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5.1 Introduction

Automated mathematical building performance optimization (BPO) paired with building performance simulation (BPS) is a promising solution for evaluating many different design options and obtaining the optimal or near-optimal solution for a given objective or combination of objectives (e.g., lowest life-cycle cost, lowest capital cost, highest thermal comfort) while complying with constraints (e.g., net zero-energy) (Brown, Glicksman, and Lehar, 2010; Bucking *et al.*, 2010; Charron and Athienitis, 2006; Christensen and Anderson, 2006; Wetter, 2001). Traditionally, buildings have been designed based on heuristic rules separating the design process into several major design stages with multiple disciplines (architects, mechanical engineers, structural engineers, electrical engineers, etc.). Optimization can facilitate greater continuity between disciplines and design stages by identifying and evaluating major building design parameters (see Figure 5.1), in a holistic way. Based on this perspective, the previously, often ill-defined, design problem would be defined as a problem with explicit multiobjective criteria. This will promote fully integrated net zero-energy building (Net ZEB) designs where the building designers can act to influence the direction of the optimization. Despite optimization's potential for Net ZEB buildings, it remains largely a research tool and has yet to enter common industry practice.

This chapter discusses major obstacles to BPO in the building design and construction industry including 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 chapter is to document the current state-of-the-art and future research and development needs for Net ZEB optimization tools in practice and its use for design and operation of buildings for energy, comfort, and cost optimization. The content is intended to aid the reader in better understanding areas of active research in building optimization as well as tools and methods commonly used by researchers and designers.

5.1.1 What is BPO?

Automated building performance optimization is a process that aims to select the optimal solutions from a set of available alternatives for a given design or control problem, according to a set of performance criteria and constraints. Such criteria are expressed as mathematical functions, called objective functions. Automated optimization is a combination of different types of optimization algorithms, setting each algorithm to optimize one or more design functions. The optimization objectives for Net ZEBs are to identify impacts on cost, energy, environmental impact (embodied energy, materials life cycle), comfort, and indoor air quality.

An objective function is defined as a mathematical function subjected to optimization. Optimization searches for the optimal solution with respect to the objective functions to

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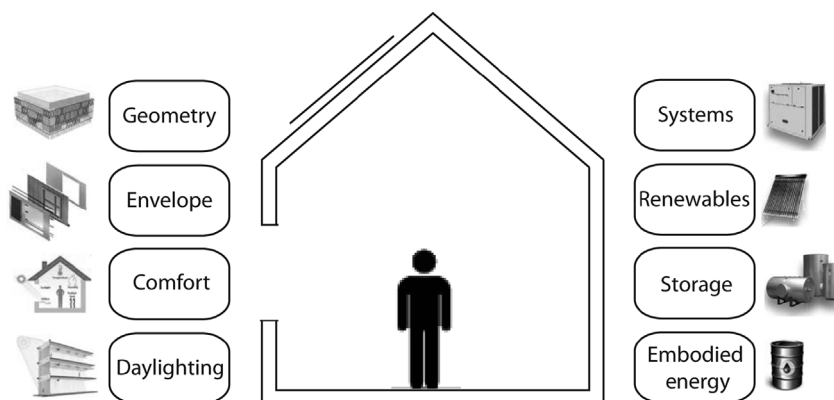


Fig. 5.1 Optimization as a holistic approach for multiobjective approach for Net ZEB design

be maximized or minimized, subjected to some constraints (e.g., of the dependent variables and objective functions). If no constraints are specified, the problem is denoted an unconstrained optimization problem. A constraint limits the problem space to a subset of elements (Snyman, 2005). If the optimization problem aims at minimizing a single objective function, it is called a single objective optimization problem; otherwise, if the objective functions are more than one, it is called a multiobjective optimization problem.

Visualization techniques are helpful to facilitate the extraction of relevant information regarding performance trade-offs, propagation of uncertainties, and sensitivity analysis. By providing visualization during the optimization process, it is possible for the designer to interact with the optimization process (Flager *et al.*, 2009). This facilitates a hybrid approach between traditional design (Chapter 4) and optimization (current chapter).

5.1.2 Importance of BPO in Net ZEB design

Since building performance optimization of Net ZEBs is aimed at an absolute goal, the number and complexity of energy efficiency measures forming the energy concept may be high (Athienitis *et al.*, 2010). The Net ZEB 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 with each other, thus requiring optimizing the building and systems together rather than merely the systems on an individual level (Hayter *et al.*, 2001).

One promising solution is to use automated mathematical BPO paired with BPS as a means to evaluating many different design options and obtain the optimal or near-optimal solutions. A number of energy simulation engines exist and are often used in different stages of the design process of a building. However, out of the 406 BPS tools

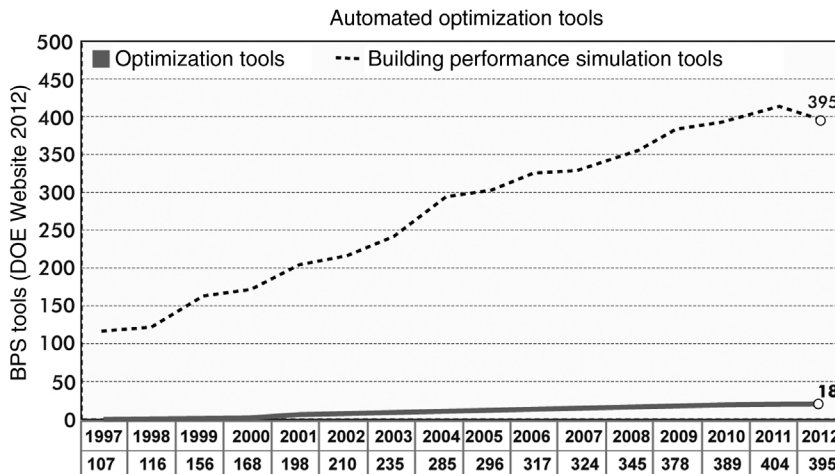


Fig. 5.2 Evolution of building performance simulation and optimization tools (Attia *et al.*, 2013)

listed on the U.S. Department of Energy (DOE) Web site in 2012, less than 19 tools are allowing BPO as shown in Figure 5.2.

Based on a literature review, Figure 5.3 reports the number of times a given BPS and BPO tool has been used to optimize a building design. Progressions in building simulation tool development and in coupling or combining complementary BPS tools at run-time expand the domains where BPS optimization studies can occur.

In the architecture, engineering, and construction (AEC) industry, there is a growing research trend for automated optimization approaches to be used to map out and find pathways to building designs with desirable qualities, such as aesthetics, geometry, structure, comfort, energy conservation, or economic features, rather than focusing on one particular outcome. Although optimization studies are most commonly performed in the early design stage, where the majority of design decisions are made, optimization approaches can be equally useful in the late design and operation stages. For example, optimization can be used for selecting and fine-tuning heating, ventilation, and air-conditioning (HVAC) control strategies, including model predictive control.

The use of optimization as a means of providing input to energy policy (e.g., for setting levels for minimum performance standards or incentive measures) is one of its most important applications in recent years. For example, using optimization to evaluate the energy and cost-savings potential from constructing more efficient new homes and net-zero energy homes in the United States (Christensen, 2005). Also, this includes the call of the European Commission for implementing a methodology to calculate cost-optimal levels in the Energy Performance of Buildings Directive (EPBD) framework. European Member States are required to define cost-optimal levels of minimum energy performance according to their specificities (Constantinescu, 2010).

