Assessing Gaps and Needs for Integrating Building Performance Optimization Tools in Net Zero Energy Buildings Design

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Abstract

This paper summarizes a study undertaken to reveal potential challenges and opportunities for integrating optimisation tools in Net Zero Energy Buildings (NZEB) Design. The paper reviews current trends in simulation-based Building Performance Optimisation (BPO) and outlines major criteria for optimisation tools selection and evaluation. This is based on analyzing user's needs for tools capabilities and requirement specifications. The review is carried out by means of a literature review of 165 publications and interviews with 28 optimisation experts. The findings are based on an inter-group comparison between experts. The aim is to assess the gaps and needs for integrating BPO tools in NZEB Design. The findings indicate a breakthrough in using evolutionary algorithms in solving highly constrained envelope, HVAC and renewable optimisation problems. Simple Genetic Algorithm solved many design and operation problems and allowed measuring the improvement in the optimality of a solution against a base case. Evolutionary Algorithms are also easily adapted to enable them to solve a particular optimization problem more effectively. However, existing limitations including model uncertainty, computation time, difficulty of use and steep learning curve. Some future directions anticipated or needed for improvement of current tools are presented.

Keywords: Simulation-based optimisation, zero energy buildings, evolutionary algorithms, needs, gaps, review, interview

List of abbreviations

AEC Architectural, Engineering, Construction

ACOA Ant colony optimisation algorithm

BPO Building Performance Optimisation

BPS Building Performance Simulation

DOE Department of Energy

EPBD Energy Performance Building Directive

GA Genetic Algorithms

GUI Graphical User Interface

HVAC Heating, Ventilation and Air Conditioning

IBPSA International Building Performance Simulation Association

IEA International Energy Agency

NSGA Non-dominated Sorting Genetic Algorithm

NREL National Renewable Energy Laboratory

nZEB nearly Zero Energy Building

NZEB net Zero Energy Building

MPC Model Predicted Control

SQP Sequential Quadratic Programming

WWR Window-to-Wall Ratio.

Introduction

During the coming years, the building design community at large will be galvanised by mandatory codes and standards that aim to reach Net Zero Energy Buildings (NZEBs) [1-3]. The recast of the European Performance of Buildings Directive (EPBD) requires all new buildings to be “nearly zero energy” buildings (nZEB) by 2020, including existing buildings undergoing major renovations. As building performance objectives become more ambitious and absolute, the number and complexity of energy use-reducing measures, implemented in design, tend to increase [3,4]. The building performance objectives have raised the bar of building performance, and will change the way buildings are designed and operated. This means that evaluating different design options is becoming more arduous than ever before. The building geometry, envelope and many building systems interact, thus requiring optimizing the combination of the building and systems rather than merely the systems on an individual level [5]. One promising solution is to use automated mathematical building performance optimisation (BPO) paired with building performance simulation (BPS) as a means to evaluating many different design options and obtain the optimal or near optimal (e.g., lowest life-cycle cost, lowest capital cost, highest thermal comfort) while achieving fixed objectives (e.g., net zero energy) [6-10].

Despite optimisation's potential in NZEB design, it largely remains a research tool and has yet to emerge in common industry practice. As this paper reports, major obstacles to BPO in industry include lack of appropriate tools, lack of resources (time, expertise), and the requirement that the problem be very well defined (e.g., constraints, objective function, finite list of design options). The objective of this paper is to document the current state-of-the-art in terms of NZEB optimisation tools and practice. With this information disseminated, it is anticipated that software developers will be better informed of the needs of building design processionals.

Major components of the paper include a literature review of more than 150 publications on BPO and existing optimisation tools, followed by the results of an interview that was used to gain an understanding of how people currently use optimisation tools, which tools they use, the major limitations they have encountered, and their vision for the future of optimisation. A qualitative study design was employed, using semi-structured interviews. Optimisation experts working in academia or practice were recruited. Experts were identified as researcher or professional who has at least three or more publications in the field of BPO. The participants were identified from the IBPSA International and Regional Conference Proceedings between 1995 and 2010 [11]. A sampling framework was developed to include experts in the study from Asia, Europe and North America. These groups represented the range of possible optimisation users, from researchers and designers considering optimisation in the design of net zero or High energy performance buildings. A list of potential optimisation experts was created (40 potential experts) and circulated between the IEA Task 40 Subtask members [3]. Every interviewed expert was asked to revise the list and add any potential candidate to be interviewed. Recruitment continued until experts from different countries had been represented and thematic saturation had been attained for the sample as a whole. An additional group of experts had been invited during IBPSA 2011 Conference in Sydney. In total, 28 experts were interviewed between January and November 2011.

The interview questions were formulated by the authors and classified under five categories namely, background, methodology, output, integration in design and shortcomings and needs. The questionnaire aimed to probe the user's experience with computational optimisation tools and techniques for the design of NZEBs. Prior to interviewing the experts, the authors set up a pilot study to tests and improve the questionnaire reliability and internal validity. Comments and suggestions were requested from peer reviewers. Reviewers were asked to revise the questionnaire and provide critical feedback in order to optimise the clarity and relevance of the questionnaire.

The scope of the study is limited to nZEBs, NZEBs and high energy performance buildings. Those building types are emerging as a quantifiable design concept and promising solution to minimizing the environmental impact of buildings sector. These buildings, which minimize energy consumption and optimally use renewable resources, both passively and actively are usually defined as those which export as much energy as they import, over the course of a year (also known as net zero site energy by Torcellini et al. 2006 [12]. The term 'net zero' is used for identifying those buildings connected to the grid. The grid is used both as an ideal source and an ideal storage medium and energy losses are not taken into during the energy supply from the grid to the building, and the energy feeding from the building into the grid. The issues of modelling, design and optimisation of such buildings are being addressed by Subtask B (STB) of the IEA SHC Task 40/ECBCS Annex 52 [1].

