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Review

Performance Simulation Integrated in Parametric 3D Modeling as a Method for Early Stage Design Optimization—A Review

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Academic Editor: Ching-Ming Lai

Received: 28 March 2017; Accepted: 2 May 2017; Published: 5 May 2017

Abstract: During the last decades, standards on building construction have risen sharply to integrate new, ambitious demands regarding energy efficiency, as well as thermal and optical comfort in the design procedure. Building simulation software assists in the accurate calculation of a hypothetical or existing building's performance on several aspects; but they are, in their vast majority, assessment-oriented, rather than focused on dynamically supporting the decision-making procedure. During the last two decades, a clear shift of design professionals and academia towards addressing performance issues from the conceptual stages of a building's design is observed. In this review, the methodology of performance-driven design optimization using computational/parametric design and optimization is presented, and the core literature available on the topic is reviewed in order to identify the current status, different approaches, obstacles, and areas of future research on the subject. The review findings confirm that there is enormous potential for the design of better-performing buildings using this technique, but there are still many obstacles to overcome and areas for future research.

Keywords: building simulation; design optimization; energy efficiency; performance-based design; multidisciplinary design optimization; performance-driven design; evolutionary algorithms; early design stages

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1. Introduction

1.1. Background and General Context

Almost four decades after the 1970s energy crisis [1], and under the concrete scientific facts on human contribution to climate change, the environmental, or "green", design of buildings has become both a major concern and a very active research field. This is demonstrated, among other ways, by the large number of building sustainability assessment schemes that have been developed worldwide, such as Building Research Establishment Environmental Assessment Method—BREEAM (Britain), Leadership in Energy and Environmental Design—LEED (USA), Green Building Tool—GB Tool (Canada), Comprehensive Assessment System for Built Environment Efficiency—CASBEE (Japan), and so on. These schemes may present variations and singularities [2] but, in their vast majority, they integrate both social–economic criteria (management, innovation, economics, social, culture, and quality of services) and environmental performance ones (sustainable site, transport, indoor environmental quality, energy, waste, water, material, pollution) [3] since they are based on the concept of sustainability.

In this context, standards on building design construction have risen sharply to integrate new, ambitious demands regarding the minimization of impacts on the environment (energy efficiency, waste, and resource management) and the enhancement of indoor conditions (thermal, optical comfort, air quality) in the design procedure [4]. New approaches have emerged, which adopt a more holistic viewpoint, taking into account other factors, such as cost and life cycle considerations [5]. Moreover, they tend to emphasize the interdisciplinary collaboration of the design and construction team (integrated design) and the exploitation of technological advances, such as building information modeling (BIM) [6].

The use of building performance simulation (BPS) tools is essential in the process of green building design and such tools have assisted architects and engineers enormously in achieving better standards by evaluating the proposed measures. Many BPS software tools exist to assess building performance in terms of energy efficiency, indoor air quality, daylight-artificial lighting, acoustics, solar and photovoltaic analysis, etc. [7]. However, even though the use of BPS software is mostly valuable in the initial design stages, most BPS tools are assessment-oriented [8], rather than focused on dynamically supporting the decision-making procedure.

When no optimization routine is present, the architect must explore the design space manually to achieve a better design. This is normally done through an ineffective and time-consuming creative process, where a small number of design alternatives is tested, and then, based on the results, parameters are modified gradually to improve the design through trial and error. Since the late 1990s, a continuously-growing number of studies and reviews on the integration of performance simulations in the early design stages has been observed, indicating a clear shift of design professionals and academia towards a more comprehensive exploration of the design space to optimally address performance issues from the conceptual stages of a building.

The combination of BPS and design optimization is both a design philosophy and a practical technique [9] that has been around in the design practice and research for many decades. Several different names have been given to this approach: CDO—computational design optimization [10], performance-based design [11,12], design by simulation [13], MDO—multidisciplinary design optimization [14–17], GDS—generative design system, or GOD—goal-oriented design [14,16]; however, the term performance-driven design optimization [18] accurately represents its philosophy. When used under a computational/parametric 3D modeling environment the term "generative" or "computational" could add clarity to its description among architects who are familiar with these terms. It has now become clear that computational performance-driven design optimization (CPDDO) is an active research field, continuously gaining momentum among building professionals and academia.

1.2. Purpose and Significance of This Review

The primary objective of this review is to provide a comprehensive overview of computational performance-driven design optimization techniques through a concise presentation of works that integrate the simulation and optimization procedures in a parametric 3D modeling environment, and to highlight the different approaches of engineers and architects on the subject. In an attempt to encourage the use of CPDDO in the everyday architectural practice, emphasis is given on works that utilize commercially- or freely-available and widely-used software packages, rather that privately-developed tools for academic or commercial research purposes [16,19–24].

The significance of this review lies in the fact that even though most architects are highly concerned with the environmental performance of their designs, they are not familiar with simulation and optimization software, due to the nature of architectural education in the last decades (which typically lacks the encouragement of skills' development in coding, technical aspects, and analytical calculation). They approach green building design based on general principles, rules of thumb, and passive design strategies. Engineers, on the other hand, have studied building physics and optimization problems for many years, under a more technical perspective over the building envelope and systems. They are accustomed to coding, dynamic building simulations, optimization algorithms, etc. Therefore, an effort of bridging these two approaches together in one combined, seamless, and effective methodology is extremely important and timely. Finally, this review can act as a valuable tool for architects to gain an overview of the available research on performance-driven optimization so that they can integrate valuable results in their particular field of study or practice, avoid already-made mistakes, and identify areas of future research.