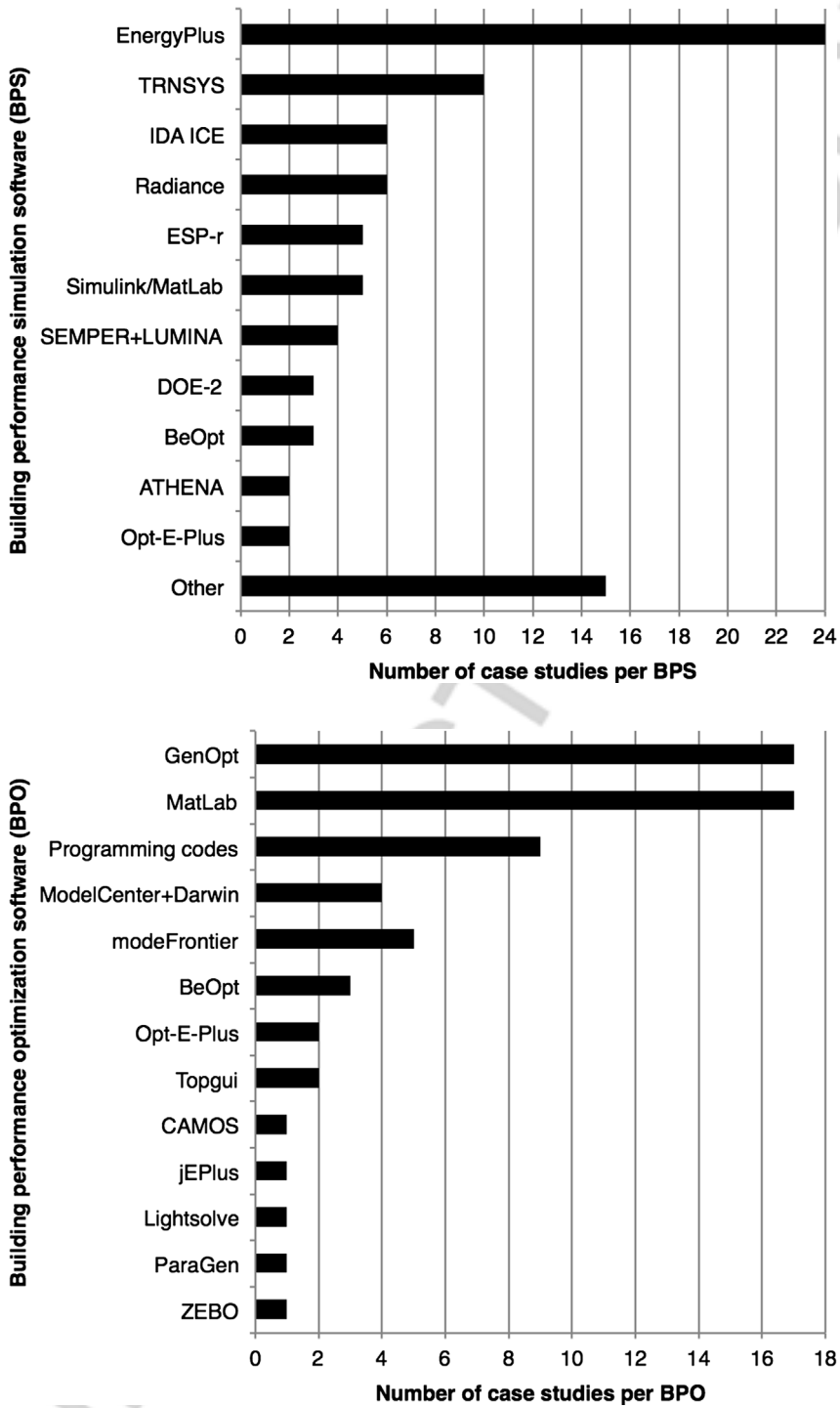


Fig. 5.3 Distribution of BPS tools used in literature

5.2 Optimization fundamentals

The suitable application area for optimization methodologies related to building design and control is vast and constantly evolving. The most appropriate search algorithms and modeling approaches vary depending on the application area including optimization objectives.

5.2.1 BPO objectives (single-objective and multiobjective functions)

In mathematics, optimization is the discipline concerned with finding inputs of a function that minimize or maximize its value, which may be subjected to constraints (Pardalos and Resende, 2012). In the AEC community, most BPO methods have focused on solving single-objective or multiobjective functions (Caldas, 2001; Choudhary, 2004; Hamdy, 2012; Hopfe, 2009; Nielsen, 2002; Pedersen, 2007; Verbeeck, 2007; Wang, 2005; Wetter, 2004).

In the case of single-objective functions, an optimum solution of the problem is either its global maximum or minimum, depending on the purpose. On the other hand, in multiobjective optimization problems, a specific building variant is often not able to simultaneously minimize or maximize each objective function. Instead, when searching for solutions, one comes to limit variants such that a further improvement toward the minimum value of one of the objective function causes the others to deviate from the minima. Therefore, the aim of a multiobjective optimization problem consists in finding such variants and possibly in quantifying the trade-off in satisfying the individual objective functions. The role of the optimization algorithm is to identify the solutions that lie on the trade-off curve, known as the Pareto Frontier (a set of optimal solutions plotted in the form of a curve; named after the Italian–French economist, Vilfredo Pareto). These solutions all have the characteristic that none of the objectives can be improved without prejudicing another.

In the past two decades, researchers have solved design problems for real buildings using single-objective or multiobjective functions. Figure 5.4 shows the distribution by objective of 92 papers that use optimization algorithms, applied to buildings. It is observed that most researchers consider energy as the main objective for BPO.

5.2.2 Optimization problem definition

The formal goal of a minimization study is to find the value x^* of a design variable vector, \mathbf{x} , such that $f(x^*)$ is the minimum value of $f(\mathbf{x})$, with x varying within a certain feasible design space. More formally

$$\min_{\mathbf{x} \in \mathbf{X}} f(\mathbf{x}) = f(x^*) \quad (5.1)$$

where \mathbf{x} is the design variable vector $\mathbf{x} = (x_1, x_2, \dots, x_N)^T$ in design space $\mathbf{X} \subset \mathbb{R}^N$; the objective or fitness function, $f()$, maps the set of design variables onto an objective vector $\mathbf{y} = (y_1, y_2, \dots, y_M)^T$ where $f_i \in \mathbb{R}^M$, $y_i = f_i(\mathbf{x})$, $f_i: \mathbb{R}^N \rightarrow \mathbb{R}^1$ for $i = 1, 2, \dots, M$, describes the objective solution space $\mathbf{Y} \subset \mathbb{R}^M$; the search for $\min\{f(\mathbf{x})\}$ is subject to L constraints $g_i(\mathbf{x}) \leq 0$ where $i = 1, 2, \dots, L$; feasible design

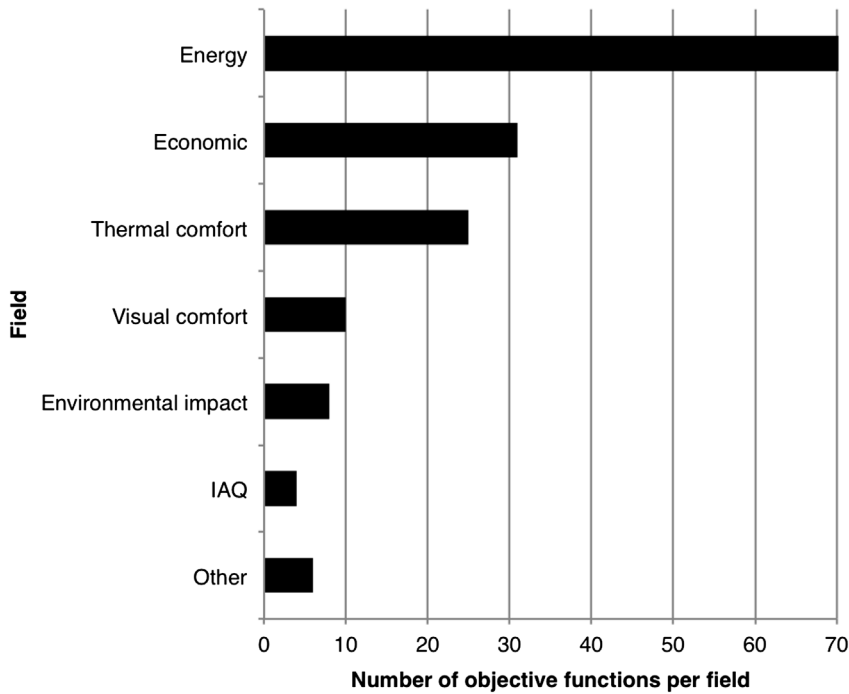


Fig. 5.4 The distribution of objective functions using BPO in literature

vectors set $\mathbf{x} | g_i(\mathbf{x}) \leq 0$ form the feasible design space \mathbf{X}^* , and corresponding objective vectors set $\mathbf{y} | \mathbf{x} \in \mathbf{X}^*$ form feasible objective space \mathbf{Y}^* ; for a minimization problem, a design vector $\mathbf{a} \in \mathbf{X}^*$ is Pareto optimum if no design vector $\mathbf{b} \in \mathbf{X}^*$ exists such that $y_i(\mathbf{b}) \leq y_i(\mathbf{a})$, $i = 1, 2, \dots, M$.

5.2.3 Review of optimization algorithms applicable to BPS

In this section, suitable optimization approaches for building simulation studies are reviewed. A general overview of several methods and algorithms, which have proven to be versatile in BPS applications, are presented. The following approaches are discussed: (i) deterministic searches, (ii) population-based searches, and (iii) hybrid search approaches.

A deterministic search attempts to operate on individual building representations to identify optimal regions by changing the value of variables using small increments or decrements. Although the goal of a deterministic search is to identify global optimums, there is a risk of preconverging to local optimums in multimodal problems. Two deterministic searches are discussed: (i) hill-climbing search and (ii) Hooke–Jeeves search. These searches are called deterministic, as a search operation on a given individual will always result in the same outcome.