Key results of the interview indicate that optimisation tools that do exist are primarily catered to research, and consequently, they do not reflect the needs of industry (fast turn-around, high return on invested time, ease of use, shallow learning curve, user-friendly interfaces). Some future directions anticipated or desired by those who were surveyed faster computing (e.g., cloud computing and real-time feedback of results), improved visualization of results, improved methodologies (e.g., automated error-checking, validation, uncertainty analysis) and standardized costs and performance databases.

This paper is organized into six sections. The first section identifies the research problem within the BPO community. The second section is a literature review that defines the simulation based BPO and illustrated various related studies, methods and tools to support it. The literature review forms the basis for the interview questions. The interview results and analysis are discussed in section three and four. The final two sections are discussing the interview findings and providing feedback to tool developers and to the architectural, engineering and construction communities.

Literature Review

This section presents the state-of-the-art with respect to building design optimisation tools and optimisation algorithms coupled to building simulation tools. The content is intended to aid the reader in better understanding areas of active research in building optimisation as well as tools and methods commonly used by researchers and industry.

What is BPO?

Automated building performance optimisation is a process that aims at the selection of the optimal solutions from a set of available alternatives for a given design or control problem, according to a set of performance criteria. Such criteria are expressed as mathematical functions, called objective functions. Automated optimisation is a combination of different types of optimisation algorithms, setting each algorithm to optimize one or various design functions. The optimisation objectives are to identify the cost or energy or environmental impacts.

Therefore, an objective function is defined as a mathematical function subjected to optimisation. Optimisation is a process that searches for the optimal solution with respect to the objective functions to be maximized or minimized, possibly subjected to some constraints of the dependent variables. If the constraints are not specified, the problem is denoted unconstrained optimisation problem. A constraint limits the problem space to a subset of elements [13]. If the optimisation problem aims at minimizing a single objective function, it is called single objective optimisation problem, otherwise if the objective functions are more than one, it is called multi objective optimisation problem.

Visualization techniques are essential to facilitate the extraction of relevant information regarding performance trade-offs, propagation of uncertainties and sensitivity analysis. By allowing for visualization during the optimisation process, it is possible for the designer to interact and inform the optimisation process.

Brief history of BPO

Automated optimisation has become increasingly popular in a wide variety of application domains, as reflects a book entirely devoted to this topic [14]. In the late 1980s, a large group of technologically savvy engineering, mathematics and scientific groups tackled the application of automated optimisation in the field AEC industry aiming to optimise building design and operation. By the end of 1990s decade, many scientific groups that have well-used BPS made a transition and coupled their simulation work to mathematical optimisation models. Through the 2000s, the development of mathematical and algorithmic techniques and the advancement of BPS tools gave way to BPO tools that could solve multi objective optimisation problems of a design. Mechanical and structural engineers working on complex buildings have been among the early adopters of BPO techniques, but architects and other engineers now start using these techniques as well. Today, there is a strong trend towards population-based search algorithms such as evolutionary algorithms and particle swarms. These algorithms have been proven to be very successful in optimizing one or many performance criteria while handling search constraints for large design problems [15-17]. It has now become common practice for populations of building simulations to be carried out simultaneously on multi-core processors and distributed computing to greatly reduce the time needed for an optimisation study (GenOpt [18], modeFrontier [19], Phoenix Integration [20]. Researchers have found success in combining deterministic searches and population-based searches to improve search resolution and the reproducibility of optimal solution sets in building design problems.

Importance of BPO

In the architectural, engineering and construction (AEC) industry there is a growing research trend for automated optimisation approaches to be used to map out and find pathways to buildings designs with desirable qualities, be it aesthetics, geometry, structure, comfort, energy conservation or economic features, rather than focusing on one particular outcome. Although optimisation studies are most commonly performed in the early-design stage, where the majority of design decisions have yet to be made, optimisation approaches can be equally useful in the late-design stages for selecting and fine-tuning control strategies and HVAC design and during building operations to best select building control based on model-predictive control strategies [21-24]. The most appropriate search algorithms and modelling approaches vary depending on the application area, but the suitable application area for optimisation methodologies related to building design and control is vast and constantly evolving.

Moreover, the use of optimisation as a means of providing input to energy policy, incentive measures is one of its most important usages in the recent years. For example, using the Building Energy Optimisation model (BEopt) developed by the National Renewable Energy Laboratory (NREL) to evaluate the energy and cost savings potential from constructing more efficient new homes and Net Zero-Energy Homes in the USA Christensen C, et al. [25]. Also this includes the call of the European Commission for implementing a methodology to calculate cost-optimal levels in the EPBD framework. European Member States are required to define cost-optimal levels of minimum energy performance according to their specificities [26].

Combination of BPO and Simulation

Inevitably, optimisation is coupled to BPS tools. BPS tools are essential in the process of building design aiming to assess their energy performance, environmental impacts, costs etc [27-28]. A number of energy simulation engines exist and are often used in different stage of the design process of a building [29-30]. Out of the 406 BPS tool listed on the DOE website in 2012, less than 19 tools are allowing BPO as shown in Table 1 and Figure 1 [31-33].

When designers decide to improve the building performance, they usually make estimation for various values of the design variables to be modified in the building envelope, the Heating Ventilating and Air-Conditioning (HVAC) system and the types of energy generation and run the simulation many times. Then, designers will try to find the effect of the design changes on the simulation results and to conclude a relation between those variables and the objectives of the simulation. This is an inefficient procedure in time and labour. Besides, the relation between the simulation variables and the objectives may not be simply understood, especially when there are many parameters to be studied, and possibly due to the nonlinearity of the problem. Therefore a better design is not always guaranteed. To overcome such difficulties, automated simulation based BPO search techniques are applied. Progressions in building simulation tool development and in coupling complimentary BPS tools at run-time expand domains where BPS optimisation studies can occur.

