CI decision support system may have in the early stages of architectural design, where the most important decision decisions are being made, and which govern the direction of the overall project.

Fusion of intelligent with cognitive approaches, as outlined in the approach proposed by this thesis, offers the unique advantage of a decision support approach that is both powerful, owing to the extensive capabilities of intelligent search algorithms, and flexible, owing to the extensive knowledge modeling capabilities of cognitive approaches. As such, it is uniquely suited to the early conceptual design stage where the need to explore large design spaces, flexibly redefine the design problem, and satisfy preferences that are not included in the primary design goals, are all paramount.

As part of the proposed approach, the proposed surrogate modeling method and derived model for daylight approximation based on computational cognitive machine learning models, allows increased flexibility at the conceptual design stage, as the model is flexible enough to represent multiple single spaces within a building, and prevents model re-fitting even after major design changes. Besides, the model offers a view of greater detail in the interior distribution of the quantity modeled, e.g. daylight or glare distribution, in comparison with models that output aggregate values based on either concrete building properties or abstracted features.

On the other hand, the proposed auto-associative computational cognitive preference treatment method offers a systematic approach to post-Pareto optimality analysis, with emphasis on an aspect that is much too often overlooked: second-order preferences on object properties, i.e. those found in the decision variable space. The formulation of the model is one that allows the decision-maker to exercise their preferences as they naturally would – examining solutions in a parametric model and adjusting values of decision variables to achieve their desired attributes. The proposed auto-associative model is inserted in between the decision-maker and the parametric modeler and performs continuous, subtle adjustments as necessary to keep the solution in the set of near-optimal solutions, allowing some flexibility in goal satisfaction in favor of preference accommodation.

The overall approach is integrated into a comprehensive workflow, with multi-objective optimization at its center, complemented by the cognitive machine learning components described above.

§ 6.4 Recommendations

This section summarizes some recommendations on potential future research directions of the research presented herein.

Given that machine learning is the governing method behind the intelligent-cognitive approach presented in this thesis, one cannot but consider the extension of the methods presented through the use of deep learning neural network architectures as have been pioneered in the past decade. Such a development could potentially pave the road for applications in even more complex design problems where high dimensionality and highly non-linear relationships could be addressed by the increased complexity of the models. Naturally, such an application would require datasets that are orders of magnitude larger than the ones utilized in this thesis, and for this, a well-planned research project should be conceived.

The genetic algorithm that underlies the intelligent search that is part of the proposed workflow has not been part of this thesis' investigation, and a standard algorithm has been considered (NSGA-II). However, given the evolving state of art in Evolutionary Computation and the influence of the No Free Lunch theorem (Wolpert and Macready 1997), it is recommended that comparison among different algorithms is performed at least as a cursory investigation into their performance on the problem at hand.

Finally, it is noted that the models derived as part of the proposed approach (surrogate model, auto-associative model) embody a significant amount of knowledge, which offers potential for re-use that exceeds the confines of a specific project. To this end, the research field of knowledge transfer offers a good opportunity for future research. In particular, Transfer Learning (TL) (Thrun and Pratt 1998) is an established paradigm. TL aims to improve learning in a target domain D_T, through the use of knowledge in a different but related source domain D_S. Consider the knowledge embodied in a model applied to an original design problem is considered as a source domain. It is desirable to derive another model for a different design problem, the target domain, which has similarities to the original. This can be formulated as a TL problem, where knowledge from the model on the original problem may be used to improve the performance of the model pertaining to the target domain.

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Biography

Ioannis Chatzikonstantinou graduated in 2007 from the School of Architecture of the Aristotle University of Thessaloniki. In 2011 he received an MSc. in Building Technology from Delft University of Technology with a specialization in Computational Intelligence and applications to design. His thesis was voted as the best thesis in the Building Technology department for the year 2011. He was employed as a researcher in the Chair of Design Informatics from 2011 to 2012, working under the supervision of prof. dr. Özer Çiftçioğlu and dr. Michael Bittermann on stochastic optimization approaches for challenging constraint optimization problems. Subsequently, he worked as a lecturer from 2012 to 2017 at the Faculty of Architecture at Yaşar University in Izmir, Turkey. In 2016 he was awarded the Outstanding Researcher Award by the same university for his contribution to research.

Since 2018 he is employed at the Information Technologies Institute at the Centre for Research and Technology Hellas (ITI/CERTH) in Thessaloniki, Greece, where he works in the field of robotics and computational intelligence. As part of his employment at ITI/CERTH, he has participated in four European Union Horizon2020 programs, in the field of collaborative robotics and healthcare, where he served as coordinator and contactsperson in several tasks within the program work packages.

Ioannis Chatzikonstantinou is the author and co-author of over 30 publications in scientific journals (Automation in Construction, Architectural Science Review, and others) and international conferences (IEEE CEC, eCAADe, TMCE, and others). He is a reviewer for several journals, among which Building and Environment, Architectural Science Review, Energy Efficiency, and Solar Energy.

In parallel, Ioannis runs his own small technology business, where he designs and manufactures advanced motion control components for robotics.

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