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Energy performance optimization as a generative design tool for nearly Zero Energy Buildings

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Abstract

In order to effectively design nearly Zero Energy Buildings, the assessment of energy performance in the early design stages through simulation is an important, although very demanding and complex, procedure. Over the last decades, various tools and methods have been developed to address performance-related design questions, mostly using Multi-Objective Optimization Algorithms. Technological advances have revolutionized the way Architects design and think, automating complex tasks and allowing the assessment of multiple variants at the same time. In this paper, a new nZEB design workflow methodology is proposed, integrating evolutionary algorithms and energy simulation, and its capabilities and current limitations are explored.

Keywords: nZEBs; optimization; evolutionary algorithms; multi-objective optimization; environmental design; visual programming; generative design; parametric modelling

1. Introduction

On our path to achieve a sustainable and low-carbon society and in order to address the incredibly high percentage of end-use energy buildings consume, energy conservation measures have been introduced in the building design and construction industry, during the last decades, worldwide. Consequently, the environmental design of buildings has evolved to a major research topic. In this context, the Directive on Energy Performance of

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Buildings - recast (EPBD) [1] establishes the "nearly Zero Energy Buildings" (nZEBs) as the target for all new buildings in the EU from 2021.

The methods currently used for the design of nZEBs, rely on the application by the Architects of standardized bioclimatic design measures according to their professional expertise and intuition. The assessment of these measures' impact on the building's energy performance and the thermal/optical comfort of its occupants through simulation is a complex procedure, which normally requires a great amount of effort, time and special skills. For these reasons, it is normally conducted after the decision on major building elements, or in 2-3 alternative solutions. The idea of the energy simulation as a design factor in the early design stages is not new. A number of tools and methods have been developed towards that direction, to address performance-related design questions, mostly using Multi-Objective Optimization algorithms.

Technological advances, on the other side, have revolutionized the way Architects design and think, making it possible to partially automate the design procedure and integrate in it huge amounts of data. Computational Generative Design or Parametric/Algorithmic Modelling, an emerging trend in architecture during the last decades, is now considered a valuable tool to explore design potential and enrich the process of architectural synthesis. 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. Visual/graphical coding tools for design, such as Dynamo Studio for Autodesk Revit or Grasshopper for Rhinoceros 3D, offer the opportunity to implement parametric design concepts using visual logic, thus automating complex tasks.

This paper aims to explore the capabilities and current limitations of performance-driven generative design in architecture, through a review of present and potential applications. A new workflow methodology is then proposed, integrating genetic algorithms and energy simulation through Grasshopper for Rhinoceros 3d and the plugins Ladybug and Honeybee, for a comprehensive exploration of performance-based design alternatives in the building scale.

Nomenclature

nZEBs	Nearly Zero Energy Buildings
MOO	Multi-Objective Optimization
VP	Visual Programming
EAs	Evolutionary Algorithms
MOEAs	Multi-Objective Evolutionary Algorithms
BPS	Building Performance Simulation
RES	Renewable Energy Sources

2. Performance simulation in building design and nZEBs

Computer simulation tools are increasingly used for the assessment of a building's energy performance and the thermal/optical comfort of their occupants. They represent a powerful tool for studying the environmental performance of buildings since they provide useful feedback for the on-going process of design. In 2000, W. N. Hien et al. [2] concluded that the main reasons architectural firms would not use simulation tools in the design process were lack of pressure/appreciation from the client, high cost of software acquisition and insufficient staff training/skills due to steep learning curves and not user friendly interfaces that would extend the, already limited, design time. Since that time, a lot has changed in the field, and simulation software has become widely available and specialized, influencing the way buildings are designed, analyzed and constructed. In the Building Energy Software Tools (BEST) directory website [3], formerly hosted by the US Department of Energy, one can search and find information on all the available simulation software for energy, lighting, acoustics, indoor air quality simulation, solar and photovoltaic analysis, etc.