In order to automate and make more efficient the testing and comparison of several design building variants, a number of researchers have coupled energy simulation tools with optimisation techniques through self-produced tools, commonly based on MATLAB™ [34], or other dedicated software [35].

Figure 1

Optimisation design variables

The most common design variables in BPO studies are either energy related or economic related. Multiple objectives can simultaneously be considered through weighting strategies or by using a multi-objective optimisation algorithms which preserves trade-offs between two or more conflicting search objectives [36]. Before conducting an optimisation search, first the designer must identifying which input design variables should be included in the optimisation search. Designers can perform a sensitivity analysis to identify which inputs have the largest impact on an objective. An alternative is to refer to previous research to aid in identifying influential input variables. In the recent years, several studies applied BPO techniques in order to optimize a specific aspect of the building design or operation. A list follows disaggregated by the objective of the optimisation:

- Building layout and form [37-41].
- Geometry, position and density of fenestration [42].
- Building envelope and fabric constructions [15, 43-51].
- Daylighting performance [52-53] and automated control of solar shadings [54-55].
- Natural ventilation strategies [56-57].
- Shape and functional structure of buildings as well as heat source utilization [58].
- Heating, ventilating, and air-conditioning (HVAC) systems sizing [59-63].
- HVAC system control parameters and/or strategy [64-68].
- Thermal Comfort [69-75].
- HVAC system configuration synthesis [76-77].
- Managing of energy storage [78,79] and automated model calibration [80,81]
- Simultaneous optimisation of building envelope and HVAC elements [7, 15, 16, 65, 82-90].
- Simultaneous optimisation of building construction, HVAC-system size, and system supervisory control [91-93].
- Simultaneous Optimisation of building construction, HVAC elements and energy supply system including RES [94-98].

Also several PhD work approached BPO including the work of Caldas 2001, Nielsen 2002, Wetter 2004; Wang 2005, Pedersen 2007, Verbeeck 2007, Choudhary 2004 and Hopfe 2009 [99-106].

However, there are significant disparities between the above BPO applications. Some of them apply multi-objective optimisation while the others do single objective ones. The implemented optimisation algorithms range from enumerative to stochastic ones. The size and complexity of the addressed solution spaces are quite different. Some studies used detailed BPS tools while others used simplified ones. In order to reduce the simulation time, three strategies are common:

- Custom simplified thermal model are developed and used instead of existed detailed BPS software [77,100, 107-109].
- Detailed BPS tools are used for simulating geometrically simplified models: e.g. a single zone model is used for representing one floor single family house [85], a two zones model for a two-story house [17], a simplified model for representing a 200 m^2 house [110], and two representative zones are used to evaluate the thermal performance of one floor in office building [111].
- Detailed BPS tools are used for simulating a model only for a representative period: e.g., few days are used as a weather samples [112-113] and six months is used as a representative period [111] for the whole year weather conditions (temperature, humidity, wind speed and solar radiation).

BPO Objectives *(single-objective and multi-objective functions)*

Generally speaking, optimisation can be either single-objective or multi-objective according to the number of objective functions that define the optimisation problem. In the case of optimizing a single-objective function, an optimum solution of the problem is either its global maximum or minimum, depending on the purpose. In general, it is a convention in mathematical optimisation, that optimisation problems are commonly defined as minimizations of the quantity, *Instead, if an optimisation problem consists in the maximization of an objective function, it is sufficient to minimize its opposite* [114]. In many real problems, it is required to satisfy simultaneously more than one objective function. Such problems are denoted multi-objective optimisation problems.

In multi-objective optimisation problems, a single solution could not be able to minimize (or maximize) simultaneously each objective function. Rather, when searching for solutions, one comes to limit variants such that, a further improvement towards the minimum value of one of the objective function causes a worsening of the closeness to minimum of the others. Therefore, the aim of a multi-objective optimisation problem consists in finding such variants and possibly in quantifying the trade-off in satisfying the individual objective functions. The role of the optimisation algorithm is to identify the solutions which lie on the trade-off curve, known as the Pareto Frontier, which is in words, a set of optimal solutions plotted in the form of a curve (named after the Italian-French economist, Vilfredo Pareto, see Figure 10.5). These solutions all have the characteristic that none of the objectives can be improved without prejudicing another. The variants of a Pareto Frontier are defined as elements that are better than others in relation to, at least, one objective function and simultaneously not worse concerning all other objective functions.

Algorithms used in BPO

Optimisation of a building as a whole is a complex problem due to the amount of design variables as well as the discrete, non-linear, and highly constrained characteristics. The popular optimisation methods for solving multi-objective optimisation problems are generally classified into three categories: (1) enumerative algorithms, (2) deterministic algorithms, and (3) stochastic algorithms.

The enumerative methods search in a discrete space. They evaluate all the solutions and choose the best. These algorithms are computationally expensive and consequently they are not suitable for exploring wide solution spaces. Two types of methods can be found: (1) gradient and (2) gradient-free deterministic. The gradient ones use the gradient of the evaluation functions either by going in the direction where the gradient is the smallest or by searching solutions that have a gradient vector equal to zero. The gradient-free ones such as Hooke-Jeeves direct search [115], constructs a sequence of iterates that converge to a stationary point if the cost function is smooth and coercive. Emmerich et al. [116,117] used the Hooke-Jeeve algorithm is used to minimize the energy consumption considering different building scenarios and characteristics. A gradient-free sequential quadratic programming (SQP) filter algorithm is proposed and test in Pedersen's PhD work [103]. The algorithm can converge fast and in a stable manner, as long as there are no active domain constraints.