Hill-climbing searches are a simple deterministic search strategy. Building design variables are incrementally changed to improve an objective function. Typically, the order in which variables are searched and the particular building design representation being searched will greatly affect the search outcome. Renders (1994) recommended integrating a hill-climbing search into the mutation operator of a genetic algorithm or as a forked process interwoven into the search algorithm. Bucking *et al.* (2010) compared the search performance of using hill-climbing searches at the beginning and end of an Evolutionary Algorithm (EA). This research demonstrated that performing a hill-climbing search on weakly interacting variables at the start of the hybrid algorithm and locking them inside an EA improves algorithm performance and search resolution. Performing a hill-climbing search after an EA was found to only marginally improve search outcomes.

The Hooke–Jeeves (HJ) search (Hooke and Jeeves, 1961), a member of the general pattern search family (Audet and Dennis, 2002), is a deterministic search algorithm that explores defined step-sizes in each continuous design variable coordinate. The algorithm selects the design variable, for a given step-size, that best improves fitness. If fitness is not improved, then the process is repeated to find the best step-size improvement in the other design variable coordinates. When no further improvements are made, the step-size is decreased, as previous step-sizes are assumed to be too large to resolve local optimums. Decreasing step-sizes requires the algorithm to be constantly converging. This feature can be overcome by combining the HJ algorithm with other global searches, as demonstrated by Wetter and Polak (2004).

Figure 5.5 illustrates a Hooke–Jeeves pattern search using a two-dimensional test function. The cross with round circles represents the search grid. The search grid has the

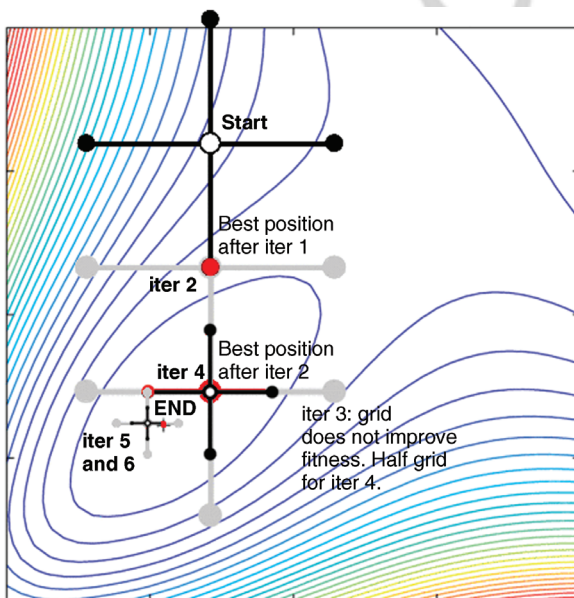


Fig. 5.5 Example of Hooke–Jeeves pattern search on the Broyden function

same number of dimensions, as there are optimization variables. Dots represent the selected direction of the next search iteration. Note in the third iteration (3) that the fitness is not improved so the algorithm halves the search grid size and continues from the last known improvement. Step-sizes are decreased again in iterations 4, 5, and 6 until the global optimum is found and the search terminated.

Population-based algorithms perform operations on populations of representative building designs. Often, they are called metaheuristics due to their nature of finding near-optimal solutions to a wide range of problems. Two common population-based search algorithms used with BPS are genetic, which is an evolutionary algorithm, and particle swarm optimizations.

The first algorithm selected for discussion from the group of population-based algorithms is the Genetic Algorithm (GA), from the EA family. GAs have become popular due to their ease of implementation and proven ability to solve multimodal and multiobjective problems. Computational pseudo-evolution was first demonstrated by Goldberg (1989) using biological inspirations. Performing genetic operations, such as mutations and crossovers, on representations in combination with selection operators emulate the “survival of the fittest” found in biological evolution. Eiben and Rudolph (1999) described members of the EA family as “adaptive systems having a “basic instinct” to increase the average and maximum fitness of a population.” In typical implementations, design variables are represented using binary or discrete formats. Genetic algorithms are a well-studied group within the broader metaheuristic family. Wang, Rivard, and Zmeureanu (2006) used a GA to perform a multiobjective optimization using lifecycle cost and exergy on a green building with a polygonal-shaped floor plan. Caldas (2008) used a GA to simultaneously optimize building geometry, energy efficiency, and visual comfort. Many modifications exist combining the best elements of other search strategies from the evolutionary algorithm family, such as Differential Evolution (DE) (Price, Storn, and Lampinen, 2005), Evolutionary Strategies (ES) (Eiben and Smith, 2003), and Genetic Programming (GP) (Poli, Langdon, and McPhee, 2008). Literature commonly refers to a modified GA by their more general family name, EA, to avoid confusion. EAs have been scaled to building optimization problems with many design variables. For example, Kampf and Robinson (2010) optimized the layout of a buildings cluster to maximize available solar radiation, while considering design parameters, such as insulation in ceilings and walls, window types and areas, infiltration, and thermal mass. A benefit of EAs is the flexibility to include subspecialized search strategies. For example, multi-island EAs allow for the population in one generation to be divided into subpopulations, or islands, where specialized subpopulation searches can be performed. This approach is useful to deconstruct large optimization problems into smaller, more solvable problems. Ooka and Komamura (2009) utilized a multi-island EA to design, schedule, and control an HVAC system for a hospital in Japan.

A particle swarm optimization (PSO) is fundamentally different from evolutionary cycles found in EAs (Eberhart and Kennedy, 1995). Instead of forming a new population of individuals at each iteration, the existing population is allowed to gravitate toward other more fit individuals, or particles, in the population. Particles are updated using the best local and global particles in the swarm. Representations are vectors of continuous

design variables, although binary and discrete representations can also be used (Kennedy and Eberhart, 1997). PSO competes favorably with other optimization algorithms. For example, Elbeltagi, Hegazy, and Grierson (2005) compared five evolutionary-based algorithms and found that PSO outperforms the other algorithms for a discrete design problem, with regard to reproducibility of optimal solutions and ability to scale with increasing problem sizes. PSOs are the primary population-based search approach used in the Generic Optimization Program (GenOpt) (Wetter, 2001). Hasan, Vuolle, and Siren (2008) utilized GenOpt's PSO algorithm to optimize envelope and HVAC systems with respect to life cycle cost of a single detached home in Finland using IDA-ICE as a simulation tool. Wetter and Wright compared a GA, with HJ search using GenOpt (Wetter and Wright, 2004). They found that stochastic methods are effective at finding near-global optimums; however, deterministic searches may be required to further resolve searches.

More recently, researchers have combined the strengths of population-based and deterministic algorithms into a hybrid approach. Population-based algorithms identify near optimal regions; deterministic searches intensify the search process around near optimal landscapes. Although hybridization can occur at different levels, the most common approach is to augment a population-based search with a local deterministic search (Feoktistov, 2006). The GenOpt tool performs an HJ search on the optimal individual resulting from a PSO (LBNL and Wetter, 2011). This algorithm was found to have better convergence properties for nonmultimodal problems compared to a hybrid DE algorithm (Kampf, Wetter, and Robinson, 2010).

5.2.4 Integration of optimization algorithms with BPS

Several steps are required to use an optimization algorithm with BPS, see Figure 5.6. First, the upper and lower limits of design variables are defined within the optimization algorithm. These limits define the entire possible set of designs available to the optimization algorithm. Design representations of the algorithm are converted into simulation files. Simulation files are evaluated using a building simulation tool to evaluate the performance of each design under analysis. The optimization algorithm uses databases, such as text file or SQL interactions, to store relevant simulation information. Building representations are improved upon in the optimization iteration

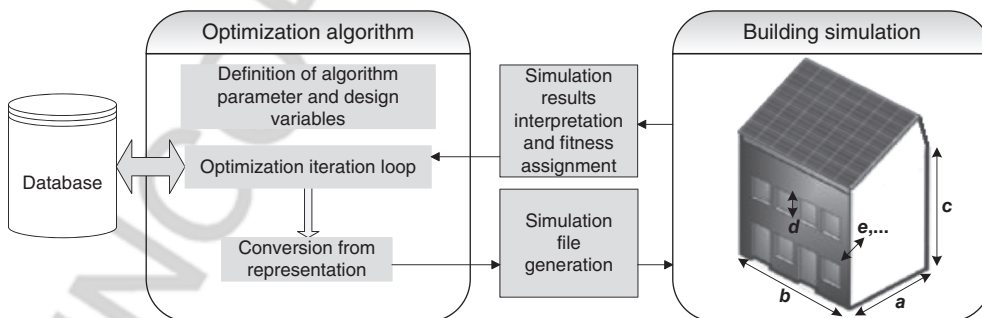


Fig. 5.6 Integration of an optimization algorithm with BPS

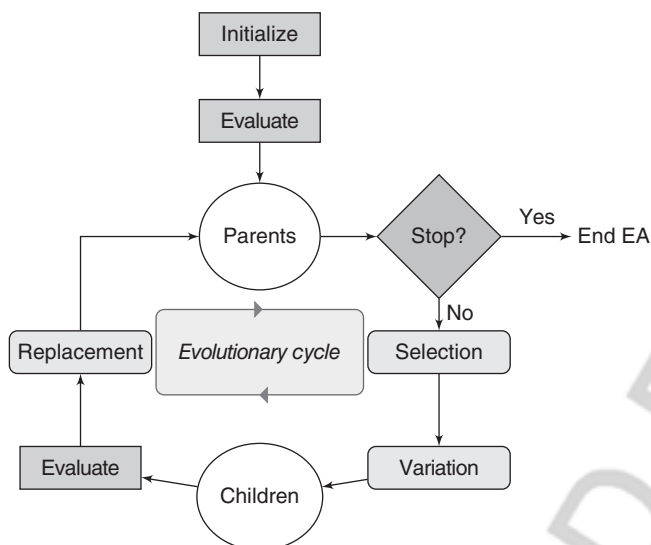


Fig. 5.7 Overview of evolutionary algorithm

loop until a termination criterion is satisfied. Figure 5.7 presents an overview of the evolutionary cycle common to an EA.