A considerable amount of comparative studies and reviews concerning Building Performance Simulation (BPS) in building design is available. T. Ostergard et al. [4] have categorized these studies into several topics, such as solar design [5], simulation software and tools [6], sensitivity analysis methods [7], computational optimization methods [8] etc. Whilst BPS is mostly valuable in the early design stages (when design decisions on the building geometry and envelope which have a major impact on the resulting environmental performance, construction and operational costs are made) its application is still limited in the final design stages due to several challenges, such as time-consuming modeling, large design variability, conflicting requirements, input uncertainties and other factors [4].

For the design of nZEBs, in which energy consumption goals are clear, two issues must be addressed as early as possible in the design procedure: the maximization of the building's energy efficiency and the coverage of the resulting energy demands from systems that utilize Renewable Energy Sources (RES). It is clear that the use of BPS tools is fundamental for the delivery of instantaneous feedback and support the decision making for passive and active design strategies in nZEBs. As stated before, the disadvantage of most existing BPS software (90% of tools) is that they operate as post design evaluative tools [9]. In addition, the informative support they offer concentrates mainly on envelope and systems, rather than the geometry setup.

3. Computational building optimization and evolutionary algorithms

From as early as 1990, N. M. Bouchlaghem and K. M. Letherman [10] have 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 [11], but soon it became clear that multi-objective optimization (MOO) methods where 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 W. Marks [12] "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 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.

Evolutionary Algorithms can be used to assist in the resolution of MOO problems, by mimicking the systems and techniques encountered in evolutionary biology. 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-eighties [13], substantial literature has been developed, by both engineers and Architects, and several types of EAs (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) have been identified. Of all the EA types mentioned, Genetic Algorithms dominate the field of building design optimization in the aspects of Envelope, Form, HVAC and Renewable Energy systems [8].

Due to rapid technological advances, the nature and scope of Computer Aided Design has evolved from, initially, a replacement method for hand drawings (to maximize efficiency), to, later, a tool for rule-(or grammar)-based design generation, and currently into tools that can handle some of the complexity of biological design processes which are still being discovered by scientists (bio CAD). With the development of software such as the Galapagos Evolutionary Solver [14], evolutionary algorithms 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.

4. Generative/Parametric Design and technological advances in Architecture

In 2013, W. Jabi defined Parametric 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" [15]. Parametric or generative or algorithmic design is mainly an efficient way of flexibly describing -and creating- geometry through scripting, a way in which decision variables are linked to geometry. P. Janssen identified four kinds of parametric modelling techniques: object modelling, associative, data flow and procedural, that mainly vary in their ability to support iteration [16].

To aid designers in the process of writing scripts in order to produce parametric models, Visual Programming (VP) systems were developed. In 1990, B. A. Myers [17] defined a VP system as “any system that allows the user to specify a program in a two-(or more)-dimensional fashion”. D. C. Halbert [18] had already identified VP systems as a valuable tool for nonprogrammers to create fairly complex programs with little training. Since then, it is clear that VP systems have evolved enormously, making parametric modelling increasingly accessible to the design practice through software like Grasshopper [19], Dynamo [20] and GenerativeComponents [21] (Fig. 1).