Generally, the deterministic algorithms need that the evaluation functions have particular mathematical properties like the continuity and the derivability [15,82]. Therefore, they are not the best choice for handling discontinuous building and HVAC problems with highly constrained characteristics and multi-objective functions. On the other hand, the advantage of the stochastic algorithms is that they do not have much mathematical requirements for solving the optimisation problem [118]. Examples of stochastic algorithms that are designed to deal with highly complex optimisation problems are [119]: annealing [120-122], tabu search [123], ant colony [124], particle swarm [125] and genetic algorithms [126-128].

Stochastic element was added to Pattern search algorithm for optimizing the topological design of the bracing system for a free-form building [129]. Ant colony optimisation algorithm (ACO) was used to search for a trade-off between light intake, thermal performance, view, and cost for a panelled building envelope for a media centre in Paris [130]. A strength multi-objective particle-swarm optimisation (S-MOPSO) was used for the optimisation of a heating, ventilation, and air conditioning (HVAC) system in an office building [131].

Instead of the above algorithms, the last ten years has seen an increasing interest in using Genetic Algorithms (GAs) for optimisation of building and HVAC systems. The GAs are the most efficient stochastic algorithms when the optimisation problem is not smooth or when the cost function is noisy [132.133]. The GAs consider many points in the search space simultaneously, not a single point, thus they have a reduced chance of converging to local minimum, in which other algorithms may end up [107]. The GAs with the Pareto concept are used widely in energy and buildings studies [7, 16, 40, 41, 47, 48, 92, 94,102,110,134,135,136]. According to the studies of Zitzler [137] and Deb [128], the elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) seems to be the most efficient GAs. The NSGA-II is implemented to find trade-off relations between energy consumption and investment cost or thermal comfort level of buildings [70, 71, 72,86, 106, 111, 138, 139]. The NSGA-II [128] could be one of the most suitable optimisation algorithms to handle multi-objective multivariate building and HVAC design problems with discrete, non-linear, and highly constrained characteristics. However because its stochastic behaviour, it could occasionally fail to get close to the Pareto-optimal front, particularly if low number of evaluations is implemented [86, 87]. The high number of iterations is chosen to avoid the early breakdown of the optimisation [106]. Since building simulation is often very time-consuming, a large number of iterations could not be practical. Deterministic optimisation phases and archive strategies are added to the original NSGA-II in order to perform rapid optimisation –using a low number of simulation runs- and/or to guarantee optimal or close-to optimal solution set for building design problems [17, 87, 98]. The proposed algorithms/approaches (PR_GA, GA_RF, PR_GA_RF, and a NSGA-II) reduce the random behaviour of the original NSGA-II enhancing the repeatability of the optimisation results.

Tools of BPO

As shown in Table 1, BPO tools can be classified into two main group's stand-alone optimisation packages and simulation based optimisation tools. The list of stand-alone optimisation tools is not very long, however we chose to present the most frequently mentioned tools in literature namely GenOpt®, MATLAB®, modeFrontier® and Topgui®. However, in the past ten years, several advances have been made to develop building simulation tools that are driven by feedback from performance objectives. Largely these tools are directly toward industry to dramatically decrease the energy footprint of new buildings. Consider the most mentioned two tools in literature that attempt to merge both optimisation and simulation techniques developed at National Renewable Energy Laboratories (NREL): BeOpt™ and Opt-E-Plus™.

GenOpt®

GenOpt® is stand-alone optimisation software developed at Lawrence Berkeley National Laboratory (LBNL). GenOpt is a generic optimisation program that can be used with any simulation program that has text-based input and output, such as EnergyPlus, DOE-2, IDA-ICE, SPARK, BLAST, TRNSYS, or any user-written code [140]. It is suitable to be coupled with any text-based simulation program. This tool is able to access a library of different optimisation algorithms, and can use either continuous or discrete variables. The modularity, flexibility, and ability to select from a range of optimisation strategies make GenOpt a robust platform, but its visualization capabilities are limited. The tool is aimed to solve problems where the objective function is computationally expensive and its derivatives are not available or do not exist, thus it is not suitable for linear programming problems, quadratic programming problems and problems where the gradient of the objective function is available. The independent variables can be continuous, discrete or both. Constraints on dependent variables can be implemented using penalty or barrier functions. GenOpt® provides multidimensional and one-dimensional optimisation algorithms. However, its library does not include multi-objective algorithms.

The algorithms for multidimensional optimisation are: (i) Generalized pattern search methods for continuous independent variables (the Coordinate search algorithm and the Hooke-Jeeves algorithm), which can also be run using multiple starting points; (ii) Discrete Armijo gradient for continuous independent variable, (iii) Particle swarm optimisation algorithms for continuous and/or discrete independent variables, which can be used in the versions with inertia weight or with constriction coefficient and with a modification that set the continuous independent variables on a fixed mesh in order to reduce computational time, (iv) Hybrid generalized pattern search algorithm with Particle swarm algorithms for continuous or/and discrete independent variables, (v) Simplex algorithm of Nelder and Mead for continuous independent variables [141,142]. On the other hand, the algorithms for one-dimensional optimisation are: (vi) the Golden section interval division and (vii) the Fibonacci division. GenOpt® automatically allows parallel computing if the computer has multiple CPUs, significantly reducing computational time [143]. The modularity, flexibility and wide availability of optimisation techniques make GenOpt® a robust optimisation environment, but its post-processing capabilities are limited [47].

In the field of BPO, GenOpt has been used by several researchers including Coffey et al. 2008 and 2010 [144,145], Congradac et al. 2009 [107], Corbin 2011 [22], Djuric et al 2007 and 2011 [146, 147], Jacob et al. 2010 [148], Hasan et al. 2008 [85], Henze 2004 [153], Kummert 2007 [149], Magnier et al. 2008 and 2009 [150,151], Palonen 2009 [86], Park et al. 2004 [152], Stephan et al. 2009 [57], Wetter 2004 [15] and Wright et al. 2001 [91].