The focus on parametric 3D modeling is performed for various reasons:

- New generations of architects are becoming increasingly accustomed to digital processes of design generation and representation, demonstrating a global trend on algorithmic or parametric design in architectural practice and academic environment.
- New software tools have been developed that exploit powerful synergies, making it possible for building design simulation and optimization to be seamlessly integrated in digital representation software, thus allowing instantaneous feedback for the ongoing process of synthesis.
- The need to address multiple, contradicting objectives at the same time, during all stages of the design process, is becoming more and more imperative, making the establishment of a holistic approach for sustainable building design an urgent request.

1.3. Review Contents and Methodology

At first, the general topic of performance-driven design optimization is briefly presented by its analysis in three combining aspects: environmental performance simulation, design optimization, and digital/computational design. Then, previous reviews on relevant subjects are referenced and core literature on computational performance-driven design optimization is identified through a review of relevant works, mostly journal articles and conference proceedings. Finally, the conclusions drawn are presented after the discussion section.

The thirteen works that are referenced in Section 2.4 [25–37] were identified as those that present an integrated and automated procedure of computational performance-driven design optimization for specific case studies, without the manual exchange of files between different software tools or extensive custom scripting; i.e., those works that utilized parametric modeling as an organizing framework with simulation, optimization, and graphical 3D representation integrated and already available in the same software package. Therefore, works that did not fulfil all of the above criteria (such as generic optimization [38] or parametric studies [39], computational design studies without an automated optimization procedure [14,40–43], energy consumption assessment studies, etc.) were excluded from the study, leading to a very limited number of publications.

2. Analysis

2.1. Computational Performance-Driven Design Optimization

The topic of computational performance-driven design optimization consists of three aspects: environmental performance simulation, design optimization, and parametric/computational design. Each individual aspect is considered, by itself, a wide and active research field, but together they form a powerful synergy for the effective and optimized design of environmentally friendly buildings (Figure 1).

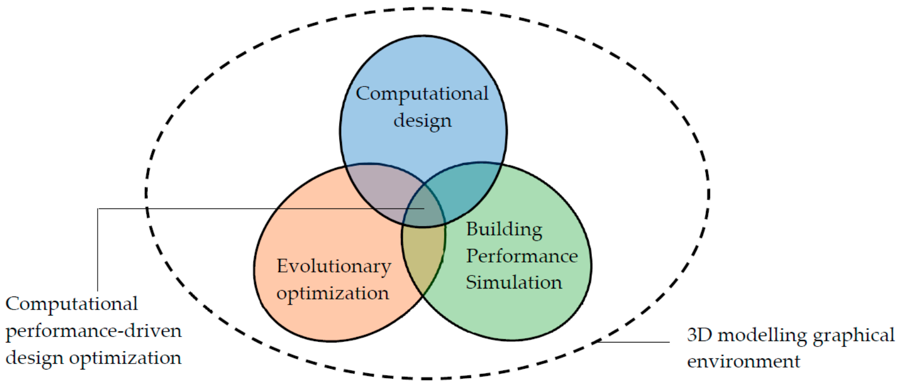


Figure 1. Computational performance-driven design optimization is the combination of computational design, evolutionary optimization, and BPS in a 3D modeling graphical context.

2.1.1. Building Performance Simulation

Building performance simulation (BPS) refers to the methods used to accurately calculate a hypothetical or existing building's performance on several aspects, such as energy, daylight, acoustics, Heating, Ventilation and Air Conditioning (HVAC) systems, indoor air quality, costs, etc. The use of BPS software is essential in the process of green building design, which aims at reducing the negative impacts on the environment and the occupants through strategies that conserve resources, reduce waste, minimize the life-cycle costs, and build a healthy environment for people to live and work. During the last two decades, simulation software tools have become widely available and specialized, but their organic integration in the design process is still limited due to obstacles already identified by Hien et al. in 2000 [44], such as a lack of pressure/appreciation from the client, high cost of software acquisition, insufficient staff training/skills (due to steep learning curves), and CAD-BPS interoperability issues [45] that extend the, already limited, design time.

BPS is mostly valuable in the early design stages, since design parameters, such as shape, orientation and envelope configuration can affect a building's performance by up to 40% [46], but also affect substantially its construction and operational costs. Nevertheless, most BPS tools are assessment-oriented [8] and are used to validate the performance or maximize the efficiency of a project with an already-established geometry (post-optimization) [30], rather than to dynamically support the decision-making procedure. In addition, the informative support they offer concentrates mainly on the envelope and systems, rather than the geometry setup. Several challenges contribute to these facts, such as time-consuming modeling, large design variability, conflicting requirements, input uncertainties, and other factors [47].

2.1.2. Design Optimization and Genetic Algorithms

The need for design optimization arose from the simple fact that when designing a building, the architect is faced with choices and measures which may have contradicting effects on the building's performance. As Coley and Schukat pointed out [48], simply minimizing the heat loss from a building is not sufficient for an exemplary low-energy design, since overheating or compromising of the building's functionality may occur. Moreover, low energy consumption can be achieved until a certain point by individual measures, but exceptional performance requires the concerted application of measures that, combined, optimize the performance of the whole building system.