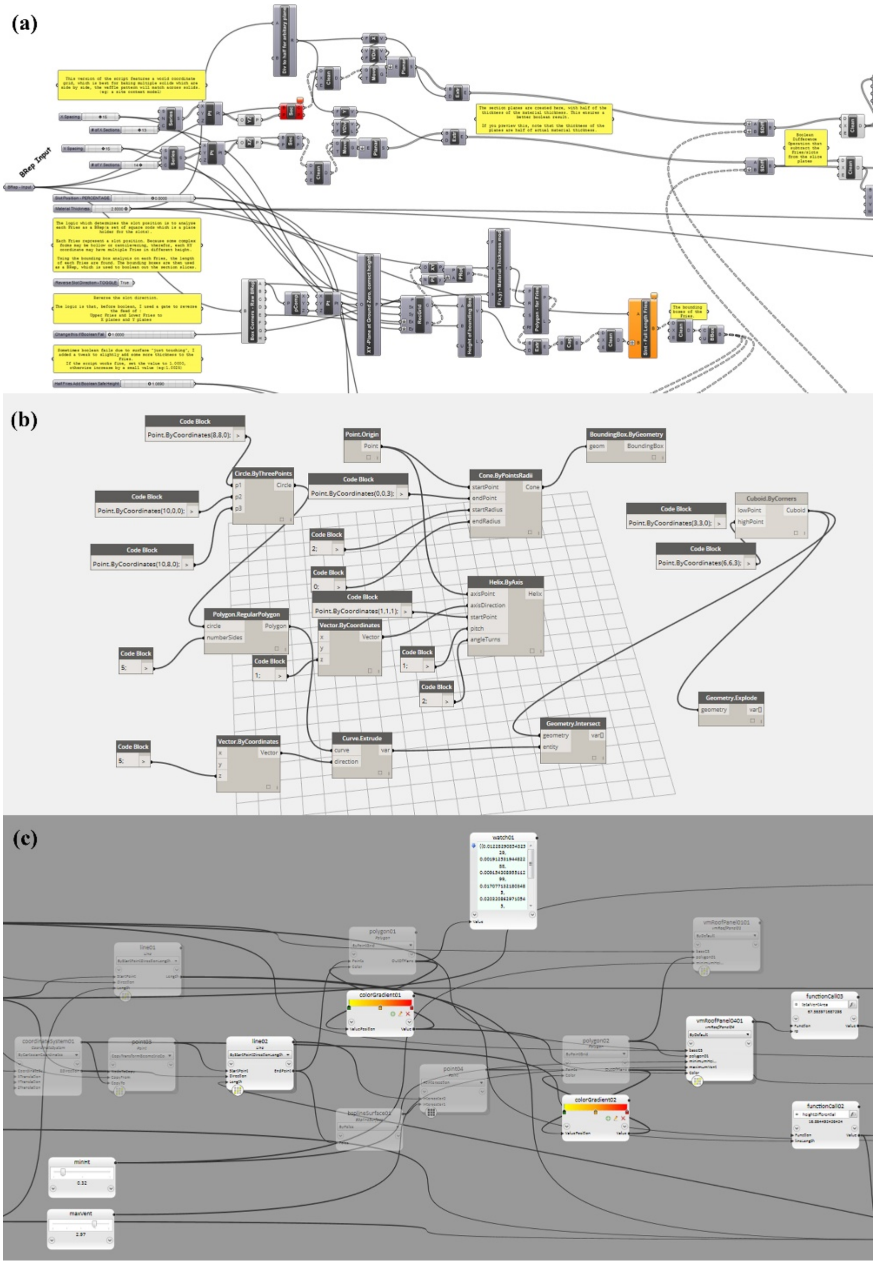

Fig. 1. Screenshots of User Interfaces from Software Grashopper (a), Dynamo (b) and GenerativeComponents (c) [Online image sources: http://simplydynamo.blogspot.gr, http://www.grasshopper3d.com, http://4.bp.blogspot.com].

Parametric design mimics nature's formation procedures by playing mostly with parameters of end geometry, making it possible to access the developmental stages of the building's form. In combination with BPS tools, they, undoubtedly, form a powerful synergy for the effective and optimized design of nZEBs. As stated before, the era of using CAD as a tool to transcribe paper based design has almost drawn to a close. Designers have moved from 2D to 3D CAD and from 3D to BIM to increase efficiency, with remarkable success. And now, a context of unprecedented connectivity, cloud based computation and use of resources, direct digital manufacturing, human behavior modelling, and increasingly powerful capabilities in computers and smart devices, is set to dramatically change not only CAD, but the creation process itself, towards genetically based and optimized design processes [22]. Even though many designers consider Generative Design as an advanced CAD technique, it is more about embedding intelligence into it, by fully exploiting its inherent capabilities.

5. Proposed nZEB architectural design workflow methodology

The proposed workflow methodology combines Parametric modelling and MOEAs to integrate Energy Simulation in the early design stages of a building, in order to minimize its lifecycle energy requirements and achieve the nZEB standards. The software tools proposed for seamless operation are Grasshopper [19] for Rhinoceros3d [23] with Galapagos Evolutionary Solver [14], Ladybug and Honeybee [24]. Therefore, a decision support tool is introduced, to overcome the limitations of the current practices in energy efficient building design (bioclimatic design), which are based on the Architect's intuitive application of fragmentary measures rather than the aim to optimize the building as a whole system of inter-connected parameters.

