Renewable and Sustainable Energy Reviews 31 (2014) 101–112

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Algorithms for optimization of building design: A review

Vasileios Machairas [a,*], Aris Tsangrassoulis [b], Kleo Axarli [c]

[a] Department of Civil Engineering, Aristotle University of Thessaloniki, Thessaloniki, Greece
[b] Department of Architecture, University of Thessaly, Volos, Greece
[c] Department of Architecture, Aristotle University of Thessaloniki, Thessaloniki, Greece

ARTICLE INFO

Article history:
Received 12 January 2013
Received in revised form
24 September 2013
Accepted 18 November 2013
Available online 11 December 2013

Keywords:
Building
Design
Algorithms
Optimization
Review

ABSTRACT

Building design is quite a complicated task with the design team trying to counterbalance various antagonistic parameters, which in turn are subject to various constraints. Due to this complexity, performance simulation tools are employed and as a consequence, optimization methods have just started being used, mainly as a decision aid. There are examples, amongst the architectural community, where probabilistic evolutionary algorithms or other derivative-free methods have been used with various decision variables and objective goals. This paper is a review of the methods and tools used for the building design optimization in an effort to explore the reasoning behind their selection, to present their abilities and performance issues and to identify the key characteristics of their future versions.

Contents

1. Introduction

Building performance simulation tools have been widely used by the research community, but only during the last decade, did they begin to be used in the architectural design process. There are many reasons for this delay, starting from the difficulty of using these tools, the acquisition of necessary skills, their associated costs, the uncertainty in the results and the general impression that the designer is restricted by the limitations of the tools.

Nowadays, a large number of simulation tools do exist with user friendly interfaces and a plethora of available training material. With their use, design teams, after defining a number

* Corresponding author. Tel.: +30 69420 55297; fax: +30 24620 87589.
E-mail addresses: vasilis@maheras.gr, vmaheras@civil.auth.gr (V. Machairas).

1364-0321/$ - see front matter
http://dx.doi.org/10.1016/j.rser.2013.11.036

of decision parameters, can explore new designs which were not accessible through the traditional approach. For example, current legislative changes in Europe have led to the revision of national building energy codes in order to include a more advanced computational approach. Therefore, in most cases, compliance with codes is the driving force behind their use, this fact does not guarantee the optimization of building energy consumption. Thus far, studies concerning the impact of various parameters on building design have relied on parametric analyses which in turn were based on detailed building simulations. The latter are computationally expensive and using a brute force technique to evaluate all possible solutions is not a viable process. It was the need, therefore, to explore the solution space more efficiently and fast that gave rise to the adoption of optimization techniques. It has to be mentioned that the transfer of a real world design problem into the mathematical domain has limitations and that the commonly used optimization algorithms applied to building design problems cannot ensure that the optimal solution will be found. Nevertheless, better building performance may be obtained compared to common practice where no optimization is used. Therefore, the understanding of optimization method's strengths and weaknesses is crucial in order for them to be used effectively in related design problems.

Optimization is the procedure of finding the minimum or maximum value of a function by choosing a number of variables subject to a number of constraints. The optimization function is called cost or fitness or objective function and is usually calculated using simulation tools. Because of code features, the results may be non-linear and have discontinuities, making necessary the use of special optimization methods that don't require the computation of the derivatives of the function. Optimization methods can be applied to a number of different building design problems such as massing, orientation, façade design, thermal comfort, daylighting, life cycle analysis, structural design analysis, energy and of course cost. The structural design (i.e. selection of beam/columns cross section) and building controls (operation/scheduling) optimization are not part of the present review. However, in some of the reviewed cases optimization of both building design and setpoint scheduling or more advanced multi-disciplinary optimization was applied.

The review is separated into four major sections exploring different viewpoints of the subject. The first section deals with the optimization algorithms which have been utilized in building design problems. The next one presents the optimization tools and some of their characteristics. The third section lays out three building performance evaluation methods that affect the optimization approach differently and discusses the strengths and weaknesses of each method. The forth section reviews the optimization targets exploring the objective functions and the design variables commonly used for building design problems. Finally, future perspectives on the use of building design optimization are presented.

2. Optimization algorithms

Generally, an optimization problem can be represented in mathematical form as:

$$\min_{x \in \boldsymbol{X}} f(x)$$

where $x \in \boldsymbol{X}$ is the vector of the design variables, $f : X \to \mathbb{R}$ is the cost or the objective function, and $\boldsymbol{X} \subset \mathbb{R}^n$ is the constrain set.

When there is more than one objective function for optimization then a multi-criteria or a multi-objective optimization problem arises. This is common in building design problems and these functions are often contradictory. Typically, there are two popular approaches for multi-objective optimization problems. The first one uses a weighted sum function where each of the objectives is normalized and summed up with their associated weight factors to get only one cost function. Typical optimization algorithms can be used to solve it but the information on how the different sub-objectives interfere with each other cannot be extracted. Testing different weight factors causes an increase in the number of optimization problems, which in turn, demands longer processing times.

The other popular approach for multi-objective optimization is proposed by Pareto [1]. A solution is Pareto optimal or non-dominated when there isn't any other feasible solution that improves one objective without deteriorating at least another one. The multi-objective algorithms result in a set of non-dominated solutions which is called Pareto frontier. When the problem consists of two objectives, the Pareto frontier can be represented as a curve. Fig. 1 presents a typical example of Pareto frontier for a minimization problem with two objectives.

The above mentioned multi-objective approaches have both advantages and disadvantages. As Cao et al. [2] indicate, the algorithms that provide Pareto solutions focus on exploiting the diversity of the solutions, but often present issues of inadequate efficiency and effectiveness. The weighted sum methods are more efficient and easier to implement, but require prior knowledge and they don't provide information on the compromise between the objectives.

The selection of the optimization algorithm depends on the problem that needs to be solved. There are some situations where an analytical solution of the objective function can be obtained, as Adamski [3] and Marks [4] proposed. They mathematically describe the shape of a building and solve it with numerical methods, finding the true optimal. When the solution space is relatively small and the calculation of the objective function is fast, the entire space can be searched to find the true optimal. Such examples are presented by D'Cruz and Radford [5] who used a simple building model and Pareto optimal Dynamic Programming to optimize thermal load, daylight, planning efficiency and capital cost. Jedrzejuk and Marks in [6,7] described the building design problem mathematically and solved it numerically, by applying the CAMOS computer system. Castro-Lacouture et al. [8] used a mixed integer optimization model to select materials that maximize green building LEED credits. Michalek et al. [9] used CFSQP, a C implementation of Feasible Sequential Quadratic Programming to solve their building geometric layout problem. Chakrabarty [10] used non-linear programming in his proposed HudCAD tool for optimization of housing and urban development projects. Petersen and Svendsen [11] presented a simplified economic optimization method from an early stage near-optimum economic design. Stavrakakis et al. [12] used sequential quadratic programming

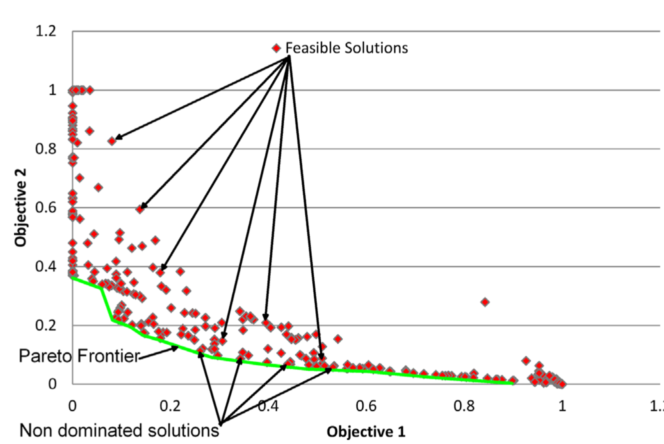

Fig. 1. An example of Pareto frontier.
Source: Prototype.

(SQP) to solve their building design problem with the help of artificial neural network meta-model.

Explaining the details of each optimization algorithm operation is outside the scope of the present work. This review focuses on optimization problems where the objective function or parts of it, is evaluated using whole building performance simulation programs, typically on an annual basis. Simulated phenomena in building design can be non-linear and require efficient optimization algorithms which don't compute or approximate derivatives. Such “derivative-free” algorithms are the deterministic direct search and the probabilistic evolutionary one.