From as early as 1990, Bouchlaghem and Letherman [49] introduced a numerical optimization method applied to the thermal design of non-air-conditioned buildings, combining an optimization technique and a thermal analysis model. Early optimization studies used the generic optimization process [50], but soon it became clear that multi-objective optimization (MOO) methods were more suitable to the complex nature of building optimization, because they would allow the assessment of multiple variables or conflicting objectives, and find sets of global Pareto optimal (non-dominated) solutions. According to Marks [51]: "the basic notions in the formulation of a multicriteria optimization problem are decision variables, constraints, and optimization criteria, also called objective functions". The designer can choose his preferred solution over several Pareto optimal ones [52] using an additional criterion, such as personal aesthetics. On this basis, one can seek to minimize building and heating costs, greenhouse emissions and other parameters related to the sustainable building design. Therefore, the environmental design of buildings arises as a MOO problem which, in current design practices, is solved intuitively and by human judgment.

Stochastic methods, such as evolutionary algorithms (EAs), can be used to assist in the resolution of MOO problems, by mimicking the systems and techniques encountered in evolutionary biology, thus shortening the timeframe through a more efficient search of the global solution space (Figure 2). Concepts, such as inheritance, mutation, natural selection, and crossover, are used to aid in the search for an optimal set of solutions to a given question. Since the first multi-objective evolutionary algorithms were introduced in the mid-1980s [53], they have seen a rapid increase in publications and applications in multiple scientific and engineering disciplines. Several types of EAs have been utilized in building design optimization, (genetic algorithms, evolutionary programming and genetic programming, covariance matrix adaptation evolutionary strategy, differential evolution, harmony search, particle swarm optimization, ant colony optimization and simulated annealing) and genetic algorithms (GAs) dominate the field in the aspects of envelope, form, HVAC, and renewable energy systems [54] optimization.

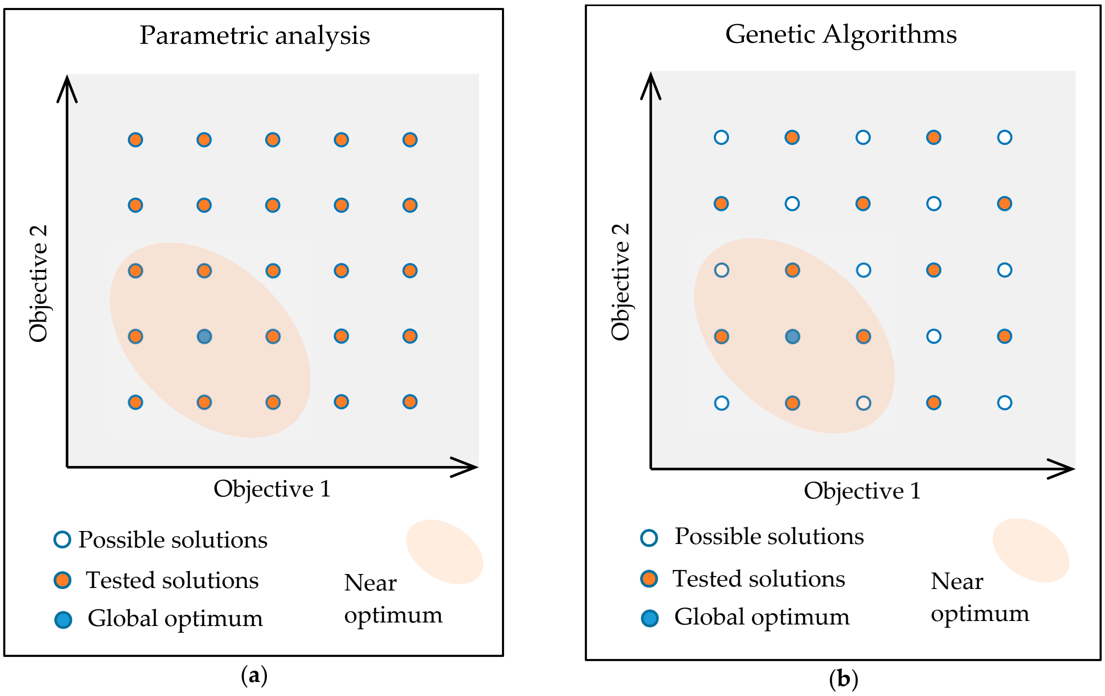


Figure 2. Diagramatic illustration of how genetic algorithms shorten the time-frame of a solution space search. In conventional parametric analysis (**a**) every possible solution is tested to identify the global optimum whereas when using genetic algorithms; and (**b**) a more efficient search is conducted utilizing evolutionary principles.