MATLAB

For less simulation efforts and feasible optimisation results, it is essential to develop the link between existent building simulation tools and trusted optimisation tools. In environmental design of buildings, since the number of design variables is usually large and the true nature of solution space (linear or non-linear) cannot be known, optimisation tool has to provide access to different types of algorithms to suit problem needs. This aspect is provided into MATLAB which is trusted tool comprises a lot of optimisation solvers able to deal with different types of optimisation problem. Additionally, with this approach, the user can utilize all MATLAB functions which provide significant tools to attain and analysis the optimal results

MATLAB Optimisation Toolbox™ provides a variety of algorithms for optimisation problems. These algorithms solve constrained and unconstrained continuous and discrete problems. MATLAB includes functions for linear programming, quadratic programming, binary integer programming, nonlinear optimisation, nonlinear least squares, systems of nonlinear equations, and multi-objective optimisation. This allows finding optimal solutions, performing trade-off analyses, balancing multiple building design alternatives, and incorporating optimisation methods into algorithms and models [34].

In the field of BPO, MATLAB has been used by several researchers including Bucking 2010 [9], Choudhary 2004 [105], Coffey et al. 2008 and 2010 [144,145], Jacob et al. 2010 [148], Hasan 2008 [85], Hamdy et al. 2009 [87], Henze 2004 [153], Kummert 2007 [149], Park et al. 2009 [152], Shea et al. 2006 [130], Wetter 2004 [101], Wright et al. 2001 [91].

modeFRONTIER

modeFRONTIER is a multidisciplinary and multi-objective software that allows complex algorithms to spot the optimal results, even conflicting with each other or belonging to different fields. The tool be coupled to different other software packages in different input/output interchange formats including: EnergyPlus, ESP-r Fluent, and MATLAB. Once data has been obtained, the user can turn to the extensive post-processing features to analyze the results. The software offers wide-ranging toolbox, allowing the user to perform sophisticated statistical analysis and data visualization.

The tool has been used by Xing Shi [154] find the best insulation strategy to minimize the space conditioning load of an office building while keeping the insulation usage at minimum. Also the tool has been used by the unit of building physics and systems, Eindhoven University of Technology in the Netherlands, including the work of Hoes [138] and Loonen [139].

Topgui

Topgui is a MATLAB™ graphical user interface (GUI) program originally developed to be coupled with finite element analysis models for executing topology optimisation. In the current version, it provides several single-objective and multi-objective optimisation techniques: Hooke Jeeves algorithm, Generalized pattern search methods, Particle swarm optimisation algorithms, Evolutionary strategy, Non-dominated sorting genetic algorithm II (NSGA-II), Smetric selection evolutionary multi-objective optimisation algorithm (SMS- EMOA).

In the field of BPO and according to the literature review, Topgui has been used mainly by Hopfe [106] and Emmerich et al. [116,117] aiming to evaluate optimisation methodologies for future integration in BPS tools.

Opt-E-Plus™

Opt-E-Plus is a tool developed by NREL that uses EnergyPlus simulation engine. Opt-E-Plus utilizes various search routines to identify optimal buildings designs for energy usage [155]. The framework consists of a collection of EnergyPlus input and output files, system directories, and computer routines that use an XML data model to transfer information among the various components. The user is able to modify parameters in a .xml file, rather than directly modifying the EnergyPlus input files. This application integrates with multiple data sources, is modular to allow distributed programming, and supports selection of automation and optimisation strategies. Although this is not a stand-alone optimisation tool, it is developed to guide the user, through the comparison of various design options, towards the most economical energy savings. The structure of the program is modular to allow distributed programming [155]. Visualization of the trade space however is limited, and it does not support multidisciplinary optimisation. Also the program is restricted to North American context. Opt-E-Plus has been used by NREL researchers and others including the work of Herrmann et al [156] and Long et al. [157].

BEopt™

BEopt™ is a tool developed by NREL and is designed to identify optimal building design variants on the path to net zero energy target. The software allows the user to select discrete options for various building variables regarding building envelope and HVAC systems and calculates energy savings with respect to a user-defined reference case or a climate-specific Building America Benchmark [158,159]. Regarding energy simulation, BEopt™ can use as simulation engine either DOE-2 [160] or TRNSYS [161] and the optimisation is executed by a sequential search technique in order to find the most cost effective combination of energy efficient measures and photovoltaic systems [8]. The software rapidly provides the user a design space (or problem space); however the proposed design space and the selectable objective functions are limited. Also the program is restricted to North American context.

Construction variables such as window and wall types were used as inputs for a DOE-2.1 energy model and TRNSYS was used to implement solar modules. More recently, the energy model has been update to use EnergyPlus for both building and solar component simulations. An objective of BEopt's approach is not to focus on one final optimal solution, but on pathways to optimal designs such that the user can select designs which best suit their financing available for the housing project. Integration with SketchUp, a computer aided design tools, greatly simplify the creation of building models used for building simulation. Opt-E-Plus is a commercial building optimisation tool which uses sequential searches and EnergyPlus for building simulations. Opt-E-Plus also integrates with SketchUp to create building models used for optimisation studies. The application includes a Graphical User Interface (GUI) that allows the user to select from a range of predefined and discrete building alternatives to be used in the optimisation process. BEopt allows the user to rapidly generate and visualize the design space through a browser, but its flexibility is limited as a result of having predefined building alternatives and its inability to consider a wide range of objective functions.

BEopt has been used by NREL researchers and others including the work of Anderson et al [162], Givler [163] and Polly [163].