2.1. Evolutionary algorithms

A popular evolutionary algorithm is the genetic algorithm [13] that uses the principle of natural selection to evolve a set of solutions towards an optimum solution. Genetic algorithms (GA) are population-based algorithms and they can efficiently handle non-linear problems with discontinuities and many local minima. These are widely used in the field of building optimization. Wright and Farmani [14] used GA for simultaneous optimization of the fabric construction, HVAC system size and the control strategy. Coley and Schukat [15] used GA to minimize annual energy use while Znouda et al. [16] optimize the design of Mediterranean buildings. Oliveira Panão et al. [17] used GA for the optimization of the urban building efficiency potential and Rakha and Nassar [18] to optimize the ceiling form to achieve predefined daylight uniformity. Pernodet et al. [19] used GA for multi-criteria optimization of building refurbishment. Yi and Malkawi [20] used GA to optimize the form of the building. Charron and Athienitis [21] presented a GA based optimization tool for Net-Zero Energy Solar Home Design while Tuhus-Dubrow and Krarti [22] built a similar tool for the building envelope design of residential buildings. Turrin et al. [23] presented the ParaGen tool which combines GA with parametric modeling to support the exploration of design alternatives.

There have been many developed variations of the GA to be adapted for specific problems. Magnier and Haghghat [24] used one of the most popular multi-objective algorithms, the Non-dominated-and-crowding Sorting Genetic Algorithm II (NSGA-II) developed by Deb [25], for optimization of building design. Chantrelle et al. [26] developed a NSGA-II based tool for multi-criteria optimization of building renovation. Evins et al. [27] proposed the NSGA-II for their building optimization problem. Palonen et al. [28] used the NSGA-II and the Omni-optimizer for simulation-based optimization problems and a hybrid version of this algorithm with Hooke–Jeeves which will be described in the following paragraphs. Different types of multi-objective genetic algorithms are used in [29,30–33], for their building design problems. Caldas and Norford [34] used a micro-GA procedure to build a design optimization tool and in [35] use a micro-GA and Pareto GA based generative design system (GENE-ARCH). Cao et al. [2] presented a boundary-based fast genetic algorithm for sustainable land use optimization. Lee [36] proposed a design optimization tool based on CFD simulations and a multi-island genetic algorithm.

Some other evolutionary algorithms which are generally popular but rarely found in papers focusing on the optimization of building design, are the particle swarm optimization (PSO), the simulated annealing (SA) and the ant colony optimization. The PSO algorithm is the most common of the three and has been implemented in GenOpt [37] which is a generic optimization program with ready-made routines offering coupling with thermal simulation software. Rapone and Saro [38] used PSO to optimize curtain wall façades of office buildings. Hasan et al. [39] presented a hybrid PSO with the Hooke–Jeeves algorithm for the minimization of the life cycle cost of a detached house. Michalek et al. [9] use GA and SA to search for global solutions for their architectural layout design optimization problem. Fesanghary et al. [40] built a multi-objective optimization model based on harmony search algorithm (HS) for the minimization of the life cycle cost (LCC) and the carbon dioxide equivalent (CO_2-eq) emissions of the buildings.

2.2. Other derivative-free search methods

A well-known derivative-free optimization algorithm family is the direct search methods. These algorithms use heuristic rules to search through the solution space and require that the objective function be continuous without estimating derivatives. They are not as effective as derivative-based methods, but as Torczon [41] indicated they are usually more robust for noisy functions, when analytic derivatives are unavailable, or finite difference approximations to the gradient are unreliable.

Peippo et al. in [42] used the Hooke and Jeeves pattern search method which is characterized by a series of exploratory moves that traces the behavior of the objective function at a pattern of points [43,44]. Eisenhower in [45] used the derivative-free method (NOMAD) which contains the mesh adaptive direct search (MADS) algorithm. This is a direct search algorithm with rigorous convergence properties, but it works on a surrogate meta-model after identifying and correcting the discontinuities of the simulation-based model.

Bouchlaghem in [46,47] used the simplex method of Nelder and Mead [48] and the non random complex method of Mitchell and Kaplan [49] to optimize building thermal performance. The Nelder–Mead simplex algorithm is very popular within the research community but as Lewis et al. indicate, there is a question regarding its robustness. This method can work very efficiently, often finding a solution in far fewer evaluations of the objective function than other direct search methods, but it can also fail [43]. Such an example is presented in [50].

A not so common method can be found in [51], where Gong et al. proposed a new approach for building design optimization; to evaluate the significance of seven parameters and their interactions using an orthogonal array method. After that, the listing method was used to estimate one parameter at a time, while keeping the other parameters fixed at the standard value. Saporito et al. in [52] used the lattice method for global optimization (LMGO) to reduce the number of simulation tests and to identify the relative importance of various energy saving features.

An interesting optimization method is the sequential search which has been implemented in BEopt [53]. This program is capable of evaluating building designs along the path to zero net energy, using a method that identifies intermediate optimal points and allows the use of discrete building options. The additional benefit of this search strategy is the identification of near-optimal alternative designs [54]. In [55], [54,56] the sequential search method was used to optimize the energy efficiency in residential buildings while Ellis et al. [57] using this method, built an automated multivariate optimization tool for “in-house” research use.

2.3. Hybrid algorithms

Another popular approach within the optimization community is to use more than one optimization algorithms in a hybrid operation. The typical procedure is to use a global search algorithm to find a near optimal solution and then use the result as a starting point for a local optimizer. A good example of this operation has been implemented in GenOpt [37] where a Particle Swarm Optimization starts global searching for an optimal point. When PSO finishes the Hooke–Jeeves method continues searching in order to refine the result. Hasan et al. [39] work using this hybrid PSO+Hooke–Jeeves algorithm for the minimization of the life cycle cost of a detached house has already being mentioned.

Juan et al. [58] used a hybrid approach that combines A* graph search algorithm with genetic algorithms (GA) to analyze all possible renovation actions and their trade-offs in order to develop an optimal solution. Kämpf and Robinson [59] proposed the hybrid covariance matrix adaptation evolution strategy (CMA-ES) with the hybrid differential evolution (HDE) to optimize solar energy utilization through building form.

An interesting hybrid algorithm operation was proposed by Hamdy et al. in [60]. Their proposal was to run a deterministic algorithm before (PR_GA) or after (GA_RF) a multi-objective genetic algorithm. This can prepare the initial population for the GA (PR_GA) or refine the GA results (GA_RF). PR_GA combination is suggested in order to reduce the random behavior of GA and as a result, to obtain good solutions with a lower number of evaluations. GA_RF combination is suggested when high quality results are required, offering a well-defined criterion for terminating the process. Hamdy et al. in [61] combined the two methods to form a PR-GA-RF approach in an effort to use the advantages of both methods.

2.4. Performance of the optimization methods

The performance of the algorithm depends on the type of problem being used and its mathematical description. This is the reason why so many methods are still in use. Optimization methods coupled with whole-building simulation programs need a lot of processing resources. The computation time required by an annual building simulation depends on many parameters and can last from just a few seconds to several hours or even more. An optimization analysis requires from a small number to several thousand evaluations just to get a near-optimal solution, resulting in processing times varying from some minutes to hours or even days. Selecting the appropriate approach and applying specific techniques can significantly decrease the simulation runtime. These techniques together with the performance of the optimization algorithms are discussed in the following paragraph.

Tuhus-Dubrow and Krarti in [22] verified the results of a GA against the PSO and the sequential search method. The verification analysis has indicated that the GA was more efficient than the sequential search and the PSO approaches in cases where more than ten parameters were employed in the optimization. In more details, it was found that the GA approach can locate the optimal solution with an accuracy of 0.5%, demanding less than 50% of the iterations required by PSO and sequential search methods. Bichiou and Krarti in [62], presented an optimization study for residential buildings, comparing the robustness and the effectiveness of the same three algorithms. The computational efforts for the sequential search technique were, in general, significantly higher than both the PSO and the GA. The savings in computational time when using GA (the algorithm with the best performance at their tests) were compared to that of the SS technique and were as high as 70% for a full optimization when both the building envelope and HVAC system features were used. In the same paper, a sequential optimization approach was tested as well, starting with the building envelope features and continuing with the HVAC system options. The results showed a reduction in CPU time from 33% to 95% in comparison to the full optimization. In general, full optimization provides slightly more accurate results but these are associated with increased computational effort. Lee in [36] used a two-step process to lower the optimization calculation load. A simple analysis using a coarse mesh was carried out at the beginning to reduce the load and then, a detailed CFD analysis using a fine mesh was applied on the cases ranked top during the first step.