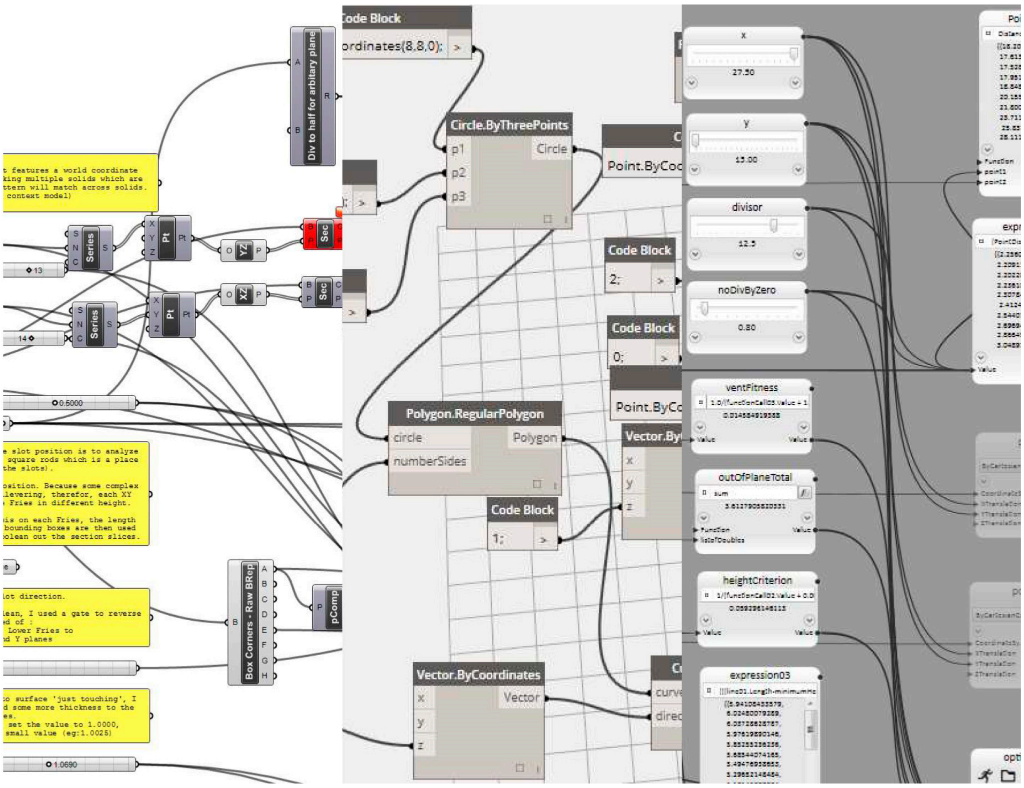
GAs are used to search the solution space (building parameter combinations) more efficiently, since they can handle non-linear problems of many dimensions and are capable of processing large quantities of noisy data efficiently [48]. Moreover, they can be applied in search spaces with many local minima, because of their ability to search using a population of points and not a single point, which limits the probability of the search getting trapped in a local minimum [55]. GAs have been used in building design applications for spatial problems (floor layout, usage assignment on buildings and building sites) [46,51,56], optimization of the sizing and control of HVAC systems [57], and for structural analysis and optimized design of trusses, beams, and columns [21,58]. The latest attempts follow the whole-part approach [46], attempting to apply GAs on the design of three-dimensional shapes [26,29] to help architects at early stages of design.

2.1.3. Digital/Computational Architectural Design and Parametric 3D Modeling

Due to rapid technological advances, the nature and scope of computer aided design (CAD) have evolved from, initially, a replacement method for hand drawings (to maximize efficiency), to, later, a tool for rule-(or grammar)-based design generation [59] and, currently, into tools that can handle some of the complexity of biological design processes which are still being discovered by scientists (bio-CAD). Therefore, there needs to be a distinction between CAD (computer-aided design) and DAD (digital architectural design), since the first imitates paper-based design, whilst the second is introducing a different, computational method of conceptualization and synthesis [60].

In 2014, Jabi [61] defined computational design as "a process based on algorithmic thinking that enables the expression of parameters and rules that, together, define, encode, and clarify the relationship between design intent and design response". Algorithmic or computational design is mainly an efficient way of flexibly describing and creating geometry through scripting, a way in which decision variables and constraints (parameters) are linked to geometry, interdependencies are established between objects, and transformational behavior of these objects is defined [59]. When designing forms or systems, this method offers dynamic control over geometry and components, allowing the designer to seek appropriate solutions on complex problems with the assessment of multiple variants at the same time.

In an attempt to make scripting more accessible to architects and designers, for them to be able to produce parametric 3D models, visual programming (VP) systems were developed. In 1990, Myers [62] defined a VP system as "any system that allows the user to specify a program in a two- (or more) dimensional fashion". In the same way, VP systems make it possible for nonprogrammers to create fairly complex parametric 3D models with little training. Since then, it is clear that VP systems have evolved enormously, making parametric 3D modeling increasingly accessible to the design practice through software like Grasshopper (Robert McNeel & Associates) [63], Dynamo BIM (Autodesk, Inc.) [64], and GenerativeComponents (Bentley Systems) [65]. Figure 3 is intended to provide a general sense of the user interfaces (UIs) of the above-mentioned widely-used VP systems, in order to highlight the difference, not only in mindset, but also in the every-day designing practice (software layout, UI, drawing tools) of architects when using CPDDO.



(a) (b) (c)

Figure 3. Screenshots of parametric 3D modeling software user interfaces from: (**a**) Grasshopper [63] for Rhinoceros 3D [64]; (**b**) Dynamo BIM [65]; and (**c**) GenerativeComponents [66].