Even if existing standards for the design of nZEBs are used, the resulting solutions can be furtherly optimized by utilizing the proposed methodology. The concept of a decision support tool for architectural design traces back to 1970, when Nicholas Negroponte proposed an "Architecture Machine" that could serve as an all-purpose cybernetic design assistant [25]. In performance-based generative design, the performance of a building becomes the driving factor for its design (form and geometry generation, envelope materials, HVAC systems etc.), instead of being the outcome of already made decisions [26].

In 2001, L. G. Caldas [27] had already developed a Pareto-based, shape-generative method using EAs and suggested its possible extension over solid parametric modelling tools. Parametric design offers to the designer guidance, since it forces him to mentally decompose the problem and, when paired with MOO, enables the visual tracking of the optimization progress. Figure 2 describes the necessary steps for the proposed methodology, as analyzed in the following sections.

5.1. Stage 1: Parametrization

When designing nZEBs or energy efficient buildingsc in general, the Architect cannot interfere with the climatic conditions at the building site, but he can make decisions over the building's characteristics (each one of which affects its thermal performance in a different way), such as (but not limited to):

- General layout and form (shape and orientation)
- The thermophysical properties and thickness of the envelope's materials (walls, roof, floor, windows etc.)
- Location of doors, windows and their sizes
- Shading of openings and envelope
- Ventilation rate
- Thickness and material of internal partition walls
- Electromechanical systems (heating, cooling etc.)

Inside the Grasshopper [19] User Interface, hosted in Rhinoceros 3D [23], the designer can define rules/concepts linking the above variables and other standard constrains (surface area, number of levels etc.) to geometry, in order to create an initial population of randomly generated design solutions that will proceed to the "breeding" process.

5.2. Stage 2: Optimization and Performance Simulation iterations

As stated by Ostergard et al. [4], building optimization procedures typically consist of six distinct steps that can be repeated in an iterative manner:

1. Identification of design variables and constraints.
2. Selection of simulation tool and creation of a baseline model.
3. Selection of objective function(s).
4. Selection of optimization algorithm.
5. Running simulations until optimization convergence is achieved.
6. Interpretation and presentation of data.

Using Genetic Algorithm solvers such as the Galapagos Evolutionary Solver [14] (plugin for Grasshopper), one can discover the optimal combination of values for a given set of variables by applying the Darwinian theory of evolution on the design alternatives. The result after several iterations and the elimination of unfit solutions, is a pool of optimized design alternatives which meet the objective function set.

Performance simulations run along with the optimization procedure, to evaluate the fitness of the semi-optimized design solutions until the objective function is met. Software tools such as Ladybug and Honeybee [24] for Grasshopper can be used to connect the parametric geometry to energy and daylight simulation software (EnergyPlus, Radiance, Daysim etc.) to support the decision-making process during the initial stages of design.