Kämpf et al. in [63] compared the performance of two hybrid metaheuristic optimization algorithms, by minimizing standard benchmark functions and real-world building energy. The chosen metaheuristics were the Covariance Matrix Adaptation Evolution Strategy together with the Hybrid Differential Evolution (CMA-ES/HDE) and the hybrid Particle Swarm Optimization with the Hooke–Jeeves (PSO/HJ). Kämpf indicated that CMA-ES/HDE performs best on highly multi-modal functions such as Ackley and Rastrigin, because the algorithm was especially designed for this kind of functions. PSO/HJ frequently converges to the global minimum for functions with one or two minima such as Rosenbrock or Sphere. These algorithms were compared for a large and a small office at different climates, as well. The performance for the small office was quite similar for both algorithms. The PSO/HJ provided slightly significant better results only for one climate. A similar performance was obtained for the large office too, but the resultant parameter sets were different, indicating that the objective function was multi-modal or locally flat. As no algorithm was significantly favored over the other, it seems that the test building optimization problem was neither multi-modal nor had it one or two minima. As the nature of the objective function can't be determined a priori, Kämpf suggests using the hybrid CMA-ES/HDE algorithm.

Another comparative study of optimization algorithms for building design problems has been carried out By Wetter and Wright [50]. The algorithms were PSO, GA, Coordinate Search, Hooke–Jeeves, Nelder–Mead, Discrete Armijo gradient and a hybrid version of PSO and Hooke–Jeeves (and some variations e. g. PSO on a mesh). The Nelder–Mead and the Discrete Armijo gradient algorithms didn't perform well in their tests and it was recommended that these algorithms shouldn't be used for problems solved by EnergyPlus. The GA got close to a solution with a low number of simulation runs. The hybrid PSO+Hooke–Jeeves achieved the biggest cost reduction but required more simulation runs. The PSO global searches for a near optimal solution and then Hooke–Jeeves refine the search locally. If the discontinuities in the cost function are small, Hooke–Jeeves achieves a good performance with only a few iterations. In the same paper, discontinuities in the cost function in the order of 2% were also observed. As indicated, these discontinuities can cause optimization algorithms which require smoothness of the cost function to fail. A solution for the above mentioned problem is provided by Wetter in [64,65] where a new building energy and daylighting simulation program (BuildOpt) is presented, built on smooth models. Wetter and Polak in [66,67] used that program with a precision control algorithm, applying coarse precision approximations to the objective function when far from a solution, but progressively increasing it as a solution was approached. During their building design optimization experiments, their precision control scheme proved very efficient as it managed to reduce the computation time by four, in comparison to the standard Hooke–Jeeves algorithm.

Wright and Alajmi in [68] reached an interesting conclusion. The GA was insensitive to the selection of the control parameters since the mean difference in objective function values was statistically insignificant for their test problems.

Several techniques targeting the reduction of computational efforts were found during the literature review. A good approach, when aiming at simplifying problems with a large search space size, is to perform sensitivity and uncertainty analysis before the actual optimization search. As Eisenhower et al. [69] indicated the uncertainty analysis can identify how parameter variation influences the statistics of key output, while sensitivity analysis can spot the parameters that influence output variation the most. Heiselberg et al. [70] presented a methodology of sensitivity analysis using an office building as an example. Mechri et al. in [71] presented the analysis of variance (ANOVA) approach that can be used to identify the design variables which have the greatest impact on an office building energy performance. Eisenhower et al. in [45] proposed an approach that uses uncertainty and sensitivity analysis to identify critical parameters that are most effective for optimization. Large discontinuities in the cost function were identified using a filtering method and reduced order meta-models were created in partitioned subsets of the global feasible set, separated by these discontinuities. A direct search algorithm (NOMAD) is then used on each meta-model while an uncertainty-weighted cost function was employed to obtain the best optimized solution for each feasible subset. In [69], a similar approach was used and a methodology for meta-model based optimization was presented. Having used an analytic meta-model of the building, the researchers were able to apply a gradient-based optimizer IPOPT (Primal-Dual Interior Point algorithm with a filter line-search method for nonlinear programming) which outperforms the direct search method applied to the meta-model.

Choudhary et al. in [72] proposed a different approach. The analytical target cascading (ATC), a multi-level engineering design optimization framework, was developed and its use was extended to thermal and HVAC design in buildings. ATC is a multidisciplinary hierarchical optimization methodology that provides a systematic process for propagating desired top-down performance targets in an effort to acquire lower level performance values.

In general, direct search methods are very powerful at improving good solutions as long as they have mechanisms to overcome small discontinuities of the cost function and small local optima. It should be pointed out that the performance of the algorithms is depended on the simulation program as well. Some simulation programs are built to ensure smoothness of the cost function, thus a large number of algorithms can be used with better performance.

Evolutionary algorithms are population-based algorithms and mostly used for global searching. Starting with an initial random population and applying stochastic operators cannot ensure a better solution than what is suggested by common practice. This can be avoided by adding user-defined cases in the initial population. Local optimizers are very powerful but they usually can't handle discrete variables and they require either an experienced building designer to suggest good solutions as starting points or to run a global search beforehand. Algorithms with better performance are usually designed in such a way as to solve a specific kind of problem but they may fail for other problems. As it will be presented, the best tools and algorithms for the building design problem are the ones that enable researchers to use their expert knowledge in order to minimize the size of the solution space or drive the search to the right direction.

It should be pointed out that the commonly used optimization algorithms for the building design problem cannot ensure finding the optimal solution. The stochastic behavior of evolutionary algorithms, the plethora of configuration options and the diversity of building design problems cannot allow safe conclusions about the performance of these algorithms. As the number of papers regarding optimization of building design increases, some optimization targets become typical and more comparisons of algorithms and simulation programs are anticipated.

3. Optimization tools

The tools used for the optimization of building design can be separated into three categories:

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

Custom programmed algorithms require advanced programming skills and their main benefit is their flexibility. Examples using this approach can be found in [3,5,21,40,47]. Unfortunately, detailed reporting on their optimization implementation is not available, so safe conclusions regarding their features cannot be reached.

General optimization packages encountered during this review were the modeFRONTIER [73] which was used in [33,74] and the Matlab which is frequently used for the optimization of building controls. Matlab has also been used in many cases of building design optimization, such as in [20,22,60,61,75,76,77]. These packages have a graphical user interface and among others include many effective optimization algorithms and post processing capabilities. As Hamdy et al. indicated in [60], the use of Matlab gives the designer an opportunity to take advantage of its additional features such as the excel link, the use of databases, data analysis, plotting functions, curve fitting functions, graphical user interface etc. Custom features can be integrated by the user as well.

In the same category a quite commonly used optimization tool is GenOpt [37]. GenOpt is a generic optimization program for the minimization of cost function that is evaluated by an external simulation program. It was used in many optimization studies such as in [24,28,38,39,50,63,75,78,79] and can be coupled with any simulation program that reads its input from text files and writes its output to text files as well. It currently includes examples for EnergyPlus, TRNSYS, Dymola, IDA-ICE and DOE-2 and Radiance [80]. Genopt currently provides the Golden Section and Fibonacci algorithms for one-dimensional minimization, the Nelder and Mead's Simplex algorithm, the Discrete Armijo Gradient algorithm, the Hooke–Jeeves and the Coordinate Search which are pattern search algorithms, the particle swarm optimization (PSO), and a hybrid PSO with the Hooke–Jeeves algorithm. The source code of the program is provided (in JAVA) and it's possible to add more optimization algorithms to its library. The authors have already implemented a simple genetic algorithm, a multi-objective GA (NSGA-II), a synchronous parallel pattern search algorithm and a hybrid version [81,82]. GenOpt provides a parallel processing capability, filtering of already evaluated functions, a mesh generator and a parametric search.

There are several optimization tools under the third category coupled with building performance software. Charron and Athienitis in [21] proposed an early stage design tool based on a GA with TRNSYS. Tuhus-Dubrow and Krarti in [22] presented a tool which couples the GA of Matlab to DOE-2 simulation program. Chantrelle et al. in [26] present MultiOpt: a multicriteria tool for building renovation optimization. MultiOpt has a graphical user interface and it uses the NSGA-II coupled to TRNSYS together with financial and environmental databases. Caldas and Norford, in [34], proposed a GA with DOE-2 tool aimed for intermediate to late stages of design. Caldas in [35] applied GENE_ARCH in several test cases. GENE_ARCH is a micro-GA and Pareto GA based generative design system which uses DOE-2 as the building simulation engine. Lee in [36] has proposed a tool based on CFD simulations and a multi-island GA. An interesting approach which can be used for multi-disciplinary optimization design was developed by Turrin et al. [23], called ParaGen. ParaGen combines parametric modeling, performance simulation software and a GA to explore design alternatives. The example applications of this tool include both structural and energy performance design of a long span roof using the same design framework but with different performance evaluation software. The examined literature refers to the implementation description of the above mentioned tools, but details of specific features and their performance cannot be obtained. The majority of the tools in this third category use a GA implementation coupled to a whole building simulation program.