A set of genomes, or simplified representations of building designs, forms the population. In Figure 5.7, the population is initialized by randomly creating a population of a specified size. The fitness of each individual is evaluated using a building simulation tool. This population becomes the parent population as it enters the evolutionary cycle. Parent selection is used to select genomes for variation operators, such as recombination and mutations. The fitness of new individuals, called children, is evaluated. Survivor selection, or replacement, selects which genomes from the old and new population will survive in the next generation. The process is repeated until a termination criterion is reached, typically a set number of evolutionary cycles sometimes called iterations or generations. Individuals are elite if there exists no other individual in the present population with a better fitness. Elitism is an algorithm feature where a specified number of elite individuals pass to the next generation.

5.2.5 BPO experts interview

This section presents a sample of results from an interview of 28 optimization experts that took place in 2011. Each interview included 25 questions. The complete study report results can be found in Attia (2012) and Attia *et al.* (2013). The most important findings of this report are listed here; namely, the major obstacles and opportunities of integrating optimization techniques in Net ZEB design.

The major obstacles of integrating optimization techniques in Net ZEB design can be classified under two main categories: (1) soft obstacles and (2) hard obstacles. The main

four soft obstacles – those based on attitudes, processes, and skills – and their frequency are listed as follows:

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

The interviewees indicated that in practice, there is a lack of awareness and confidence on the use of optimization. Also, it is very important that users understand the optimization 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 and uncertain information on costs (19)
- Difficulty of problem definition (objectives arrangement, constraint violation) (12)
- Lack of software environments integrating and linking simulation and optimization seamlessly (16)
- Low interoperability and flexibility of models for exchange between different design, construction, simulation, cost estimation, and optimization tools (11)
- Lack of environment with friendly GUI allowing postprocessing and visualization techniques (7).

The interviewees agreed that computation time is very long and this may inhibit the initial take-up of optimization in practice. The optimization process 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.

According to the interviewees, BPO has been applied successfully in numerous Net ZEB projects. However, the building simulation community still rarely uses optimization and little investment has been made to advance BPO. Interviewees indicated that many opportunities exist in integrating simulation-based BPO in Net ZEB design and operation. The most mentioned opportunities include the following:

- *Supporting the decision making for Net ZEB design.* Many elements, including government policy that pushes the design of low-energy buildings, have driven the rise of building performance simulation. At present, any increase in the use of optimization will be driven by the extent to which it aids design decision making. In this respect, one of the most powerful forms is multiobjective optimization, 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 less capital investment on the increase in carbon emissions. This kind of information is useful in decision making of Net ZEB, requires little effort, and generates different ideas and alternatives.

- *Designing innovative integrated Net ZEBs with smart and efficient thermal (and visual) comfort control systems* is difficult to achieve because it involves complex dynamic interactions. Optimization algorithms 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 Net ZEBs* by analyzing and synthesizing multiphysics 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, BIPV, BIPV/T, solar thermal collectors, and microwind turbines. The complexity of such systems poses a serious challenge to designers. The use of BPO is an opportunity to inform designers of optimal and cost-effective design decisions during building design and operation.
- *Allowing optimal systems scheduling through Model Predictive Control (MPC)* taking into account the dynamics of Net ZEB systems and anticipated future energy load. When solving the optimal control problem using the MPC algorithm, it determines near-optimal control settings during design and operation are determined and the load-matching problem is addressed.

5.3 Application of optimization: cost-optimal and nearly zero-energy building

5.3.1 Introduction

According to the recast of the European Energy Performance of Buildings Directive (EPBD-r) (European Parliament and Council, 2010), the minimum energy performance requirements of buildings should be set with the aim of achieving cost-optimal levels for buildings, building units, and building elements (Constantinescu, 2010). Higher-energy performance levels, like net-zero energy, should also be economically feasible. The EPBD indicates that all new buildings should be “nearly zero-energy buildings” (Nearly ZEB) by the end of 2020, and two years prior to that for public buildings. According to the Recital 15 of the EPBD-r

As the application of alternative energy supply systems is not generally explored to its full potential, alternative energy supply systems should be considered for new buildings, regardless of their size, pursuant to the principle of first ensuring that energy needs for heating and cooling are reduced to cost-optimal levels

(European Parliament and Council, 2010).

These combinations should range from those in compliance with the current regulations to solutions that realize Nearly ZEBs. Those should also include various options for renewable energy generation.

Finding optimal solutions requires exploring the environmental and economic viabilities of all compatible designs (Constantinescu, 2010). Figure 5.8 shows the cost-optimal curve that would be found from the exploration where the environmental and economic viabilities are presented in terms of PEC (Primary Energy Consumption) and dLCC (Difference in Life Cycle Cost) per square meter of a building, respectively. The dLCC is the difference between the LCC for any design and that for the reference one. The

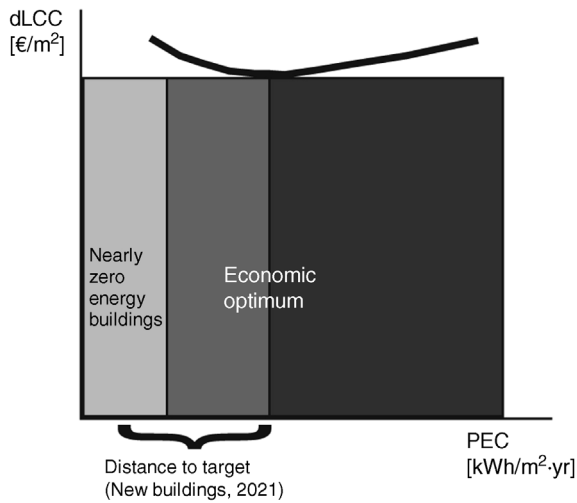


Fig. 5.8 Cost-optimal curve

lowest part of the curve (the economic optimum) is the cost-optimal range of solutions. The part of the curve to the right of the economic optimum represents solutions that underperform in both aspects (environmental and economic). The left part of the curve, starting from the economic optimum point, represents the optimal solutions toward Nearly ZEB, where the extreme left of the curve is the Net ZEB optimal solution.

Here, we summarize a multistage optimization method for cost-optimal and Nearly ZEB solutions in line with the EPBD-recast 2010. The method (Hamdy, Hasan, and Siren, 2013) provides efficient, transparent, and time-saving explorations:

- *Efficient exploration* is performed by combining a two-step optimization approach (PR_GA) (Hamdy *et al.*, 2009, Hamdy, Hasan, and Siren, 2009) and a detailed building performance simulation program (IDA-ICE 4.0). In the first optimization phase, a single-objective deterministic algorithm is used to minimize the two-objective functions (PEC and dLCC) one by one, sequentially, then to minimize the first objective considering maximum value of the second as a constraint. From the evaluations' history of the first optimization step, optimal solutions are found by sorting code and fed as a seed (a good initial population sample) to the second optimization step, continuing the optimization process by multiobjective genetic algorithm, which is a variant of the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) by Deb *et al.* (2002). This two-step optimization approach improves the quality and the repeatability of the optimization results,
- *Transparent exploration* is presented via multistage optimization showing the effect of the design-variable combinations,
- *Time-saving exploration* is achieved by speeding up the exploration by avoiding the unrealistic/unfeasible design-variable combinations and using presimulated results instead of running time-consuming simulations (when possible).