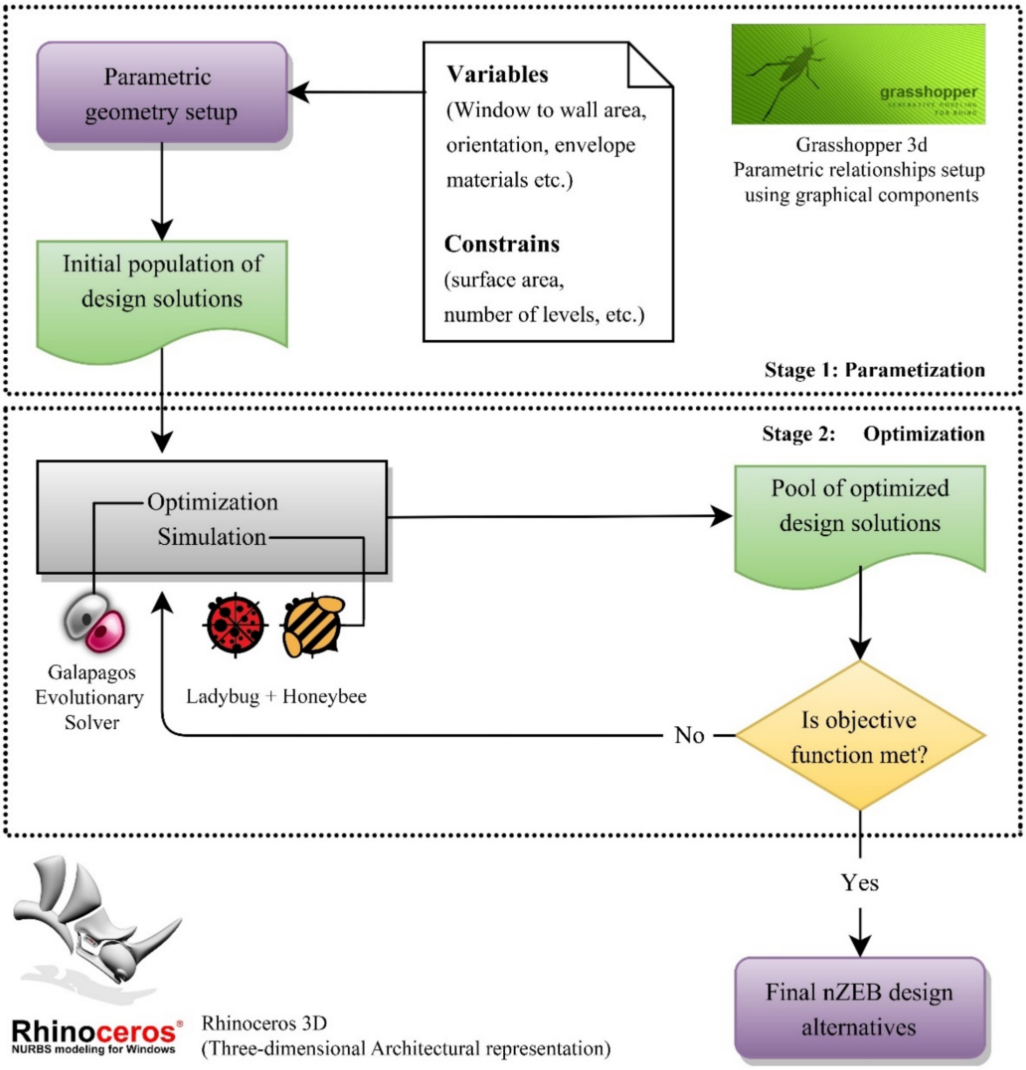

Fig. 2. Flow chart of the proposed workflow methodology (official logos are used).

6. Conclusions

Parametric design of nZEBs using integrated energy simulation and form optimization with genetic algorithms is an interesting area that exploits powerful synergies between existing software tools and shows promise for improving the architectural synthesis process. The success of generative design demonstrates that if we make procedures and software more user friendly, this technique can *revolutionize* the way Architects design. The need to address multiple, contradicting objectives at the same time, during all stages of the design process, is getting more and more imperative, making the establishment of a holistic approach for sustainable building design an urgent request.

New software tools have been developed, which address issues such as automation and interoperability, so as to simplify tasks, reduce modelling time and aim interdisciplinary collaboration. These tools now enable Architects to comprehensively explore the vast solution space in an efficient manner, driving the design towards optimized alternatives in the early design stages. Digital design and optimization should not be treated as a threat for conventional Architecture since they are merely tools under the Architect's control, assisting him to identify the better performing solutions over a problem, and cannot embed qualitative criteria such as aesthetics.

However, more work needs to be done in order to fully utilize technological advances and overcome diachronic problems of building design: Inefficiency in the collaboration between architects, engineers and contractors must be tackled by emphasizing in the development of advanced and user friendly, integrated data systems. Interoperability between existing software is a key factor that will allow the seamless execution of complex workflows. New possibilities are now open for exploration: collaborative, cloud-based technology will transform business models in the construction industry, by allowing us to design better buildings in less time through data management and integration. Cloud systems now offer a combination of massive computational resources and connectivity in an unprecedented scale across a wide range of activities. They provide reliable and scalable computational power to many enterprises without the associated costs and internal IT teams. BIM is the evolution of old CAD, but its use in the early stages of the design procedure seems rather problematic, due to its detailed nature.

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