Griego et al. [55] used the BEopt software for the optimization of residential buildings in Salamanca and Anderson et al. [54] used it to explore the design of new homes with zero peak cooling demand. BEopt's graphical interface permits the selection of predefined options in various categories [83]. It currently uses DOE2.2 or EnergyPlus as simulation engine and the sequential search method as the optimization algorithm. This tool can utilize the multithreading capabilities of modern computers and it seems to be one of the easiest to use for practicing design teams. It has an easy to use graphical user interface and support is provided through an abundance of training videos. An important feature of this tool when using the sequential search optimization technique is the ability to identify multiple near-optimal designs.

There are also some commercial products that recently presented optimizers for their building simulation suites. Such solutions are from IES [84] and DesignBuilder [85]. Unfortunately, no implementation details and worked examples in literature are available, but both seem promising and probably make use of multi-objective optimization algorithms.

The evaluation of the cost function by a whole building simulation program requires much more processing time than that required to determine the values for the next iterate. Thus, the essential characteristics of an optimization tool for every-day use in a practicing design team are:

- Satisfactory performance.
- Provision of graphical user interface.
- Ability to estimate multiple solutions with similar performance.
- Parallel processing ability.
- Hybrid operation.

The last section of the present paper refers to the future perspectives of the optimization tools in more details.

4. Building performance evaluation

Building performance evaluation can be achieved using three types of models:

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

Each of the above-mentioned types is approached differently in the literature. Although, this review focuses on the last one, since it represents the state of the art for both the design and the research community, the other two are mentioned as well for completeness of this work.

4.1. Simplified analytical models

Building performance analytical models can be applied only to simple problems. Describing the problem mathematically is neither an easy task, nor is it practical for design teams, but it's used within the research community when the focus is on solving a specific problem. Such an approach offers the benefit of finding the true optimal more easily, by using specific optimization algorithms or brute force techniques to search the entire solution space. This kind of work is found in [3–5,8,9] which have already been mentioned in the optimization algorithms section. The true benefit of these models is that results can be extracted almost instantly and be used as inputs to a more detailed analysis.

The creation of specific models for a problem is more common when optimizing the building controls operation. Building analytical models is an advanced issue and it's outside the scope of this paper. Several optimization procedures may be used depending on the problem, but usually it's feasible to search all possible solutions. Some models can describe the building physic's associated phenomena well enough and extract the optimal solutions. These results may be used as they are, or can be included as candidates for further analysis during the optimization of a detailed building model.

4.2. Building performance surrogate models

Surrogate models or meta-models are statistical models that are built to approximate computationally expensive simulation codes [86]. The models created through a machine learning approach, are considered as surrogate models. Although, these kinds of models are common in control research, some examples can be found in the building design optimization literature as well. In general, a procedure using a surrogate model has 3 steps:

- Building a detailed simulation model e.g. such as a thermal model.
- Running that model for many different cases to generate a database of results.
- Using the results statistically to train and test the meta-model.

There are many specific approaches to machine learning like artificial neural networks (ANN), genetic programming, Bayesian networks, support vector machines (SVM) etc. These models can provide a good approximation of the nonlinear building behavior, offering fast cost function evaluations and ability to explore a large search space.

There are several studies using such models. Magnier and Haghighat in [24] used a simulation-based artificial neural network (ANN) to characterize building behavior, and then combined this ANN with the multi-objective NSGA-II to optimize building design. The building thermal simulation program TRNSYS was used to create a database of cases for training and validation of the ANN. Stavrakakis et al. in [12] use CFD modeling to train an artificial neural network meta-model and optimize window design by sequential quadratic programming. Wong et al. [87] used EnergyPlus to train ANN for energy analysis of office buildings with daylighting while Zemella et al. [88] an ANN based optimizer, the Evolutionary Neural Network Design (ENN-Design), to optimize building façades. Eisenhower et al. in both [45] and [69] adopted a support vector regression (SVR) machine learning approach to generate a meta-model which was used for their optimization studies. The SVR approach is similar to the learning procedure in ANN, but it has only one global solution while in ANN, many local optimal solutions may exist [45].

Optimization studies making use of a surrogate model require statistical results to train the model. In turn, the derivation of these results requires a detailed building simulation model to run for repeated evaluations until the desired model accuracy has been achieved. The number of evaluations is probably bigger than or the same as the number needed when an optimization algorithm is been coupled to a building simulation engine. Expert knowledge on how artificial intelligence works is essential as well. These are the main reasons why this approach is not common in building design problems and has a long way to go before it starts being used by practicing professionals. However, the production of surrogate models helps in solving many building control problems, because an immediate result is expected. In addition, this approach is useful in solving demanding building design problems, with numerous design variables, many local minima and a huge search space.

4.3. Detailed building simulation models

There are many simulation programs that perform building performance calculations. In the literature, TRNSYS [89], IDA-ICE [90,91], DOE2, EnergyPlus [92], APACHE, Ecotect, Radiance [93], and CFD tools are noted among others as the ones mostly used. According to Wetter and Wright [50], this kind of simulation programs usually contain code features that may cause discontinuities in the cost function. Thus, any optimization algorithm that requires cost function smoothness might fail. A building simulation tool worth mentioning is BuildOpt. BuildOpt is a building energy simulation program that is built on smooth models [64] and it has been used by Wetter and Polak [66] for building design optimization. Wetter in [64] has mentioned that the IDA-ICE program generates a differential algebraic equations (DAE) system, which it solves simultaneously. This approach might be promising for usage with direct search methods. This review has come across building design optimizations using IDA-ICE in [39,60,61,78] but no comparative study of optimization algorithms is mentioned.

A similar to BuildOpt model, capable to compute differentiable objective functions is included in the Modelica "Buildings" library and is described in [94–96]. An interesting tool that enables coupling Modelica with other tools like Matlab is the building controls virtual test bed (BCVTB) [97]. The BCVTB is a free software environment that allows expert users to combine different simulation programs for distributed simulation. It allows the simulation of a building in Energyplus while the control strategy may use Matlab/Simulink environment. These programs can exchange data during the simulation. BCVTB is currently linked to EnergyPlus, ESP-r, Radiance, Matlab and Modelica and has been mainly used in optimization studies of building controls.

The above mentioned tools are able to simulate almost all building physics phenomena and processes. The required input data are usually climatic data, building geometry, materials, occupancy and several other schedules and of course HVAC description and operation. Their output usually includes energy consumption, thermal and visual comfort metrics, daylight utilization and environmental information like the equivalent CO_2 emissions. Whole building performance simulation tools are considered very mature while standards have been developed [98] in an effort to develop a reference evaluation methodology. Based on the building energy simulation test [99] program, the methodology uses, among others, an analytical verification to examine the reasons of difference between simulation tool results and the associated analytical solutions.

5. Optimization's target and objective functions

A building design optimization analysis has at least 4 steps:

- Identification of the design variables and their relevant constraints.
- Selection of a building performance simulation tool and creation of a building model.
- Selection of an appropriate objective function.
- Selection of an appropriate optimization algorithm.

In general, building designers seek to minimize either the building initial cost or the operating cost while in some cases, the life-cycle cost of the building and the environmental impact are used as well. The design variables of a design optimization problem usually describe the construction and the geometry of the building. Russel and Arlani [100] described thirteen investor motivations for starting a building project, test several objective functions and indicated the importance of selecting an objective function that is consistent with global investor objectives.

Single and multi-objective studies can also be found in the literature. The multi-objective functions are usually treated as a weighted sum or a Pareto front result. For example, Adamski [3] optimized the shape of the building with a weighted sum objective function in order to get minimum construction cost and minimum heating energy. D'Cruz and Radford [5] presented a multi-criteria model of a parallelepiped open plan office regarding thermal load, daylight availability, planning efficiency and capital cost. Mela et al., in [101], presented an interesting study of six well-known multiple criteria decision-making methods (MCDM) for building design. The numerical study of their test problems indicates that in most cases, the methods provide different solutions.

An objective function usually contains a part that is based on comfort criteria. For example, Magnier and Haghighat [24] searched for a Pareto front result of both thermal comfort and energy consumption. Thermal comfort was evaluated by the average absolute value of the predicted mean vote (PMV), based on Fanger's model[102] representing the most common comfort metric in literature. To ensure comfort levels during the year, they added a constraint parameter to act as a penalty term, based on the number of hours with $|PMV| > 0.5$. Asadi et al. [75] used a similar approach where one of the multiple objectives was the cumulative sum of discomfort hours ($|PMV| > 0.7$). PMV was also used by Griego et al. [55] to evaluate discomfort. Bouchlaghem in [46,47] tested six different objective functions based on custom comfort criteria. Stavrakakis et al. [12] evaluated four different comfort measures to optimize the design of window openings in naturally ventilated buildings.