5.3.2 Case study: single-family house in Finland

In order to find optimal trade-off relations between PEC and dLCC for a single-family house in the cold climate of Finland, a multistage optimization method is proposed to explore more than 3×10^9 ($16 \times 8 \times 13 \times 3 \times 3 \times 4 \times 3 \times 2 \times 4 \times 31 \times 71$) combinations of the design-variable options (Table 5.1). The dLCC is calculated for 30 years. The design variables are selected to cover packages of measures ranging from compliance with the requirements of the current Finnish building code (C3-2010) to combinations that realize Nearly ZEBs (e.g., U -values typical of a Passivhaus, photovoltaic, and solar thermal collectors). The variables include a number of external wall, roof, and floor

Table 5.1 Design variables

	Design Variable	Description	Options
1	U -value of the external wall [$\text{W m}^{-2} \text{K}^{-1}$]	From 0.17 to 0.07	16
2	U -value of the ceiling [$\text{W m}^{-2} \text{K}^{-1}$]	From 0.09 to 0.07	8
3	U -value of the floor [$\text{W m}^{-2} \text{K}^{-1}$]	From 0.17 to 0.08	13
4	Building air tightness levels (at 50 Pa) [1/h]	2, 1, 0.5	3
5	Window type (all with Wood–aluminum frames)	Triple-Laminated glass (Air filled), Triple-Laminated glass (Argon filled), or Quadruple Laminated (Argon filled)	3
6	Shading type	External blinds, horizontal laths, Blinds between the outer panes, horizontal laths, Blinds between the inner panes, horizontal laths, or Internal blinds, horizontal laths	4
7	Heat recovery type	Cross-flow heat exchanger, Counter-flow heat exchanger, or Regenerative heat exchanger	3
8	Cooling options	No cooling or small cooling unit	2
9	Heating system	Direct electricity with electrical radiators (EH), oil boiler with water radiators (OB), district heating with water radiators (DH), GSHP with radiant floor heating (GSHP)	4
10	Solar thermal collector area	From 0 to 30 m^2	31
11	PV collector area	From 0 to 70 m^2	71

insulation thicknesses, three building tightness levels, three window types, four shading methods, three heat recovery units, two cooling options, four heating systems, and different sizes of on-site solar systems. The detailed description of the design variable option can be found in Hamdy, Hasan, and Siren (2013). A reference case is calculated according to the National Building Code of Finland C3-2010. The life cycle costs of the candidate solutions are calculated relative to the reference case one. Considering the impact of the design variables on the objective functions (PEC and dLCC), the exploration is performed in three stages:

- *Stage-1* aims to find the optimal combinations of the design variables that influence the building thermal performance (heating, cooling, and thermal comfort) of the house, that is, building envelope parameters and a heat recovery ventilation system;
- *Stage-2* assesses the economic and environmental viability of the studied primary heating/cooling systems to the optimal building combinations (packages) found in *Stage-1*; and,
- *Stage-3* investigates improving the economic and/or environmental viability of the optimal combinations of building envelope parameters and HVAC systems assessed in *Stage-2*. *Stage-3* addresses the renewable energy systems as supplementary systems.

The aim of *Stage-1* is to find representative energy-efficient building designs, irrespective of the type of heating, cooling, and energy supply systems. In order to achieve this, the space heating energy demand of the house and the present worth (PW, defined later) of the influencing measures (insulation level, building tightness, window type, shading method, and heat recovery type) are minimized, while a penalty function is applied when the summer comfort criterion ($DH_{27} \geq 150^\circ\text{Ch}$) is violated.

According to the Finnish building code D3, degree-hours (DH_{27}) are used to measure the summer overheating risk

$$DH_{27} = \sum_{i=1}^{8760} dT_{27} \Delta t \quad (5.2)$$

$$\begin{cases} (T_i - 27) > 0 \Rightarrow dT_{27} = (T_i - 27) \\ (T_i - 27) \leq 0 \Rightarrow dT_{27} = 0 \end{cases}$$

where T_i is the mean air temperature [$^\circ\text{C}$] at the warmest zone and Δt is a 1 h time period [h].

The minimization work is performed by the two-step optimization approach (PR_GA) mentioned earlier. The first objective (space heating energy demand), to be minimized in *Stage-1*, presents the major energy demand in the residential building in the cold climate. The second objective (PW) presents the initial and replacement costs (IC and RC) of the key influencing ESMs (external wall, ceiling, and floor insulation levels, building tightness, window type, shading method, and

heat recovery type). PW is calculated as follows:

$$PW = \sum_{i=1}^7 IC_i + \sum_{i=1}^7 RC_i \quad (5.3)$$

5.3.3 Results

Figure 5.9 presents the optimization results of *Stage 1*. The results are two optimal trade-offs (Group 1 and 2) between the space heating energy and the present worth (PW) of the influencing ESMs. Group 1 presents the optimal building designs, which satisfy the summer overheating criterion (Eq. (5.2)), while Group 2 presents the ones that do not fulfill the criterion. Groups 1 and 2 consist of 19 and 13 solutions, respectively. Group 2 packages are not eliminated as noncomfort solutions, because they could be addressed with mechanical cooling. In terms of LCC, implementing RES (e.g., photovoltaic) might improve the economic feasibility of the mechanical cooling solutions by covering a portion of their electricity demands. The feasibility of using the cooling and RES systems will be investigated in forthcoming optimization stages 2 and 3, respectively.

Figure 5.10 presents the results of *Stage-2*. The results are the dLCC and PEC of *Stage-1* optimal solutions (Group 1 and 2; Figure 5.9) when the offered primary heating systems (direct electrical, district heating, oil fire boiler, and GSHP) are installed. In line with the EPBD-recast 2010, 3% real interest rate (r) and 2% energy price escalation rate (e) are

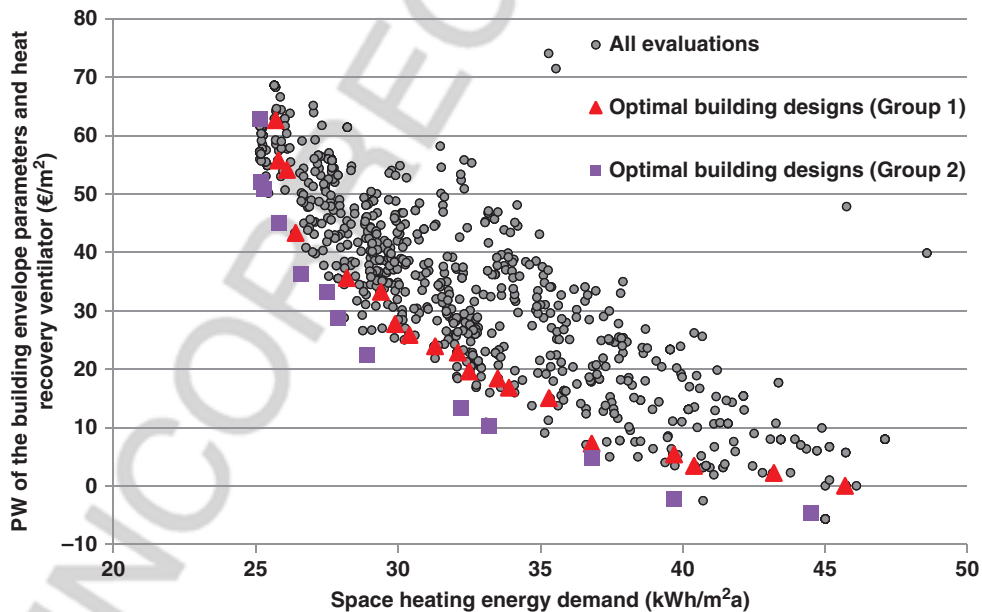


Fig. 5.9 Stage-1 optimization results (Hamdy, Hasan, and Siren, 2013)

Color Fig.: 5.10

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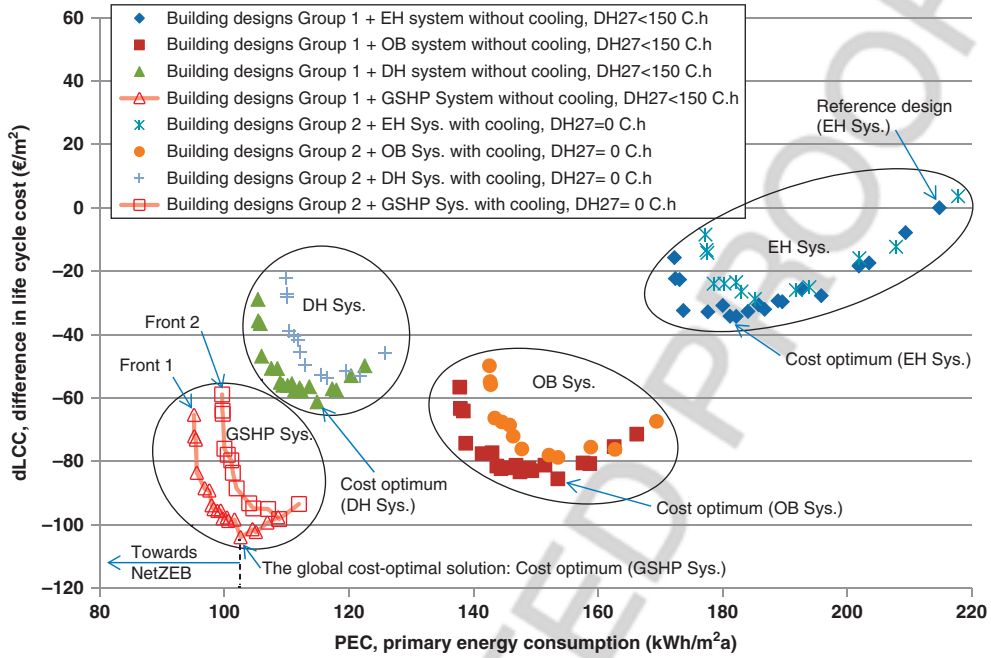