2.2. CPDDO's Influence on the Creative Process

Based on the above, it is clear that there is a shift from analytical simulation to simulation for synthesis and generation [60]. Architectural design is conventionally viewed as a process of repetitive cycles of generation/evaluation/modification until the design objectives are satisfied. Following this inefficient workflow, there is practically no way to determine that proposed solutions are even close to a realistic optimum [48]. In computational performance-driven design optimization, the desired performance can be selected and activated as a mechanism that can generate and modify designs through the optimization procedure [11,67] (Figure 4). With the development of user friendly software, such as the Galapagos Evolutionary Solver (Robert McNeel & Associates) [68], Octopus (University of Applied Arts Vienna and Bollinger+Grohmann Engineers) [69], and Optimo (Mohammad Rahmani Asl, Alexander Stoupine, Saied Zarrinmehr, Wei Yan) [70], EAs are no longer confined within the walls of the academic world and research labs, but are largely available for exploitation in real projects by architectural practices, engineers, and students worldwide. When coupled with instantaneous, dynamic building performance simulations on a 3D digital representation framework, they make partial automation of the design procedure possible, and integrate in it very large amounts of data.

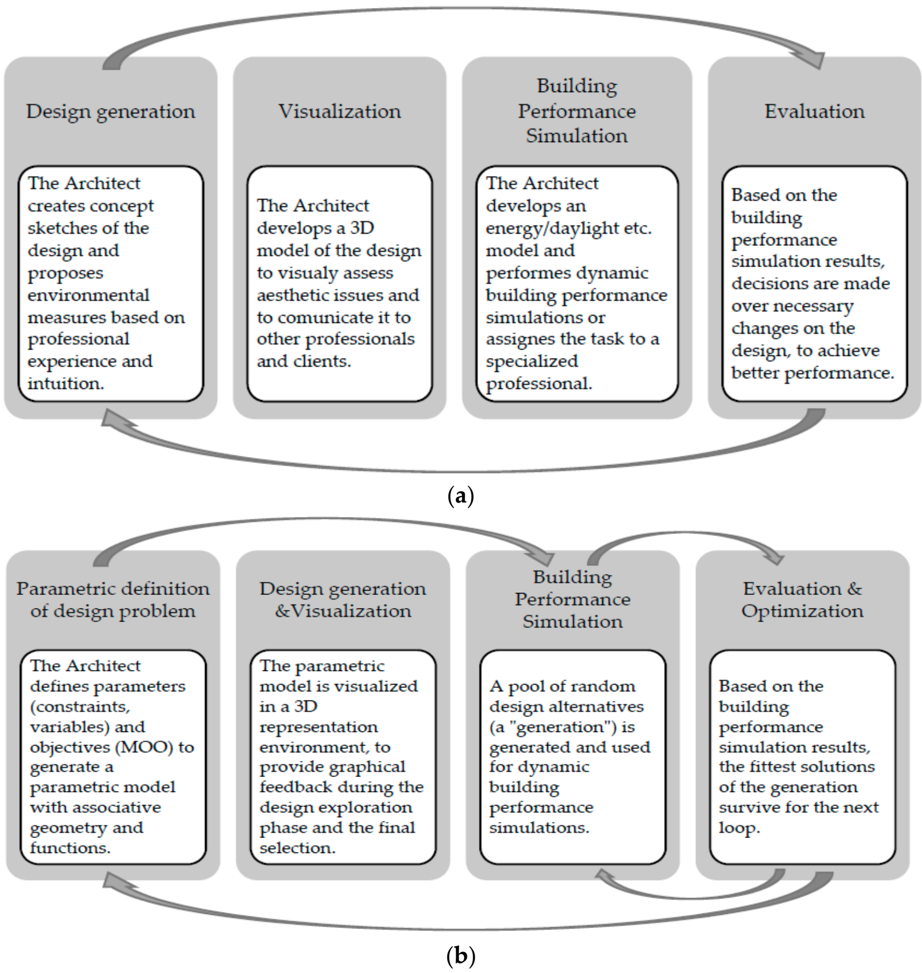


Figure 4. The iterative procedure of architectural design (**a**) as it is currently practiced; and (**b**) according to the computational performance-driven design optimization concept.

Parametric design implies a change in the perception of creativity as we know it towards a more explicit form of expression, presenting itself as a new design paradigm [71]. The creative process consists of the combination of certain measures/decisions recalled from the architect's memory based on his aspirations regarding a project (owner's needs, location, and surroundings of the site, available built area based on codes, environmental performance, cost efficiency, aesthetics, etc.). In parametric modeling, this synthetic procedure becomes explicit, and all of these parameters are expressed to form an algorithm that will drive the design process. Without an optimization procedure, parametric design is merely a conscious approach for the formulation of a problem and a tool for experimentation. If an optimization routine is present, the variation of the produced design alternatives depends on the extent of set parameters and the configuration of the optimization engine. However, even when a large number of parameters are already set, the designer can always boost the creative process by incorporating another level of "resolution", adding new parameters to define textures, patterns, and forms. Therefore, the creativity of the designer in CPDDO is not only compromised, but it is rather enhanced by the abundance of equally well-performing solutions on a Pareto front, and the ability to choose depending on his priorities and then further adjust a chosen design solution.