Another commonly used objective function is the one that is based on the results of a life-cycle analysis. Examples of such approaches are in [16,22,62,56,39,40,78]. In general, life-cycle costs take into account the initial investment costs plus the costs of operation, maintenance and repair, multiplied by a discount rate factor. An interesting multi-objective life-cycle approach is proposed by Wang et al. in [31,32] where the trade-off relationship between the life-cycle cost and environmental impacts is explored and an optimization framework is presented [103].

In more recent analyses, CO_2 emissions are found as one of the objectives of the optimization study. Such examples are provided by Evins et al. [27] and Fesanghary et al. [40] who optimized low-emission and cost, using multi-objective algorithms. Rapone and Saro [38] searched for the configuration of a building façade that leads to the minimum amount of carbon emissions but at the same time, guarantees the desired ambient conditions in an office. A similar approach was used by Zemella et al. [88] for a building façade using a multi-objective function to identify the trade-off between the energy consumption for cooling and artificial lighting. Chantrelle et al. in [26], used both mono and multi-criteria optimization, using cost, thermal comfort, energy consumption and CO_2 emissions as their objectives. Hamdy et al. [61] applied a multi-objective optimization approach to get Pareto solution of carbon dioxide equivalent (CO_2-eq) emissions and the investment cost for a two-storey house and its HVAC system.

The formulation of the objective function depends on the optimization target. Cao et al. [2] having a land use allocation target, tested different objectives based on the maximization of GDP, the minimization of conversion, the maximization of geological suitability, the maximization of ecological suitability, the maximization of accessibility, the minimization of NIMBY (Not In My BackYard) influence, the maximization of compactness and the maximization of compatibility. Castro-Lacouture et al. [8] used construction materials as design variables aiming to maximize LEED credits within design and budget constraints. Rakha and Nassar [18] developed an objective function based on ceiling daylight uniformity to find the optimized shape of the ceiling. Sambou et al. [30] adopted a GA to search for the Pareto front of the thermal insulation and the thermal inertia of a multilayered wall. Kämpf et al. in [104,77] optimized building form for solar energy utilization while Oliveira Panão et al. [17] discussed the optimization of urban building energy efficiency potential by having high solar absorbptance in winter and as low as possible during summer. Michalek et al. [9] searched for the optimal architectural design layout by minimizing accessways, hallway, lighting, heating and cooling cost. The objectives used in the above mentioned cases reveal the diversity of the optimization targets in building design.

Usually, the typical building design optimization problem does not use any kind of constraints on the objective function. Only in some cases such as in [24], were quadratic penalty functions utilized to ensure that a set of comfort conditions was met. The design variables (continuous or discrete) usually have typical box constraints, with lower and upper bound.

Discrete design variables usually with only two to ten different options are met, while the continuous ones are precision-constrained using more or less the same number of options. The larger the number of the design variables, the smaller the number of options each variable has, in an effort for the selected optimization algorithm to be converged within a couple of thousand simulations. Consequently, the processing time can be strongly affected by the antagonistic balance between the number of variables and their options. For complicated optimization problems with large number of variables/options, the use of a computer cluster might be beneficial [23].

Building design options include building geometry and construction while retrofit applications use only the construction options. Examples of typical design variables used are the orientation and the shape of a building, wall dimensions, wall/roof thickness and materials, glazing type, window to wall ratio, building thermal mass and air tightness, light intensity, HVAC system size and its options and shading options. However, it seems that in most cases, expert knowledge can be used as an aid for the definition of a specific set of options. The number of options can be restricted by local building codes and/or the construction site, since the material cost and the experience of the local contractors are area-depended. In contrast to the real world constraints, the reviewed literature shows a larger diversity of solutions. Therefore it is evident that the selection of the appropriate design variables and objective function plays a crucial role in an optimization study. Choosing only discrete options (for example 3–5–8–10 cm for insulation thickness) will make the use of some direct search methods, unavailable. This can be avoided if they are carefully described as continuous variable with specific precision options. The use of constraint methods such as the death penalty method, which adds discontinuities to the objective function, is not very well suited to the direct search algorithms.

Building designers are experts in their field and they are capable of delivering building solutions which fulfil various requirements without to need of optimization tools. However, this expert knowledge has a potential benefit for optimization: the reduction of the search space. Unfortunately, rules on the selection of the appropriate objective function and design variables could not be formulated using only the literature data.

6. Results and discussion

Most of the reviewed literature was explored using the ScienceDirect scientific database. The search through titles and abstracts using the keywords “Optimization AND Building”, resulted in 1585 papers till 2012. This number was reduced to 300, after a selection based on the paper's titles. The examination of abstracts revealed that 66% of these papers focused on the optimization of building controls or structural design analysis and had to be filtered out. The final pool of reviewed work was enriched with additional papers using the references.

In Fig. 2, the numbers of papers for specific keywords are presented. Therefore, judging by the number of building design optimization papers, it seems that this type of optimization techniques is still in its early stages. About 50% of the papers, for all keywords, have been published in the last 5 years, presenting a potential for a faster future integration of these techniques into the building design process.

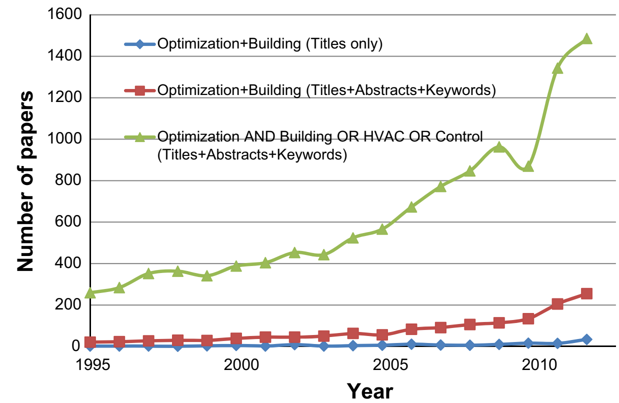

Fig. 2. Number of papers for selected keyword searches in ScienceDirect for years 1995–2012.
Source: Prototype.

These techniques have already been applied to building design in order to get better energy efficiency with lower investment cost and reduced environmental impact. Bambrook et al. [78] proved that it is possible to cost-effectively reduce the heating and cooling energy requirements of a new house in Sydney, by up to 94% compared with the legislated BASIX energy efficiency requirement for New South Wales. Griego et al. [55] achieved a minimum cost solution which resulted in nearly 52% annual energy savings for new homes in Salamanca, Mexico. Hasan et. al. [39] achieved a reduction of 23–49% in the space-heating energy of a Finnish house compared with their reference case. Ihm and Krarti [56] reduced the annual energy use by 50% compared to the current design practices for houses in Tunisia. The optimal configuration of the test cases by Kämpf et al. in [63] led to a reduction in primary energy consumption of up to 30%. Eisenhower et al. [69] achieved 45% annual energy reduction while simultaneously increasing thermal comfort by a factor of two, by applying their optimization method to a building. Anderson et al. [54] used the BEopt analysis method to reduce the total energy source usage by 60% in a Sacramento home. In all of the above mentioned cases, optimization techniques have been coupled with a whole building simulation engine. With such substantial energy efficiency improvements, it is obvious that the cost of an optimization study can be easily amortized by the energy and the investment cost savings especially in cases with large-sized buildings. As engineers become more and more familiar with such methods and optimization tools become more user-friendly, these techniques will be justified even for small-sized projects.

A detailed building performance simulation will probably last a few seconds to a few minutes or even hours in a modern workstation depending on the complexity of the model (e.g. the number of thermal zones, building elements and simulation options) and the selected simulation engine. A typical optimization study will require a few hundred to several thousand evaluations until a good solution is reached, depending on the selected algorithm and the size of the solution space. The typical runtime for such studies is several hours. The use of a simpler or a surrogate model will definitely reduce runtime, but the time and expertise needed to build those models have to be taken into consideration. Consequently, it is probably faster to implement an optimization study on a detailed model, as this is expected to be available in the near future during the design process. In addition, this model can be useful for several other studies, such as building diagnostics and controls development.

7. Future perspectives

This paragraph summarizes the review results and provides future perspectives of optimization tools and procedures. The specific research field is relatively new and possible future directions have to be emphasized, so that new techniques and tools can be realized.