Fig. 5.10 Stage-2 postprocessing results (Hamdy, Hasan, and Siren, 2013)

used as recommended values. Primary energy factors, efficiencies, capital and service costs, subscription fees, and energy prices (Table 5.2) are used to calculate *Stage-2* results (dLCC vs PEC). Since the current investigation aims to compare different designs in the specified solution space, the absolute value of the LCC is not calculated, but the difference (dLCC_{*i*}) between the LCC for any design (LCC_{*i*}) and that for the reference one (LCC_{*r*}) is calculated

$$dLCC_i = LCC_i - LCC_r$$

$$LCC = \sum_{j=1}^{11} IC_j + \sum_{j=5}^{11} RC_j + MC + OC + C \quad (5.4)$$

where IC is the investment costs of the 11 investigated design variables (Table 5.1), RC is the replacement cost of the replaced building elements and systems (e.g., window, shading, heat recovery unit, etc.), and MC is the maintenance costs of the heating systems (Table 5.2). OC is the operating cost of energy and C is a constant for other costs, such as construction and design cost, *i* denotes indexes for the design solution, and *j* is an index for the design parameter (Table 5.1).

The PEC considers the total energy use of the building including heating, cooling, ventilation, lighting, pumps, and fans, as well as the energy-saving from RES. The PEC

Table 5.2 Primary heating systems (Hamdy, Hasan, and Siren, 2013)

System	Capital Cost Formula [€]	Service Cost [€/a]	Subscription Fee [€/a]	Energy Price [€/kWh]	η_{SHS} [%]	η_{DHWS} [%]	η_{dist} [%]	Primary Energy Factor (F)
Direct electricity with electrical radiators (EH)	$50 kW_p + 2700$	30	83	13.5 10.9 ^{a)}	100	88	94	1.7
Oil boiler with water radiators (OB)	$286 kW_p + 7143$	135	83	6.12	81	81	87	1
District heating with water radiators (DH)	$50.5 kW_p + 9050$	40	404 ^{b)}	6.5	94	94	87	0.7
GSHP with floor heating (GSHP)	$592.5 kW_p + 12155$	145	83	13.5 10.9 ^{a)}	300	250	84	1.7

a) The price of day electricity (13.5 €/kWh) on weekdays, from Monday to Friday, 7 A.M. to 8 P.M. The price of night-time electricity (10.9 €/kWh) at other times.

b) Besides the 83 € annual fee for the electrical connection, 321 € is added for district heating connection.

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is calculated by using nonrenewable primary energy factors F according to the energy source (Table 5.2)

$$\begin{aligned}
 \text{PEC} &= F \text{SH}_{\text{delivered}} + F \text{DHW}_{\text{delivered}} + F \text{Ele}_{\text{delivered}} \\
 \text{SH}_{\text{delivered}} &= (Q_h / \eta_{\text{dist}}) / \eta_{\text{SHS}} \\
 \text{DHW}_{\text{delivered}} &= (Q_{\text{DHW}} - dQ_{\text{DHW}}) / \eta_{\text{DHWS}} \\
 d\text{Ele}(t) &= Q_c(t) / \text{COP}_{\text{Cu}} + \text{SH}_{\text{ele}}(t) + \text{DHW}_{\text{ele}}(t) + E_{\text{hv}}(t) + E_{\text{la}}(t) - \text{PV}_e(t) / \eta_{\text{inverter}} \\
 \text{Ele}_{\text{delivered}} &= \sum_{t=1}^{t=8761} \max\{d\text{Ele}(t), 0\}
 \end{aligned} \tag{5.5}$$

where

DHW	Domestic hot water
DHW_{ele}	The electrical portion of domestic hot water,
Ele	The electricity consumption,
E_{vh}	The electrical consumption of the HVAC system
E_{la}	The electrical consumption of the appliances and lighting
PV	Photovoltaic
PV_e	The useful electricity produced by photovoltaic system.
Q_c	Space cooling energy demands,
Q_h	Space-heating energy demands
SH	Space heating
SH_{ele}	The electrical portion of space heating,
η_{SHS}	Efficiency of the space heating system
η_{DHWS}	Efficiency of the domestic hot water system
η_{dist}	Distribution efficiency of the heating system
η_{inverter}	Efficiency of the photovoltaic inverter

Equation (5.5) divides the energy demands (Q_h , $Q_{\text{DHW}} - dQ_{\text{DHW}}$, Q_c) by the annual efficiencies to calculate the delivered ones ($\text{SH}_{\text{delivered}}$, $\text{DHW}_{\text{delivered}}$, $d\text{Ele}_{\text{delivered}}$). According to the heating application (SH or DHW), two efficiencies (η_{SHS} and η_{DHWS}) are considered as being consistent with the Finnish regulation. Based on the installed space heating system (electrical radiator, water radiator, or floor heating), the distribution efficiency (η_{dist}) is assumed to be 94, 84, or 87%, respectively (Table 5.2). The implementation of a flat-plate solar thermal collector reduces the domestic hot water demand Q_{DHW} by dQ_{DHW} . When mechanical cooling (Q_c) is needed, it will take place for a short period. Therefore, the coefficient of performance for the cooling system for nominal operating conditions (25 °C outdoor air temperature) is used. Only 13 simulations are carried out to calculate the cooling energy required for the Group 2 solutions. Implementing the mechanical cooling options, with a 25 °C indoor temperature setpoint, reduced the DH_{27} (Eq. (5.2)) of the Group 2 solutions to zero.

Color Fig.: 5.11

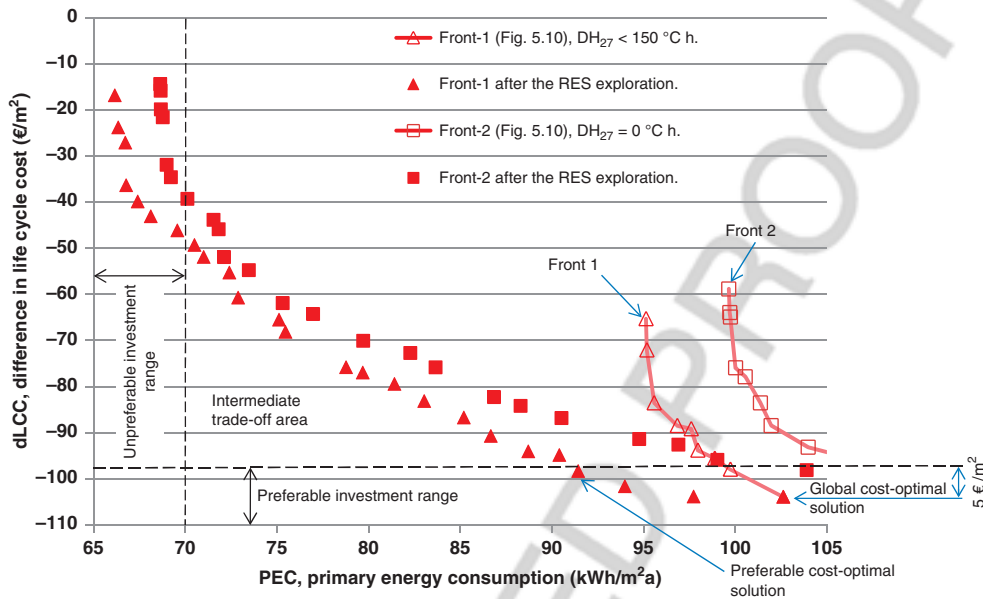


Fig. 5.11 Stage-3 optimization results (Hamdy, Hasan, and Siren, 2013). Note that the fronts labeled “Front 1” and “Front 2” are the same as those in Figure 5.10

Figure 5.11 presents improvements to the environmental viability of *Stage-2* building envelope and HVAC-system optimal solutions (Figure 5.10, front 1 and 2) by implementing optimal sizes of RES systems (solar-thermal and photovoltaic collector areas). A simulation-based optimization model is developed, using MATLAB 2008b and IDA ESBO (a building performance simulation program that includes the possibility of implementing RES systems), to find the optimal combinations of the front 1 and 2 solutions and the RES options (from 0 to 31 m² solar thermal collector areas and from 0 to 71 m² photovoltaic array area). The optimization is performed by PR_GA approach (Hamdy, Hasan, and Siren, 2009).

5.3.4 Final considerations about the case study

According to the Directive 2010/31/EU, the minimum LCC solution (global cost-optimal solution) should be used by Member States when setting the minimum energy performance requirements. However, a slightly higher LCC solution could be preferable if it reduces the PEC significantly. Figure 5.11 shows the global and preferable cost-optimal designs. The difference between the LCC of the cost-optimal solutions is 5 €/m². Based on the resulted global and preferable cost-optimal solutions, the calculated minimum energy performance level of the single-family house in Finland is 103 or 92 kWh/m² a of primary energy, depending on the decision maker’s preferences. These cost-optimal energy performance levels are 40 and 47% lower, respectively, than that for the reference case defined by the current Finnish regulation.