2.3. Previous Reviews and Key Works on Relevant Subjects

Prior to this, several reviews and studies focusing on different aspects of the subject have been published. They investigate and compare the different methodologies and means, such as algorithms and software, optimization objectives, and policy or application issues. Readers can recur to the following studies if interested for an in-depth analysis of building performance optimization aspects:

- Optimization methods and software:

Østergård et al. [47] reviewed papers on building simulations in early designs identifying the following research areas: statistical methods, optimization, proactive simulations, knowledge-based input generation and CAD-BPS interoperability. Huang and Niu [72] studied papers on the optimization of building envelope design, compared popular algorithms, objectives, limitations, and potential breakthroughs. Machairas et al. [73] studied the algorithms used for building design optimization. Tian [74] reviewed sensitivity analysis methods used in building performance analysis. Hamdy et al. [75] compared the performance of seven popular multi-objective optimization algorithms for near-zero energy buildings (nZEB) design problems. Iwaro et al. [76] proposed an integrated criteria-weighting framework incorporated into an integrated performance model (IPM) for the assessment of sustainable performance and selection of a sustainable envelope design.

- nZEBs and solar design:

Stefanovic [77] reviewed studies of simulation-based optimization of passive solar design strategies. Attia et al. [78] attempted to assess the gaps and needs for integrating building performance optimization tools in the design of nZEBs by reviewing trends in simulation-based building performance optimization (BPO) and outlining major criteria for optimization tools selection and evaluation (literature review and interviews with 28 optimization experts). Lu et al. [79] studied the issues related to the design and control of nZEBs, including design optimization issues. Kanters et al. [80] presented the results of a survey and interviews on tools and methods architects use for solar design. Zhao and Magoulès [81] reviewed models for the accurate prediction of building energy consumption, including elaborate and simplified engineering methods, statistical methods, and artificial intelligence methods. Pacheco et al. [82] conducted a review on the energy-efficient design of buildings. Ochoa et al. [83] examined the state of the art in lighting simulations related to building science research. Fumo [84] reviewed the basics and classified whole building energy estimations.

- BPS software:

Hopfe et al. [85] compared six BPS tools and their potential use in the conceptual stages of building design. Crawley et al. [86] compared the features and capabilities of 20 major building energy simulation programs. Attia et al. [87] conducted an online survey to compare ten major BPS tools. Attia and Herde [8] compared 10 early design simulation tools.

- Holistic approaches:

Negendal [88] reviewed the different ways designers and analysts use BPS in the early design stages and proposed integrated dynamic models as a combination of a design tool, a visual programming language and a BPS to provide better support for the designer. Nguyen et al. [89] provided an overview of the research and applications of simulation-based optimization methods in the building sector. Shi [18] reviewed the evolution of performance-based/driven architectural design and also discussed the optimization technique and its application in architectural design. Evins [54] reviewed research works applying computational optimization to sustainable building design problems. Shi et al. [9] analyzed and classified 116 works on building energy efficient design optimization and examined subjects such as the general procedure, the origin and development, the design objectives and variables, the energy simulation engines, the optimization algorithms, and the applications of this technique.

Table 1 summarizes the areas of focus of the above-mentioned works.

Table 1. Focused areas of previous published reviews and key works on topics related to performance-driven optimization in building design. The symbol x is used to indicate the focused topics of each paper.

Researchers	Year	Area of Focus			
		Methodology	Tools	Objective Functions	Policy and Evaluation
Østergård et al. [47]	2016	x	x	-	-
Stefanovic [77]	2013	x	-	x	-
Huang and Niu [72]	2015	x	x	x	x
Attia et al. [78]	2013	-	x	x	x
Lu et al. [79]	2015	x	-	-	-
Negendal [88]	2015	x	-	-	x
Nguyen et al. [89]	2014	x	x	x	x
Machairas et al. [73]	2014	-	x	x	x
Shi [18]	2010	x	-	-	-
Kanters et al. [80]	2014	-	x	-	x
Hopfe et al. [85]	2005	x	x	-	x
Crawley et al. [86]	2008	-	x	x	-
Attia et al. [87]	2009	-	x	-	x
Attia and Herde [8]	2011	-	x	-	-
Zhao and Magoulès [81]	2012	x	-	-	x
Pacheco et al. [82]	2012	x	-	-	-
Ochoa et al. [83]	2012	x	x	-	-
Tian [74]	2013	x	x	-	x
Evins [54]	2013	x	-	x	x
Iwaro et al. [76]	2014	x	-	x	-
Fumo [84]	2014	x	x	-	-
Shi et al. [9]	2016	x	x	x	x
Hamdy et al. [75]	2016	-	x	-	x

2.4. Practical Examples of Computational Performance-Driven Design Optimization

A number of works investigate the theoretical framework of computational performance-driven design optimization [11,12,18,19,67,90,91], including some of the above-mentioned reviews and papers [9,18,47,54,72,76,77,87,88]. However, the following 13 works were found to utilize this framework in a practical manner:

Suyoto et al. [25] used the software packages Grasshopper, Ecotect, Geco, Galapagos, and other tools to solve problems during all stages of the design process (programming, site planning, massing, structure planning, and facade planning) of a mixed use project. Specifically, he used this method to maximize the built area, to search for the shortest pedestrian pathway, to form masses in line with skyline changes and regulation requirements, to reduce heat gains due to solar radiation, to position seating areas and public activities, to optimize a diagrid structure system and to verify deflections and material behavior. Finally, exterior walls of the buildings were analyzed to identify areas that needed additional shading devices, to select types of glass, suitable shading devices, and Overall Thermal Transfer Value (OTTV) calculation.