7.1. Optimization tools

Possible characteristics of the future optimization tools can be:

- to provide many types of optimization algorithms including evolutionary algorithms, direct search methods and other methods that don't require calculation of function derivatives. The experienced engineer should be able to choose the appropriate algorithm depending on the problem. Multi-objective capability should also be provided for multi-criteria optimization problems.
- to be able to perform parallel processing evaluations on the same computer by using modern processor multi-core technology or to distribute the calculations to a cluster of computers. Such ability will substantially improve the simulation runtime. The parallel processing should be able to include custom asynchronous operations of the algorithms, and as a result, advanced direct search methods can be utilized.
- to be able to include custom solutions into the initial population of an evolutionary algorithm directing the search to selected areas, thus improving efficiency using expert knowledge.
- to have the capability to search in a grid instead of the entire continuous space. This way the expected precision can be chosen and nearby solutions will be filtered as the same.
- to be able to pause, save the current state and continue at any other time from the same point (perhaps with a different configuration and an increased number of custom solutions in the evolutionary population). If the designer changes the search method for the same template model, to be able to include solutions which have already been calculated, in the new simulation.
- to use adaptive precision for the building performance simulations starting with coarse precision for the global search and using high precision for local search later on. Such an operation may improve runtime as Wetter and Polak in [66,67] indicate.
- to filter out duplicate function evaluations.
- to save the results in a database where code statements may be used to filter out different views of the results.
- to have a graphical user interface, presenting the 3D building model, associated with a particular solution.
- to be able to work with both discrete and continuous design variables.
- to include advanced constraints like penalty or barrier functions in both the design variables and the objective function.
- to include a library with common objective functions but to give the ability for custom-built functions as well.
- to provide the multi-disciplinary hierarchical optimization methodology. A building simulation program is capable of producing many different metrics for each simulation. This ability will enable the advanced users to come up with better results by using expert knowledge to build several multi-disciplinary targets.
- to have a library with simple geometry models and materials associated with cost and environmental impact properties.
- to create and train machine learning surrogate models. These models can be used for the optimization of a difficult problem with a huge size of search space.
- to import real measured data from a building (for example indoor/outdoor environmental data) and to use the optimization algorithms for calibrating the simulation model. This might be an easy task with a properly described objective function. The calibrated model can be further used for building diagnostics and control.
- to couple with many different kinds of building performance software, including custom simple analytical models for initial estimations. It should be able to import established BIM architectural models and export thermal and structural models to multi-disciplinary software.
- to communicate with building automation hardware interfaces in order to gather sensor data, activate actuators and do model self-calibration.
- to perform sensitivity and uncertainty analysis in order to estimate the impact of each design variable. Such information can lead the optimization analysis to certain directions regarding the selection of the design variables and the search algorithm. It might be possible to use the optimization algorithm results to perform statistical analysis.

7.2. Building performance programs

Many of the building performance programs are capable of simulating various design alternatives together with their environmental impacts and costs. Transferring information from architectural models to building performance programs was made easier with the adoption of BIM (building information modeling) framework. Nevertheless, the coupling with optimization algorithms creates new challenges and some new requirements for these programs can be the following:

- A building simulation requires initialization of the building state by running a “warming period” until convergence criteria are met. When daily simulations are considered instead of annual, this warming period requires a significant percentage of the total runtime. Such situations are usually met in simulation-based building control problems, but as stated before, these problems can go hand-in-hand with building design. The ability to save the building initialization state in a file will improve the optimization runtime and it's an essential requirement for building control optimization where small variability of the initial state can lead to significant different results.
- The precision of the results must be easy to alter with the optimization tools using coarse precision when global searching as stated in previous section.
- The provision of simulation methods which will ensure the smoothness of the objective function can have some benefits and offer an alternative approach to current simulation methods.
- If the building simulation program has a multithreading ability, it should provide an option to deactivate it. As simulation programs are improving, multithreading is added to the calculation process in several places inside their code. These improve the runtime of each simulation but they cannot utilize all the computer cores at all runtime. On the contrary, evolutionary algorithms can successfully utilize all the processor cores distributing simulations to different threads. When each individual simulation runs in more than one thread, it would probably collide with a simulation running, in parallel, in another thread, resulting in worse performance
- Optimization tools are usually coupled to building performance programs via text input and output files, causing a lot of hard drive traffic. Special external program interfaces for coupling with optimization tools are worth implementing to improve the performance.

7.3. Building design process

Building design processes have changed considerably over the years. Starting with paper plans, they moved into computer-aided

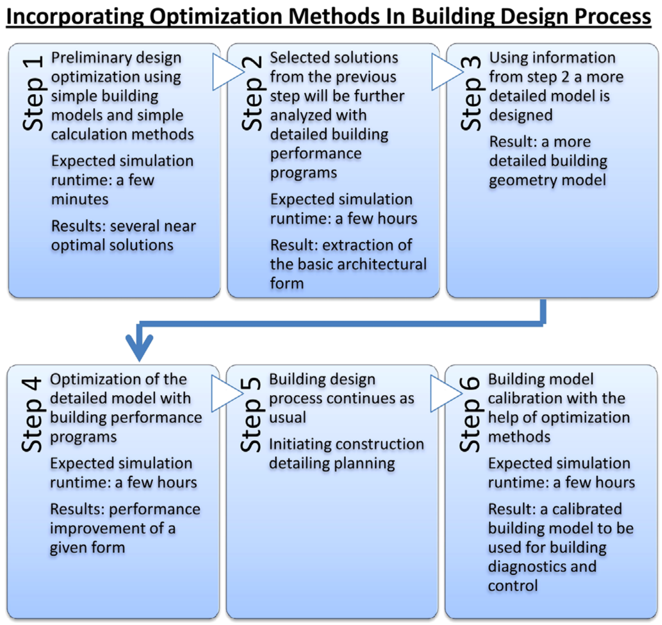

Fig. 3. A building design framework using optimization methods as a decision aid. Simulation runtime guess is based on the performance of a modern multi-core workstation.
Source: Prototype.

design. This gave the opportunity to transfer information to other decision-aid tools, marking the onset of building performance tools use. Nowadays, as these tools have matured, optimization techniques began to be incorporated into the design process offering the examination of alternative solutions which can be easily reviewed.

This review shows that optimization techniques, both in early and late building design stages, are already being used and that future building design workflows are expected to include such optimization procedures more frequently. A proposal of a future building design process that incorporates optimization techniques is presented in Fig. 3.

8. Conclusions

This paper provides an overview of the latest research developments concerning the use of optimization methods for building design. The first conclusion of this review is that the number of research papers that use these methods to optimize building design, is still small compared to the number of papers regarding the optimization of building control. A possible explanation is that the whole building simulation study became popular only in the last decade. Optimization tools coupled to a whole building simulation program exist and they are ready to be used. Additional conclusions are summarized below:

- An optimization study using a whole building simulation program is computationally very expensive, thus making the selection of an efficient algorithm quite critical.
- Evolutionary algorithms and direct search methods have been successfully coupled with building performance programs. Direct search methods can be very efficient if the objective function doesn't have large discontinuities, otherwise it can fail or got trapped in local minima. A good approach is to use an evolutionary algorithm for global search and a direct search to refine the solution.
- Optimization methods are mainly used in the preliminary design phase of a new building or for building retrofit.
- As Heiselberg et al. [70] and Mechri et al. [71] suggested, if a methodology of sensitivity analysis is applied in the early stages, it is possible to identify the most important parameters in relation to building performance.
- Expert judgment can be used to simplify the optimization problem and reduce the size of the solution search space.
- As Rapone and Saro [38] indicate, optimization algorithms have proven to be fairly efficient in finding the single solution to a problem. However, providing a diversity of solutions within a satisfactory level of performance would be beneficial for the decision process. When exploring the results, interesting design alternatives with very similar performance may be found.
- Whole building simulation is non-linear and it probably includes discontinuities in the results. The available algorithms for such problems cannot ensure that the true optimal solution will be found.
- The typical building performance improvements due to the use of an optimization analysis indicate that the cost of this analysis can be amortized by energy and investment cost savings.
- The environmental impact, the initial cost investment, the operational cost and comfort criteria are usually the targets of an optimization study. Construction materials, building geometry and orientation, HVAC system design and shading options are the typical design variables.

This work will conclude with a paragraph of Peippo et al. [42] which we agree with: “optimization procedures do not remove the fundamental subjective and creative nature of building design, often difficult to quantify. Nor are they likely to materialize in novel innovations: in the end, they only reflect the state-of-the-art of readily quantifiable design options. Nevertheless, they should help the building designer and policy maker to come up with sound design solutions with the existing technologies, and consequently contribute to preserving the integrity of low energy building design practice.”