5.4 Application of optimization: a comfortable net-zero energy house

Optimization is a versatile technique that in this case study is used to identify the most suitable technical solutions to guarantee a comfortable environment inside a building and, hence, to minimize its energy needs for space conditioning. This design strategy is a rational and promising path toward Net ZEBs (Carlucci, Zangheri, and Pagliano, 2013; Pagliano, Zangheri, and Carlucci, 2010). The European standard EN 15251 (CEN, 2007) also suggests a path, which starts with optimizing the building envelope and its passive strategies by analyzing the building in free-floating mode; the indoor thermal comfort is assessed with respect to an adaptive comfort model (de Dear and Brager, 1998; Nicol and Humphreys, 2002). Therefore, in case thermal comfort requirements cannot be met only with the building envelope and its passive strategies, efficient HVAC systems are then introduced, and thermal comfort requirements have to be verified against the Fanger comfort model (Fanger, 1970). In other words, this means designing the building envelope for achieving thermal comfort by using primarily passive strategies, so that, at the next step (if required), efficient HVAC systems need only a limited amount of energy to provide the required thermal comfort conditions. At the same time, efficient lighting and electrical appliances have to be selected to reduce the electricity demand of the building. Then, the overall energy required by the building has to be covered by renewable energy preferably produced on-site (Marszal *et al.*, 2011).

The automated computer-based workflow is applied to optimize a single family net zero-energy house in the Mediterranean climate. It uses EnergyPlus (Crawley *et al.*, 2001) as the building performance simulation engine, guided by GenOpt (Wetter, 2001) as the optimization engine. The identified optimal building variant reduces both the seasonal long-term discomfort indices to a value lower than 10% in free-floating mode, and a monocrystalline PV field with an area of 21.0 m² that can provide all the needed energy required by the house (on a yearly basis and via exchange with the electric grid). In case the identified optimal building variant is equipped with a reversible electric heat pump, the thermal comfort requirements expressed with respect to the Fanger comfort model are met with a delivered energy for heating of 7.3 kWh_{el}/(m² a) and for cooling (sensible plus latent) of 9.5 kWh_{el}/(m² a). Therefore, the area of the monocrystalline PV field shall rise to 32.6 m² to meet the overall primary energy consumption of the home. It should be noted that the proposed optimization approach can be applied to any residential or commercial building prototype.

5.4.1 Description of the building model

The case study is a detached single-family house, located in Mascalucia (CT) in Southern Italy (Figure 5.12). The single-family home is composed of one occupied story and one unoccupied basement used as a technical room. Its net floor area is 148 m² and its net conditioned volume is 445 m³.

Mascalucia is in the zone “Csa” (Köppen, 1930), characterized by a temperate climate with dry summer, also called Mediterranean climate. To simulate the most representative local weather conditions, a typical weather year was constructed using the measured

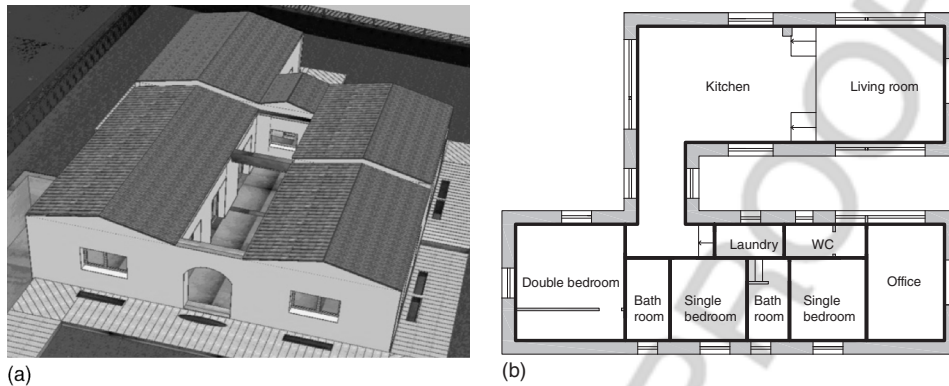


Fig. 5.12 (a) Three-dimensional model. (b) Plan and indication of the thermal zones of the house

hourly weather data recorded from 2003 to 2009 in Pedara (CT), located 1 km far from the construction site.

The daily typical occupancy schedule and the daily typical lighting and electrical appliances usage rates were defined according to owner information about intended use. In order to provide a comfortable indoor air quality, the minimum air change rate of 0.6 h^{-1} was estimated according to EN 15251 and a mechanical ventilation system, equipped with a high-efficiency (92%) heat recovery unit, was provided.

The energy simulations of the building were run with EnergyPlus release 6.0.0.23 and the default physical models for calculating heat exchanges were selected to take into account the trade-off between precision and computation time: (i) the update frequency for calculating sun paths was set to 20 days, (ii) the heat conduction through the opaque envelope was calculated via the conduction transfer function method with four time steps per hour, and (iii) the natural convection heat exchange near external and internal surfaces was calculated via the adaptive convection algorithm (Department of Energy (DOE, 2013)).

5.4.2 The adopted methodology and the statement of the optimization problem

The energy design of a building is a multivariable problem, which can accept different sets of solutions. The number of design alternatives can be very large and not all of them can be simulated in a time span compatible with the design phase of a building. In order to explore a very large number of building variants compatible with the design phase in a relatively short time, the adopted methodology consists of (i) in identifying the design parameters of the building to be optimized, (ii) in identifying the options for every design parameter, (iii) in running the dynamic energy simulations of the building in free-floating mode via EnergyPlus, and (iv) in driving the selection of the design parameters via an optimization engine.

The design parameters and the options for each of them used in the optimization are reported in Table 5.3. The number of all available building variants is larger than 17 million. The single values have been introduced in the optimization as discrete variables.

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Table 5.3 Design parameters and their values used in the optimization run

Design Parameters	Physical Quantities	Possible Alternatives
External wall construction	U -value ($\text{W m}^{-2} \text{K}^{-1}$) Time shift (h)	0.149 14.0; 0.147 9.9; 0.152 4.6; 0.261 12.9; 0.254 9.2; 0.246 2.9; 0.387 12.6; 0.387 8.9; 0.410 2.2.
Roof construction	U -value ($\text{W m}^{-2} \text{K}^{-1}$) Time shift (h)	0.154 12.3; 0.148 8.2; 0.147 4.9; 0.252 13.1; 0.251 9.4; 0.248 5.0; 0.398 12.3; 0.404 9.3; 0.381 5.8.
Floor construction	U -value ($\text{W m}^{-2} \text{K}^{-1}$) Time shift (h)	0.143 12.8; 0.150 9.6; 0.152 5.7; 0.250 13.1; 0.240 9.0; 0.246 5.4; 0.397 12.9; 0.401 9.3; 0.401 4.8.
Constructions of glazing units on south-east façade	U -value ($\text{W m}^{-2} \text{K}^{-1}$) SHGC (%)	0.586 36; 0.582 49; 1.099 38; 1.065 53; 2.667 34; 2.667 75.
Construction of glazing units on south-west façade	U -value ($\text{W m}^{-2} \text{K}^{-1}$) SHGC (%)	0.586 36; 0.582 49; 1.099 38; 1.065 53; 2.667 34; 2.667 75.
Construction of glazing units on north-east/north-west facades	U -value ($\text{W m}^{-2} \text{K}^{-1}$) SHGC (%)	0.586 36; 0.582 49; 1.099 38; 1.065 53; 2.667 34; 2.667 75.
Construction of glazing units on the central court facade	U -value ($\text{W m}^{-2} \text{K}^{-1}$) SHGC (%)	0.586 36; 0.582 49; 1.099 38; 1.065 53; 2.667 34; 2.667 75.
Control strategies for shading devices	Set-point	Indoor air temperature $>25^\circ\text{C}$; Outdoor air temperature $>25^\circ\text{C}$; Global irradiance on window $>100 \text{ W/m}^2$.
Opening pivoted windows	Percentage of the window area open (%)	0; 100.
Opening double-leaf windows	Percentage of the window area open (%)	0; 50; 100.