Jin and Jeong [26] conducted an optimization process for a free-form building shape to predict and optimize the heat gain and loss characteristics in the early design stages. They applied a GA optimization process using Galapagos Evolutionary Solver to a free-form building model in Grasshopper in order to minimize passive heat gain and loss for various climate zones. Santos et al. [27] applied the methodology on three prototype glass pavilions to determine the optimal fritting density of different glass panel clusters for energy efficiency and daylight for winter, and especially summer conditions. They used the add-on for Grasshopper Kangaroo Physics 2.0 [92] to panelize and planarize the initial NURBS models and transform them to mesh objects in order to automatically translate them to EnergyPlus. They reached energy-efficient passive solutions that resulted in percentages of improvement of almost 70%. Qingsong and Fukuda [28] used Grasshopper, Ladybug, Honeybee, and Galapagos Evolutionary Solver to optimize an office building's openings for minimum energy consumption and maximum useful daylight illuminance.

Zhang et al. [29] applied parametric modeling with Rhinoceros and Grasshopper to generate a free-form building model, and optimize its shape using a multi-objective genetic algorithm plugin (Octopus) to achieve three objectives—i.e., to maximize solar radiation gain, to maximize space efficiency, and to minimize the shape coefficient. A Pareto frontier was generated to represent the optimal solutions and to assist in final decision-making. The authors conclude that, compared with a cube-shaped reference building, the total solar radiation gain of the optimized free-form shape building is 30–53% higher, whilst the shape coefficient value is reduced by 15–20%, with a decrease of less than 5% of the space-efficiency. Rahmani Asl et al. [31] used Autodesk Revit and Dynamo to minimize energy use while maximizing the appropriate daylighting level on a residential building. A prototype of an integrated MOO system was created using a non-dominated sorting genetic algorithm-II (NSGA-II). This integrated framework for BIM-based performance optimization is later referenced as BPOpt [93] and the optimization nodes in Dynamo as Optimo [70].

Zboinska [32] used a simulated annealing optimization algorithm in Grasshopper and DIVA for Rhino to fine-tune the design of a multi-curved façade element for annual solar energy harvesting. Anton and Tanase [30] developed several architectural forms using parametric design tools and solar/daylight analysis, and a canopy optimized for the least solar energy absorbed on its faces that would, at the same time, provide the most shadow area. Both objectives were used as criteria for a genetic algorithm (using Galapagos) that searched through a series of parameters to establish the general shape of the canopy. Ercan and Elias-Ozkan [33] produced custom design alternatives for shading devices to optimize daylight while blocking out excessive solar heat gains in an office building in Larnaca, Cyprus. They used Grasshopper, Diva, and Galapagos and achieved significantly better performance compared to the initial design. The design alternatives were generated by evolutionary algorithms in accordance with daylight performance requirements and simulated to assess their shading and daylight efficiencies. Ashour and Kolarevic [34] utilizing Grasshopper, Octopus, and DIVA for a retrospective design case of the "De Rotterdam" building (designed by OMA Architects) with the aim of increasing the floor area ratio (FAR), financial profit, average daylight factor and views.

Konis et al. [35] applied this methodology on a 4982 m^2 (53,819 sq.ft) medium office building test case for four different urban settings and climates. Using Grasshopper, Honeybee, and Octopus they optimized the building's shape, orientation, window-to-wall ratio (WWR), and shading devices to minimize energy use intensity (EUI) and maximize spatial useful daylight illuminance (sUDI). Results showed that the proposed workflow can deliver between a 4% and 17% reduction in energy use intensity (EUI) while simultaneously improving daylighting performance by between 27% and 65%, depending on the local site and climatic conditions compared to an ASHRAE 90.1-compliant reference building of equal floor area. Liuti et al. [36] used this method to optimize a roof structure in Singapore for solar and structural performance. Negendahl and Nielsen [37] used Grasshopper, Ladybug/Honeybee, Termite (Andy Payne, Panagiotis Michalatos, Eddy Man Kim, and Marshall Prado) [94], and Octopus to optimize a building project for energy use, daylight, and capital cost without external shading systems.

3. Discussion

3.1. Current Status of Computational Performance-Driven Design Optimization

During the last decade, many researchers have attempted to create custom CPDDO workflows under different names (creative optimization tool, parametric method, EEPFD, PPOF, BPOpt, ParaGen, EcCoGen, etc.) [16,19–24] and using a variety of tools. However, the implementation of these frameworks outside the research teams themselves has been extremely limited for various reasons (coupling strategies and software capabilities were not adequately explained, implementation would be extremely time consuming, special skills in coding were required, etc.). Building design and construction is a multi-disciplinary process. Nevertheless, it is extremely important to address, specifically, the architects' needs with regard to computational performance-driven design optimization, since their role in the design process when it comes to performance issues is dominant (typically they decide on shape, functions, morphology, and envelope design) [91].

Based on the above it is clear that the following features are essential for the successful implementation of the CPDDO framework [24]:

(1) User-friendly interface adapted to designers' needs;
(2) Platform integration and automation between BPS and optimization engines in order to alleviate interoperability issues and reduce iteration times;
(3) Rapid generation of design alternatives utilizing computer capacity in full;
(4) Ability to evaluate the design alternatives through parallel visualizations coupled with comparative performance data;
(5) Data interpretation guidance to overcome domain knowledge gaps;
(6) Trade-off analysis for conflicting criteria; and
(7) Sensitivity and uncertainty analyses to provide guidance on the impact of the decisions made.