References

[1] Pareto V, Cours d' Economie Politique, F. Rouge, F., 1896.
[2] Cao K, Huang B, Wang S, Lin H. Sustainable land use optimization using Boundary-based Fast Genetic Algorithm. Comput Environ Urban Syst 2012;36:257–69.
[3] Adamski M. Optimization of the form of a building on an oval base. Build Environ 2007;42:1632–43.
[4] Marks W. Multicriteria optimisation of shape of energy-saving buildings. Build Environ 1997;32(4):331–9.
[5] D'Cruz NA, Radford AD. A multicriteria model for building performance and design. Build Environ 1987;22(3):167–79.
[6] Jedrzejuk H, Marks W. Optimization of shape and functional structure of buildings as well as heat source utilisation. Partial problems solution. Build Environ 2002;37:1037–43.
[7] Jedrzejuk H, Marks W. Optimization of shape and functional structure of buildings as well as heat source utilization. Basic theory. Build Environ 2002;37:1379–83.
[8] Castro-Lacouture D, Sefair JA, Florez L, Medaglia AL. Optimization model for the selection of materials using a LEED-based green building rating system in Columbia. Build Environ 2009;44:1162–70.
[9] Michalek JJ, Choudhary R, Papalambros PY. Architectural layout design optimization. Eng Opt 2002;34:461–84.
[10] Chakrabarty BK. Computer-aided design in urban development and management—a software for integrated planning and design by optimization. Build Environ 2007;42:473–94.
[11] Petersen S, Svendsen S. Method for component-based economical optimisation for use in design of new low-energy buildings. Renewable Energy 2012;38:173–80.
[12] Stavrakakis GM, Zervas PL, Sarimveis H, Markatos NC. Optimization of window-openings design for thermal comfort in naturally ventilated buildings. Appl Mathe Model 2012;36:193–211.
[13] Holland JH. Adaptation in natural and artificial systems. Ann Arbor, MI: University of Michigan Press; 1975.

[14] Wright J, Farmani R. The simultaneous optimization of building fabric construction, HVAC system size, and the plant control strategy. In: IBPSA building simulation, Rio de Janeiro; 2001.
[15] Coley DA, Schukat S. Low-energy design: combining computer-based optimisation and human judgement. Build Environ 2002;37:1241–7.
[16] Znouda E, Ghrab-Morcos N, Hadj-Alouane A. Optimization of Mediterranean building design using genetic algorithms. Energy Build 2007;39:148–53.
[17] Oliveira Panão MJN, Goncalves HJP, Ferrao PMC. Optimization of the urban building efficiency potential for mid-latitude climates using a genetic algorithm approach. Renewable Energy 2008;33:887–96.
[18] Rakha T, Nassar K. Genetic algorithms for ceiling form optimization in response to daylight levels. Renewable Energy 2011;36:2348–56.
[19] Pernodet F, Lahmidi H, Michel P. Use of genetic algorithms for multicriteria optimization of building refurbishment. In Building simulation, Glasgow, 2009.
[20] Yi YK, Malkawi AM. Optimizing building form for energy performance based on hierarchical geometry relation. Autom Construct 2009;18:825–33.
[21] Charron R, Athienitis A. The use of genetic algorithms for a net-zero energy solar home design optimization tool. In: PLEA2006—The 23rd conference on passive and low energy architecture, Geneva; 2006.
[22] Tuhus-Dubrow D, Krarti M. Genetic-algorithm based approach to optimize building envelope design for residential buildings. Build Environ 2010;45:1574–81.
[23] Turrin M, von Buelow P, Stouffs R. Design explorations of performance driven geometry in architectural design using parametric modeling and genetic algorithms. Adv Eng Inf 2011;25:656–75.
[24] Magnier L, Haghighat F. Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and artificial neural network. Build Environ 2010;45:739–46.
[25] Deb K. Multi-objective optimization using evolutionary algorithms. New York: John Wiley & Sons; 2001.
[26] Chantrelle FP, Lahmidi H, Keilholz W, El Mankibi M, Michel P. Development of a multicriteria tool for optimizing the renovation of buildings. Appl Energy 2011;88:1386–94.
[27] Evins R, Pointer P, Vaidyanathan R, Burgess S. A case study exploring regulated energy use in domestic buildings using design-of-experiments and multi-objective optimisation. Build Environ 2012;54:126–36.
[28] Palonen M, Hasan A, Siren K. A genetic algorithm for optimization of building envelope and HVAC system parameters. In: Building simulation, Glasgow, Scotland; 2009.
[29] Wright JA, Loosemore HA, Farmani R. Optimization of building thermal design and control by multi-criterion genetic algorithm. Energy Build 2002;34:959–72.
[30] Sambou V, Lartigue B, Monchoux F, Adj M. Thermal optimization of multi-layered walls using genetic algorithms. Energy Build 2009;41:1031–6.
[31] Wang W, Zmeureanu R, Rivard H. Applying multi-objective genetic algorithms in green building design optimization. Build Environ 2005;40:1512–25.
[32] Wang W, Rivard H, Zmeureanu R. Floor shape optimization for green building design. Adv Eng Inf 2006;20:363–78.
[33] Shi X. Design optimization of insulation usage and space conditioning load using energy simulation and genetic algorithm. Energy 2011;36:1659–67.
[34] Caldas LG, Norford LK. A design optimization tool based on a genetic algorithm. Autom Construct 2002;11:173–84.
[35] Caldas L. Generation of energy-efficient architecture solutions applying GENE_ARCH: an evolution-based generative design system. Adv Eng Inf 2008;22:59–70.
[36] Lee JH. Optimization of indoor climate conditioning with passive and active methods using GA and CFD. Build Environ 2007;42:3333–40.
[37] Wetter M. GenOpt, generic optimization program version 3.1. Building technologies program, simulation research group, Lawrence Berkeley National Laboratory, 2008.
[38] Rapone G, Saro O. Optimisation of curtain wall façades for office buildings by means of PSO algorithm. Energy Build 2012;45:189–96.
[39] Hasan A, Vuolle M, Siren K. Minimisation of life cycle cost of a detached house using combined simulation and optimisation. Build Environ 2008;43:2022–34.
[40] Fesanghary M, Asadi S, Geem ZW. Design of low-emission and energy-efficient residential buildings using a multi-objective optimization algorithm. Build Environ 2012;49:245–50.
[41] Torczon V. PDS: Direct search methods for unconstrained optimization on either sequential or parallel machines; 1992.
[42] Peippo K, Lund PD, Vartiainen E. Multivariate optimization of design trade-offs for solar low energy buildings. Energy Build 1999;29:189–205.
[43] Lewis RM, Torczon V, Trosset MW. Direct search methods: then and now, ICASE report no. 2000-26; 2000.
[44] Hooke R, Jeeves TA. Direct search solution of numerical and statistical problems. J Assoc Comput Mach 1961;8(2):212–29.
[45] Eisenhower B, FonoberovV Mezic I. Uncertainty-weighted meta-model optimization in building energy models. In: Building simulation and optimization, Loughborough; 2012.
[46] Bouchlaghem NM, Letherman KM. Numerical optimization applied to the thermal design of buildings. Build Environ 1990;25(2):117–24.
[47] Bouchlaghem N. Optimising the design of building envelopes for thermal performance. Autom Construct 2000;10:101–12.
[48] Nelder JA, Mead R. A simplex method for function minimization. Comput J 1965;7(4):308–13.
[49] Mitchell RA, Kaplan JL. Non linear constrained optimization by a non-random complex method. J Res Nat Bur Stand C Eng Instrum 1968;72C:24–258.
[50] Wetter M, Wright J. A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization. Build Environ 2004;39:989–99.
[51] Gong X, Akashi Y, Sumiyoshi D. Optimization of passive design measures for residential buildings in different Chinese areas. Build Environ 2012;58:46–57.
[52] Saporito A, Day AR, Karayiannis TG, Parand F. Multi-parameter building thermal analysis using the lattice method for global optimisation. Energy Build 2001;33:267–74.
[53] Christensen C, Givler T, Courtney A, Barker G. BEopt: Software for identifying optimal building designs on the path to zero net energy, ISES 2005 Solar World Congress, Orlando, Florida; 2005.
[54] Anderson R, Christensen C, Horowitz S. Program design analysis using BEopt building energy optimization software: defining a technology pathway leading to new homes with zero peak cooling demand. California: Energy Efficiency in Buildings, Pacific Grove; 2006.
[55] Griego D, Krarti M, Hernandez-Guerrero A. Optimization of energy efficiency and thermal comfort measures for residential buildings in Salamanca, Mexico. Energy Build 2012.
[56] Ihm P, Krarti M. Design optimization of energy efficient residential buildings in Tunisia. Build Environ 2012;58:81–90.
[57] Ellis PG, Griffith BT, Long N, Torcellini P, Crawley D. Automated multivariate optimization tool for energy analysis. In: IBPSA SimBuild 2006 conference, IBPSA SimBuild, Cambridge, Massachusetts; 2006.
[58] Juan Y-K, Gao P, Wang J. A hybrid decision support system for sustainable office building renovation and energy performance improvement. Energy Build 2010;42:290–7.
[59] Kämpf JH, Robinson D. A hybrid CMA-ES and HDE optimisation algorithm with application to solar energy potential. Appl Soft Comput 2009;9:738–45.
[60] Hamdy M, Hasan A, Siren K. Combination of optimisation algorithms for a multi-objective building design problem. In: Building simulation, Glasgow, Scotland; 2009.
[61] Hamdy M, Hasan A, Siren K. Applying a multi-objective optimization approach for design of low-emission cost-effective dwellings. Build Environ 2011;46:109–23.
[62] Bichiou Y, Krarti M. Optimization of envelope and HVAC systems selection for residential buildings. Energy Build 2011;43:3373–82.
[63] Kämpf JH, Wetter M, Robinson D. A comparison of global optimisation algorithms with standard benchmark functions and real-world applications using EnergyPlus. J Build Perform Simul 2010;3.
[64] Wetter M. BuildOpt—a new building energy simulation program that is built on smooth models. Build Environ 2005;40:1085–92.
[65] Wetter M. Simulation-based building energy optimization. PhD thesis. University of California at Berkeley; 2004.
[66] Wetter M, Polak E. Building design optimization using a convergent pattern search algorithm with adaptive precision simulations. Energy Build 2005;37:603–12.
[67] Polak E, Wetter M. Precision control for generalized pattern search algorithms with adaptive precision function evaluations. SIAM J Optim 2006;16:650–69.
[68] Wright J, Alajmi A. The robustness of genetic algorithms in solving unconstrained building optimization problems. In: Building simulation, Montreal, Canada; 2005.
[69] Eisenhower B, O'Neill Z, Narayanan S, Fonoberov VA, Mezic I. A methodology for meta-model based optimization in building energy models. Energy Build 2012;47:292–301.
[70] Heiselberg P, Brohus H, Hesselholt A, Rasmussen H, Seinre E, Thomas S. Application of sensitivity analysis in design of sustainable buildings. Renewable Energy 2009;34:2030–6.
[71] Mechri HE, Capozzoli A, Corrado V. USE of the ANOVA approach for sensitive building energy design. Appl Energy 2010;87:3073–83.
[72] Choudhary R, Malkawi A, Papalambros PY. Analytic target cascading in simulation-based building design. Autom Construct 2005;14:551–68.
[73] ESTECO, modeFrontier ESTECO; 2012. [Online]. Available: 〈http://www.esteco.com/modefrontier〉.
[74] Hoes P, Trcka M, Hensen JLM, Bonnema B. Optimizing building designs using a robustness indicator with respect to user behavior. In: Proceedings of the 12th International IBPSA conference, Sydney, 14-16 November; 2011.
[75] Asadi E, Gameiro da Silva M, Antunes CH, Dias L. A multi-objective optimization model for building retrofit strategies using TRNSYS simulations, GenOpt and MATLAB. Build Environ 2012;56:370–8.
[76] Asadi E, Gameiro da Silva M, Henggeler Antunes C, Dias L. Multi-objective optimization for building retrofit strategies: a model and an application. Energy Build 2012;44:81–7.
[77] Kämpf JH, Montavon M, Bunyesc J, Bolliger R, Robinson D. Optimisation of building's solar irradiation availability. Solar Energy 2010;84:596–603.
[78] Bambrook SM, Sproul AB, Jacob D. Design optimisation for a low energy home in Sydney. Energy Build 2011;43:1702–11.
[79] Djuric N, Novakovic V, Holst J, Mitrovic Z. Optimization of energy consumption in buildings with hydronic heating systems considering thermal comfort by use of computer-based tools. Energy Build 2007;39:471–7.