Interview Results & Analysis

The previous section was a literature review that defined BPO and illustrated its history, methods, characteristic and tools to support it. This section presents some of the interview results that interviewed optimisation experts in 2011. Each interview included 25 questions available in the final study report [165]. For this paper, representative questions that reflect the most important findings are selected. The complete results are presented and can be found in the final study report [165]. Prior to analysing the interview results, it is important to question the statistical significance of the interview sample. In fact, 28 participants were interviewed from a list of 40 potential users. The list was developed by the IEA Task 40 members and the interviewed experts themselves. Thus the interview sample is highly representative of researchers.

5.1 Interviewee's Background

What is your major field of discipline (architecture, engineering, computer science other)?
28 experts were interviewed where 26 had their background in engineering, 2 had their background in physics, one in architecture and one in computer science (Figure 2). Among the 28 experts 26 identified themselves as researchers and 2 identified themselves as practitioners (Figure 2). The affiliation of the interviewed experts shows that they are mostly located in universities or research labs in the Northern Hemisphere. The majority of interviewees work in the United States (29%), (18%) UK, (14%) Canada, (10%) Finland, (7%) Netherlands, (3%) Germany, (3%) Switzerland and (3%) Japan.

Figure 2

How many projects or case studies have you performed and how long does each project or case study take?
In average 40% of all interviewees (11) conducted between 5 to 10 optimisation cases or projects, 32% (9) conducted less than 5 cases or projects and 11% (3) conducted between 10 to 15 optimisations while only 14% (4) conducted more than 15 optimisations. Most interviewees mentioned that they start with the model development and calibration followed by linking the simulation tool to the optimisation tool, and then run the optimisation. Figure 3 shows the time for each case or projects. Interviewees mentioned that the development and calibration of the simulation models are one of the time consuming steps, requiring in average two to three weeks of work. However, the running time of the optimisation simulations is the most time consuming process and depending on the model resolutions the time required for every case varies significantly.

Figure 3

What kind of tools do you use for optimisation (MATLAB, GENOPT, others)? To which simulation tool do you couple it?
Figure 4 reveals that MATLAB toolbox and GenOpt are the most used optimisations tools. The left figure indicates that the most used simulation tools among interviewees is (9) EnegryPlus and (7) IDA ICE followed by (5) TRNSYS and (3) Esp-r.

Figure 4

5.2 Optimisation Methodology

Which building typologies have you used optimisation for and in which climates? (Residential, Offices, Retail, Institutional)
Figure 5 shows the building typologies, construction types and climate were the projects were optimised.

Figure 5

How many zones do you address in your model when running optimisations? And what kind of design variables do you set for optimisation?

64% of the interviewees used multi-zone model while 36% used single zones models. Interviewees indicated that the preference of choice between the single and multi-zone modelling depends on the model resolution (level of detail) and the expected interactions between the each thermal zone and the systems. Also the multi-zone model was used to differentiate between heated and non-heated zones and between frequently and less frequently used spaces of the building.
As shown in Figure 6, the most optimised design variables by the interviewed experts for NZEBs were *systems* and *controls* (53 %) followed by the *envelope* (50%). The optimisation of control systems and in particular model predictive control was considered as one of the most complex and dynamic design variables therefore, design optimisation was necessary. R*enewable systems* were optimised by 50% of the interviewees. *Thermal Storage, Layout and Geometry* was optimised by 25% of the interviewees followed by *internal gains* (18%). 11% of the experts optimised *occupancy* and 7% optimised *location and climate.* The analysis of Figure 6 shows that the most optimised design variables where late design parameters. According to the interviewees the choice of the design variable was based on the innovation of the design project and the complexity of a particular design variable.

Figure 6

What kind of objectives do you set for optimisation?

Common optimisation criteria in building design are various costs such as initial capital cost and annual operating cost, and life cycle cost, energy consumption and recently environmental impact. 70% of all interviewees do multi-objective optimisation versus 30% who do single objective optimisations. Regarding the objectives, all interviewees (28) chose *energy* as the most used optimisation objective, while 64% (18) chose *cost*.
The cost objectives included the life cycle cost, initial cost, operation and maintenance cost. Comfort followed (10) as the third most important objective while some interviewees indicated that they consider comfort as a constraint so I wouldn't call it an objective. As shown in Figure 7 Carbon (5), lighting (2) and indoor air quality (1) were ranked at the end.

Figure 7

b) What kind of constraints do you set for optimisation?

As shown in Figure 8, there was agreement among most interviewees (22) to set thermal comfort as the main constraint followed by cost (18).Interviewees refer to comfort conditions defined by standards. There was an agreement to consider constrains as primarily to define the feasible domain. Also penalty terms are used in the optimisation work to both guide the optimizer away from infeasible regions and also to consider the impact of thermal comfort boundaries on the optimisation. Constraints in this case were boundary or equation based.

Figure 8

Under which setting you run you optimisation what is your methodology? c) What kind of stopping criteria do you set for optimisation?

The answer to this question depended on the used algorithm. Interviewees indicated that some algorithms have stopping criteria built in, others run for a prescribed number of generations or simulations. However, as shown in Figure 9 most interviewees (17) set a *number of generations* as stopping criteria for their optimisation work. Some set a *time limit (4),* or *no stopping criteria* at all (4) while few (3) set a *number of simulations.*

Figure 9

5.3 Output

Do you have GUI for your own optimisation tool? And which kind of output analysis visualisation did you do using optimisation tools (1-14)?

75% of interviewees indicated that they do not have an environment or package with a GUI for output post processing and analysis visualisation. Most interviewees are forced to process and convert the output data using different processing tools, such as DView, Excell, gnuplot or writing scripts in MATLAB, in order to create interpretable output results.
Figure 10 illustrates the 14 most used output analysis graphs. 22 of the interviewees use the graph 10.5 allowing plotting the solution space using the Pareto Front. Interviewees indicated that the Pareto Front include many solution that they can pick from a variety of solutions. This was followed by Figure 10.8 (15 interviewees) that allows the visualisation of energy, cost or carbon emissions of different solution cases representing the basecase versus the optimized case. Also Figure 10.4 and 10.6 were selected by 12 interviewees to visualize the impact of any parameter variation. In general, every respondent had his or her own custom visualization techniques, for example line plots (Figure 12.2) or time series (12.7) are used for controls and in the case of comfort scatter plots (Figure 10.2) are used.