Comparing this framework to conventional environmental design, it is evident that it still requires an increased amount of effort and time even though many of the above-mentioned issues have been addressed to some extent (user-friendly interface, platform integration, evaluation of design alternatives).

Systematic literature research on the subject revealed that the most popular software for computational performance-driven design optimization among architects is, by far, Grasshopper for Rhinoceros 3D, followed by Dynamo for Revit. This is highlighted by the practical implementation examples of the previous section: twelve out of thirteen examples utilize the VP system of Grasshopper for Rhinoceros 3D, whereas only one uses Dynamo for Revit. A possible explanation for this trend is that Rhino is a widely-used software among Architects and Grasshopper is a free tool with many developers that constantly provide support and new components. Moreover, Grasshopper features a multitude of already developed tools, such as Ladybug/Honeybee, DIVA, Kangaroo, Galapagos, Octopus, and others, that provide many capabilities and render it an accessible method of using environmental performance simulation via a VP interface. On the other side, the use of BIM software in the global construction industry is expanding [95] and Revit has already integrated BPS tools in its main software package, as well as the relatively new Optimo package for Dynamo. Overall, publications on the subject with practical implementation of the workflow are very few, since CPDDO is still a relatively new methodology, and cases outside academia are usually not published in scientific journals.

It is beyond doubt that artificial intelligence is gaining momentum in architecture: computational design is now considered a valuable method to explore design potential and enrich the process of architectural synthesis in all scales, from urban [96,97] to industrial object design. In combination with the sustainable design movement, it seems that CPDDO is attracting continuously more attention from both professionals and academia as a holistic approach able to bridge the gap among architects and BPS tools, since it combines human (non-determinant decision-making, creativity, pattern recognition, aesthetics) and computer advantages (consistency, calculating, iterative) [25]. Instead of being confined in the offices of experts, used only as a compliance check for various green codes, dynamic environmental performance simulation can now play an active role in the building planning and design process [12].

3.2. Challenges and Future Work

The proposed framework still requires a substantial investment of time and interdisciplinary collaborations in the very early phase of the design, but especially requires a shift in the way we conceive the design process: from designing the building itself we must move to defining the structure and interconnections of the building's parameters. Moreover, we need to seamlessly combine modeling, methods, tools, and people that are willing to embrace technological advances and emerging computational methods in architecture. Therefore, architectural education should be adapted to foster the development of advanced logical and digital skills, required for the design of appropriate formulas, as well as the knowledge of technical aspects such as daylighting, solar, acoustics, energy, structural, air, thermal, and moisture issues.

Future research should concentrate in making user interfaces even more architect-friendly, since learning curves are still very steep, and ensure that no coding skills are required, especially in BIM-based CPDDO which presents additional challenges [14]. Additionally, further integration is needed to achieve truly seamless operation and interoperability without multiple software installation packages and the need for extensive customization. Finally, standardization of processes for typical building cases could further reduce preparation times and address the large gap that still exists between research and practice. Simplification of these procedures would also allow for older professionals to catch up.

4. Conclusions

Computational performance-driven design optimization exploits powerful synergies between already-developed software tools and can skyrocket the efficiency of environmental building design. Based on all previous sections, several conclusions can be drawn and are summarized in the following points:

- Solutions proposed in a CPDDO context are based on scientifically sound performance analysis rather than human judgment, without compromising aesthetics. Therefore, the quality of the design is enhanced by intelligent decisions, and the designer's understanding and knowledge on the project are improved.
- Overall, publications on the subject with practical implementation of the workflow are very few, a result of the fact that the integrated tools needed for its implementation were developed during the last decade.
- Rhino and Grasshopper are the software packages that currently dominate the field, but BIM growth may change this, if the right tools are developed and introduced efficiently in the BIM workflow.
- Architect-friendly platforms that seamlessly integrate all relevant functions are essential for the successful implementation of CPDDO in everyday architectural practice.
- To extend expertise in the field, architectural education must adapt to the technological advances and encourage professionals to embrace new concepts and think outside the box. CPDDO needs to be appropriately situated in the broader topic of computational design.
- Efforts need to be made to improve time feasibility, gains in performance and cost for the whole process to be meaningful enough to justify the effort involved. This includes the improvement of tools that are still too limited for the complex nature of three-dimensional problems and advanced systems, such as kinetic facades, interactive architecture, etc. Improvement of all building stakeholders' awareness on the importance of optimization in the design procedure is also essential. This could be addressed, among other ways, with comparison studies on buildings designed with and without an optimization procedure.
- More detailed simulations are advised after the final design decisions have been made, since this framework is primarily meant to offer a direction/guidance over a multitude of possible solutions.
- CPDDO should not be treated as a threat for creativity and architectural expression because its use can actually enhance an architect's imagination by informing the physical and aesthetic properties of the building envelope with different densities or patterns; and cannot embed qualitative criteria, such as aesthetics.

Acknowledgments: This research, including the costs for open access publication, is funded by the Greek State Scholarships Foundation (IKY) under the program "Research Projects for Excellence IKY/SIEMENS".

Author Contributions: This paper is part of Ph.D. research. Theodoros Theodosiou contributed in the preparation of the study and the analysis of the results. Eleftheria Touloupaki identified and analyzed the core literature works, prepared the figures, and wrote the paper.

Conflicts of Interest: The authors declare no conflicts of interest.

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