[80] Machairas V. Tutorial on GenOpt with radiance; 2012. [Online]. Available: 〈http://vasilis.maheras.gr/tutorial-on-genopt-with-radiance/?lang=en〉. [Accessed 20 12 2012].

[81] Machairas V. Optimization algorithms for GenOpt; 2013. [Online]. Available: 〈http://vasilis.maheras.gr/optimization-algorithms-for-genopt/?lang=en〉.

[82] Tsangrassoulis A, Machairas V, Axarli C. Simplified design of a specular slat profile curve using 2d ray tracing and genetic algorithms. In: Building simulation 2013, August 25–28, Chambery, France; 2013.

[83] Christensen C, Anderson R, Horowitz S, Courtney A, Spencer J. BEopt software for building energy optimization: features and capabilities, NREL—technical report; 2006.

[84] www.iesve.com, integrated environmental solutions; 2012. [Online]. Available: 〈http://www.optimise-project.org〉.

[85] DesignBuilder, DesignBuilder Software Ltd; 2012. [Online]. Available: 〈http://www.designbuilder.co.uk〉.

[86] Ong YS, Nair PB, Keane AJ. Evolutionary optimization of computationally expensive problems via surrogate modeling. AIAA J 2003;41(4).

[87] Wong SL, Wan KK, Lam TN. Artificial neural networks for energy analysis of office buildings with daylight. Appl Energy 2010;87:551–7.

[88] Zemella G, De March D, Borrotti M, Poli I. Optimised design of energy efficient building façades via Evolutionary Neural Networks. Energy Build 2011;43:3297–302.

[89] Klein SA, Duffie JA, Beckman WA. TRNSYS—a transient simulation program. ASHRAE Trans 1976;82:623–33.

[90] Sahlin P, Bring A. IDA solver—a tool for building and energy systems simulation. In: Proceedings of the IBPSA conference, Nice, France; 1991.

[91] Bjorsell N, Bring A, Eriksson L, Grozman P, Lindgren M, Sahlin P, Shapovalov A, Vuolle M. IDA indoor climate and energy. In: Proceedings of the sixth IBPSA conference, Kyoto, Japan; 1999.

[92] Crawley DB, Lawrie LK, Winkelmann FC, Buhl WF, Huang YJ, Pedersen CO, Strand RK, Liesen RJ, Fisher DE, Witte MJ, Glazer J. EnergyPlus: creating a new-generation building energy simulation program. Energy Build 2001;33:319–31.

[93] Ward Larson G, Shakespeare R. Rendering with radiance: the art and science of lighting visualization. San Francisco: Morgan-Kaufmann; 1998.

[94] Nouidui TS, Phalak K, Zuo W, Wetter M. Validation and application of the room model of the modelica buildings library. In: Proceedings of the ninth international modelica conference, Munich, Germany; 2012.

[95] Nouidui TS, Wetter M, Zuo W. Validation of the window model of the Modelica Buildings library. In: Proceedings of the fifth SimBuild conference, Madison, WI, USA; 2012.

[96] Wetter M, Zuo W, Nouidui TS. Modeling of heat transfer in rooms in the Modelica buildings library. In: Proceedings of the 12th IBPSA conference, Sydney, Australia; 2011.

[97] Wetter M, Haves P. A modular building controls virtual test bed for the integration of heterogeneous systems. SimBuild 2008, Berkeley, California; 2008.

[98] A. S. 140-2001, Standard method of test for the evaluation of building energy analysis computer programs. In: Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers; 2001.

[99] U. D. O. Energy, DOE sponsored tools—building energy simulation test (BESTEST); 2012. [Online]. Available: 〈http://apps1.eere.energy.gov/buildings/tools_directory/doe_sponsored_bestest.cfm〉.

[100] Russell AD, Arlani G-A. Objective functions for optimal building design. Comput.-Aided Des. 1981;13(6):327–38.

[101] Mela K, Tiainen T, Heinisuo M. Comparative study of multiple criteria decision making methods for building design. Adv Eng Inf 2012.

[102] Fanger PO. Thermal comfort. Copenhagen: Danish Technical Press; 1970.

[103] Wang W, Rivard H, Zmeureanu R. An object-oriented framework for simulation-based green building design optimization with genetic algorithms. Adv Eng Inf 2005;19:5–23.

[104] Kämpf JH, Robinson D. Optimisation of building form for solar energy utilisation using constrained evolutionary algorithms. Energy Build 2010;42:807–14.