Figure 10

5.4 Integration of Optimisation with Design Process

This part of the interview was structured around a series of open questions in order to get more insights on the integration of optimisation techniques in the design process. A selection of the comments and their frequency is classified as follows:

What opportunities you see in integrating optimisation techniques in NZEB design process?

According to the interviewees BPO have been applied successfully in numerous NZEB projects. However the building simulation community still rarely uses optimisation and little investment has been made to advance BPO. However, interviewees indicated that many opportunities in integrating simulation based BPO in NZEB design and operation. The most mentioned opportunities include:

- *Support the decision making for NZEB design*. The rise of simulation has been driven by many things, including government policy that pushes the design of low energy buildings. At present, any increase in the use of optimisation will be driven by the extent to which aids design decision making. In this respect, one of the most powerful forms is multi-object optimisation, since it gives a set of solutions that lie on the trade-off between two or more conflicting design objectives. The trade-off can be used to explore the impact of say of less capital investment on the increase in carbon emissions. This kind of information being useful in decision making of NZEB requiring little effort and generates different ideas and alternatives.
- *Designing innovative integrated NZEBs and thermal (and visual) comfort control systems* are difficult to design because they involve complex systems that interact dynamically. Optimisation algorithm can help in finding the optimal and near optimal solutions regarding the design and sizing of passive and active energy systems and finding the balance between demand and production.
- *Achieving cost-effective NZEBs* by analyzing and synthesizing multi-physics systems that may include passive and active facades, lighting controls, natural ventilation, HVAC, and storage of heat in the building structure combining advanced technologies such as micro-CHP, PV, PVT, solar collectors and micro-wind). The complexity of such systems pose a serious challenge to designers and using BPO is an opportunity for optimal and cost-effective design decision during building design and operation including the existing building stock.
- *Allow optimal systems scheduling through Model Predictive Control (MPC)* taking into account the dynamics of NZEB systems and anticipated future energy load. When solving the optimal control problem using MPC algorithm, it determine near-optimal control settings during design and operation and improve the NZEB load matching problem.

How can it be integrated into the decision making? How should optimisation become more practically applied during early design phases?

There was an agreement among interviewees that prior to any integration effort there must be first commercial tools available with integrated simulation and optimisation that allow seamless link between the simulation model and the optimisation process. Currently, the time and knowledge required implementing separate simulation models and optimisation algorithms is limiting the use of BPO in practice. However, on the long term the integration of BPO can be achieved through:

- *Requiring optimisation as a standard activity* during NZEBs design and operation. BPO can be integrated and become standard in practice. Consequently BPS tool will integrate optimisation techniques and the number of users will increase dramatically. In the coming year, I expect it to be a standard feature in NZEBs.
- *Planning optimisation early in the design process*. BPO should be introduced in early phases of design as part of the Integrated Design Process (IDP). The use of optimisation should be during schematic design stages. Models should be simple with some geometrical zoning simplification. Using a standard reference building and testing all kind of technologies can help in establishing initial design concepts and solutions which can have an impact on all stakeholders. Showing results from the starting point can have a strong impact on cost, energy and thermal comfort and will allow a range of ideas and solutions.
- *Informing all building stakeholders on the importance of optimisation*. Comparison studies on buildings with optimisation and buildings without optimisation will inform designers and clients. The optimisation community should show designers that the use of optimisation tools produce better results. By providing demonstration projects and real physical buildings beside the optimisation models for simulation users. This will raise the confidence in the optimisation and lead to more detailed and accurate and certain optimisation models with operation patters and hours. Education in academia and practice has a key in guiding professionals how to perform optimisation.

5.5 Optimisation Shortcomings

What are the major practice obstacles of integrating optimisation techniques in NZEB design?

The major obstacles of integrating optimisation techniques in NZEB design can be classified under two main categories: (1) soft obstacles and (2) hard obstacles. The main four soft obstacles and their frequency is listed as follows:

- Low return and the lack of appreciation among the AEC industry (19)
- Lack of standard systematic approach to perform optimisation in most cases researcher follow many different methods and ad-hoc approaches without a structure and categorisation in use (16)
- Requirement of high expertise (11)
- Low trust in the results (5)

Interviewees' indicated that in practice, there is a lack of awareness and confidence on the use of optimisation. Also it is very important that users understand the optimisation process. There is a large educational need before BPO gets applied routinely in the design process.

Regarding the hard or technical obstacles, the interviewees' comments and their frequency is listed as follows:

- Uncertainty of simulation model input (27)
- Long computation time (24)
- Missing information on cost, occupancy schedules etc. (19)
- Difficulty of problem definition (objectives arrangement, constraint violation) (12)
- Missing environments integrating and linking simulation and optimisation seamlessly (16)
- Low interoperability and flexibility of models for exchange between different design, construction, simulation, cost estimation and optimisation tools (11)
- Lack of environment with friendly GUI allowing post processing and visualization techniques (7)

Interviewees' agreed that computation time is very long and this might well inhibit the initial take-up of optimisation in practice. The optimisation processes also magnifies the idea of "rubbish-in-rubbish-out" since rather than simulate a single design solution, the errors or inaccuracies in a simulation are exposed across a wide range of the design space. This may lead to a need for better education and improved user interfaces for simulation, as well as more work on the uncertainty associated with simulation models.

Which tools would you recommend?

10 interviewees recommended GenOpt, 6 MATLAB, 4 BeOpt, 2 modeFrontier and 1 Topgui.

What features would you like to find in future tools?

Interviewees mentioned many ideas that contrast the hard obstacles mentioned previously. However, some significant ideas on future feature of optimisation tools include:

- Doing optimisation in real time within a BIM model and allowing adjustment on the fly
- Allowing parallel computing to reduce computation time
- Develop better GUI and model the building in 3D
- Couple simulation and optimisation
- Connect real physical building components performance to optimisation models for better information on cost and occupancy etc.
- Allow automation of building simulation with some default templates and strategies
- Profit from the gaming industry by developing interactive optimisation environments for example talking to an oracle friend or wizard that guides the optimisation process for better input quality and error detection and diagnostics

Discussion

From the interview results three themes were identified: the optimisation context, the locus of optimisation, and the factors that inhibit the uptake of BPO as decision support in the design of NZEBs.

Summary of main findings

For most interviewed experts evolutionary algorithms were found as a breakthrough that can help solving highly constrained Envelope, HVAC and renewable optimisation problems, while conventional algorithms just could not do it. Simple Genetic Algorithm solved many design, operation and control problems with relative ease. Evolutionary algorithms are adaptable and very powerful in finding good solutions. It is difficult to know whether they have found global minima, but this is not a critical flaw so long as they can measure the improvement in the optimality of a solution against a base case. It is also argued that the notion of trying to find an optimum is nonsense because there is so much uncertainty in the modelling that makes the simulation relates to reality. It's also the case that optimization is not so much about finding the "best" solution, but as much about exploring the design space for alternative solutions. Evolutionary algorithms are robust in exploring the search space for a wide range of building optimization problems. Unlike many other conventional or heuristic algorithms, Evolutionary Algorithms are also easily adapted to enable them to solve a particular optimization

problem more effectively.
Moreover, the rise of simulation has been driven by many things, including government policy that pushes the design of NZEBs. At present, any increase in the use of optimization will be driven by the extent to which aids design decision making. In this respect, one of the most powerful forms optimization is multi-object optimization, since this provides a set of solutions that lie on the trade-off between two or conflicting design objectives. The trade-off can be used to explore the impact of say of less capital investment on the increase in carbon emissions (this kind of information being useful in decision making). However, Decision support, time, knowledge, lack of tools, and uncertainty were the themes that ran through the experiences of the interviewed experts. The factors that inhibit the uptake of BPO are not only related to the optimisation techniques or the tools themselves, but also to the simulation models inputs, causing significant restrain in the AEC industry take-up. Interviewees' opinions about BPO, and their subsequent experiences, were found to be mostly influenced by their research work and community. From the evidence available, the optimisation process did not, in general, seem to be systematic and design centred, apart from a small group of experts who used BPO in real design practice.

Strengths and limitations of the study

The methodology used in this study literature review and structured interviews was appropriate to generate hypotheses from a large population sample. Verbatim transcriptions were undertaken and selected quotations were not edited (Attia 2012b). There was independent analysis of the data and concordance in the identification of themes. The choice of setting, IBPSA and IEA, allowed experts to be recruited from practices who represent a range of NZEB and simulation groups. Furthermore, the experts formed a representative sample in terms of the outcomes related to BPO. The experts were made aware at the beginning of the interviews that the interviewer was a researcher, architectural engineer and IEA SHC Task 40/ECBCS Annex 52 members. While this knowledge may have been helpful in allowing experts to feel comfortable in an AEC setting, thereby facilitating discussions about building performance related matters, this knowledge may have had an impact on the data. Specifically, the experts may have felt obliged to align their views with what they perceived to be the established IBPSA standpoint, for instance offering a more positive opinion on BPO than they would have done otherwise.

The number of the expert group means that statistical representation cannot be claimed. Furthermore, it was not possible to ensure that the expert represented a desired broad range of optimisation groups. The sampling strategy was therefore prospective rather than purposive, and it would have been preferable to interview more experts who declined the test and experts who do not speak English, as all of the interviewed were English speakers. Finally, it would have been preferable to interview more experts who work in practice.

Implications for practice and future research

The finding that BPO is surrounded by issues of uncertainty imposes new obligations on researchers and software developers. This involves embracing more design-centred optimisation work in addition to setting systematic frameworks of performing optimisation for design decision support, uncertainty and communication, and optimisation-based building solutions. Moreover, reliable and accurate information on building performance is crucial for experts to create robust informed design choices. Optimisation performed for designers needs to explain the impacts on the design quality both before and after the use of optimisation, and the associated uncertainties need to be discussed.

Furthermore, recognition is needed that optimisation is necessary for complex NZEBs. Designers do not rely on optimisation sufficiently due to the lack of public domain design packages integrated with open domain, object oriented analysis tools. They are also influenced, often strongly, by the design complexity, limited time and investment pressure. Policymakers must therefore respond accordingly and recognise that BPO does not start and finish in the research labs. BPO could be required as a standard activity during NZEBs design and operation and made available in a range of public NZEB design practice. The greatest possibilities, however, are afforded by the researchers. Notwithstanding the real issue of computation time and the seamless integration of simulation and optimisation model with design models. Ultimately in the future, all designers participating in the design (architects, engineers etc.) will be involved in using BPO techniques. Optimisation is about presenting design alternatives to the designer regardless of whom they are. So it might be that the architect has a different set of tools and it is a different optimisation methodology but they will not be excluded from using optimisation.

At present, the integration of BPO into the design process is a research issue. While this sample of experts confirms that BPO will add value to the design we do not have the proof. If we have solid proof designers will be very likely use optimisation techniques because it enhances the buildings they are designing, so they can get better buildings. More research is needed on the experience of designers with BPO. Research has to show designers that the use of BPO produce results better than their design. This would also allow the development of better BPO tools that are both accurate and support the decision making.

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