The optimization engine GenOpt release 3.1.0 was used to minimize specified seasonal thermal discomfort objectives. The *Long-term Percentage of Dissatisfied* (LPD) in the ASHRAE adaptive version (Carlucci, 2013) is used to quantify predicted long-term thermal discomfort by a weighted average of discomfort over the thermal zones

and over time.

$$LPD = \frac{\sum_{t=1}^T \sum_{z=1}^Z (p_{z,t} \cdot ALD_{z,t} \cdot h_t)}{\sum_{t=1}^T \sum_{z=1}^Z (p_{z,t} \cdot h_t)} \quad (5.6)$$

where t is the counter for the time step of the calculation period, T is the last progressive time step of the calculation period, z is the counter for the zones of a building, Z is the total number of the zones, $p_{z,t}$ is the zone occupation rate at a certain time step, h_t is the duration of a calculation time step (e.g., 1 h) and $ALD_{z,t}$ is the ASHRAE Likelihood of Dissatisfied calculated inside a certain zone at a certain time step, given by the equation

$$ALD = \frac{\exp(0.008 \cdot \Delta T_{op}^2 + 0.406 \cdot \Delta T_{op} - 3.050)}{1 + \exp(0.008 \cdot \Delta T_{op}^2 + 0.406 \cdot \Delta T_{op} - 3.050)} \quad (5.7)$$

where ΔT_{op} is the absolute value of the difference between the indoor operative temperature and the optimal comfort temperature calculated according to the ASHRAE adaptive model. This index, calculated for summer and winter, constitutes the two objective functions of the optimization problem.

Assuming a preference for building variants that minimize their distance from the *optimum*, *scalarization* is used to solve the bi-objective optimization problem, by adopting the weighted exponential sum method with the *utility function*, U ,

$$U = \sum_{i=1}^n w_i [F_i(\mathbf{k})]^p \quad : \quad F_i(\mathbf{k}) > 0 \quad \forall i \quad (5.8)$$

where w_i are the weighting factors of each objective function, such that $w_i > 0$, and \mathbf{k} is the vector of the values of each design parameter. For this optimization problem, there is not an apparent reason to weigh the two objective functions differently, thus the weighting factors were set to 1. The exponent p was set to 2, hence the utility function is a distance function that measures the squared distance between a certain solution point and the utopia point, so that the shorter the distance, the better the building variant. This optimization approach does not provide a set of optimal solution belonging to the Pareto frontier, but only one optimal solution; this simplifies the activity of the final user, but the use of the utility function forces the result of optimization.

The *PSO algorithm* was selected due to its robustness and efficiency to converge toward the global minimum (Hopfe, 2009). The setting parameters used are: type of algorithm is the PSO with inertia weight, neighborhood topology was von Neumann, neighborhood size was 5, 20 particles, 30 generations, cognitive acceleration was 2.8, social acceleration was 1.3, initial inertia weight was 1.2, and final inertia weight was zero. The number of simulation runs for the optimization was 600.

5.4.3 Discussion of results

The optimization procedure identified an optimal solution that provides both winter and summer aforementioned Long-term Percentage of Dissatisfied lower than 10% when the building is in free-running mode during the whole year (Figure 5.13).

The main features of such optimal building variant are: (i) external walls and the roof with very low-steady-state thermal transmittance, $U = 0.15 \text{ W}/(\text{m}^2 \text{ K})$, to reduce heat exchange with outdoor in both the seasons; (ii) the floor with relatively high steady-state transmittance, $U = 0.40 \text{ W}/(\text{m}^2 \text{ K})$, to use the basement as a heat sink during summer without compromising excessively winter performance; (iii) the roof and the floor with high time shift ($S > 12 \text{ h}$) and external walls with a lower time shift ($8 \text{ h} < S < 10 \text{ h}$); (iv) for every orientation, glazing units should have very low values of transmittance, $U_g = 0.59 \text{ W}/(\text{m}^2 \text{ K})$, and solar factor, $g = 0.36$, to reduce uncontrolled heat exchange through glazing; (v) only on the southeast orientation (such orientation is characterized by large glazed surfaces in this building), glazing units have a slightly higher solar factor, $g = 0.49$, to enhance solar gain during winter; (vi) the opening of windows (only in the living rooms) should be maximized during summer nights to provide maximum night natural ventilation cooling; (vi) the control parameter of solar shading (e.g., the beam solar radiation incident on a window) has to be selected and set considering the trade-off with other nonthermal performance aspects, such as daylighting and glare risk for occupants. The optimal building variant, in free-floating mode, offers indoor operative temperatures compatible with the 80% acceptability class of the Standard ASHRAE 55 (ASHRAE, 2010); only few deviations occur outside the Adaptive comfort zone defined in such standard (Figure 5.14).

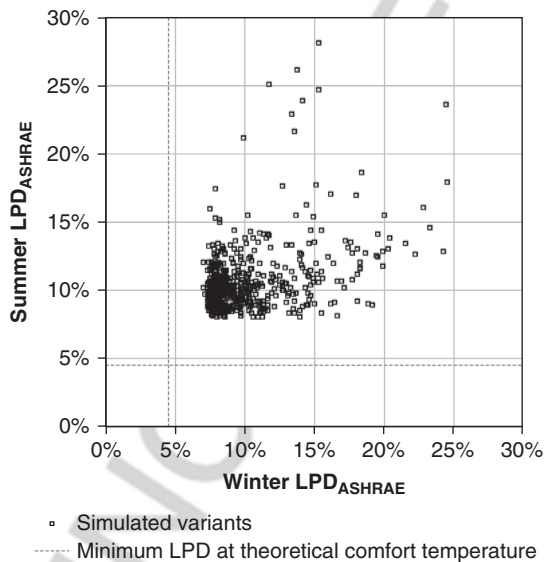


Fig. 5.13 Result of optimization run

Color Fig.: 5.14

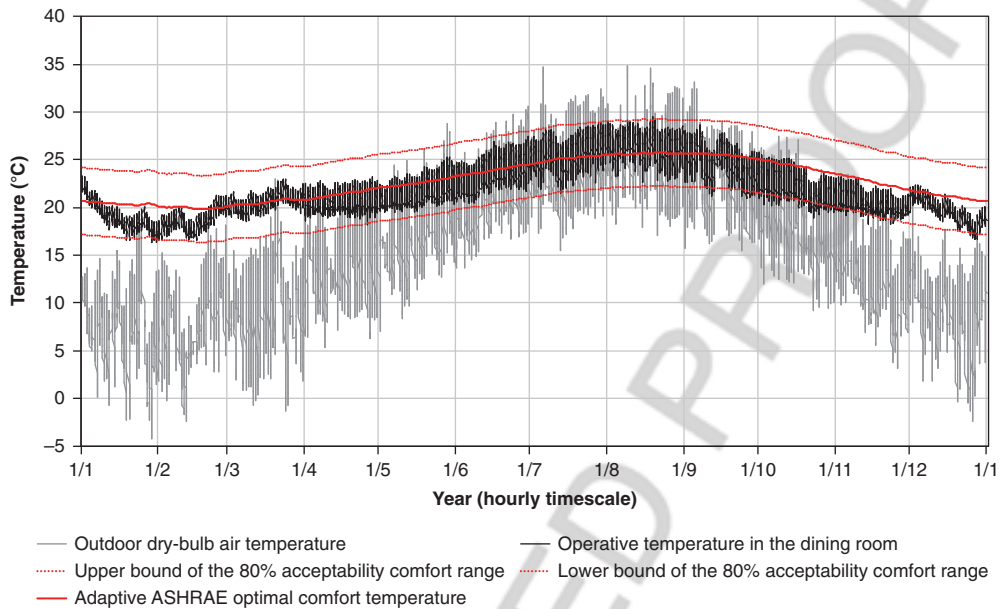


Fig. 5.14 Operative temperature profiles inside the living room in free-floating mode compared with the 80% acceptability range of the ASHRAE Adaptive model

Regarding its energy performance, the delivered energy breakdown in energy uses is (i) $3.1 \text{ kWh}_{\text{el}}/(\text{m}^2 \text{ a})$ for ventilation; (ii) $6.5 \text{ kWh}_{\text{el}}/(\text{m}^2 \text{ a})$ for lighting; (iii) $15.3 \text{ kWh}_{\text{el}}/(\text{m}^2 \text{ a})$ for electric equipment; (iv) $2.6 \text{ kWh}_{\text{el}}/(\text{m}^2 \text{ a})$ for the production of domestic hot water (DHW). The annual required electricity is $4087 \text{ kWh}_{\text{el}}$. The slope of the roof is 22° and it was assumed that a southwest-facing PV array was installed with monocrystalline modules. The single module has a nominal efficiency of 18.4% and a nominal power generation of 300 W. It is also assumed that its overall DC to AC derate factor is 0.77. Under these conditions, 13 PV panels, with a covered roof area of 21.2 m^2 , cumulate an overall nominal peak power of 3.9 kW_p , and should theoretically generate $4911 \text{ kWh}_{\text{el}}$ per year. Thus, the expected electricity production should be slightly higher than the whole electrical demand (Figure 5.15).

If these indoor conditions are not considered satisfactory for the occupants, a mechanical heating and cooling system (e.g., a reversible heat pump) may be added to the optimal variant in order to control the indoor environment in a stricter manner. In this new scenario, indoor thermal comfort requirements shall be referred to the Fanger comfort model. The seasonal optimal comfort temperatures (used as setpoint operative temperatures in the model) were calculated assuming a metabolic activity of 1.2 met, a summer clothing resistance of 0.5 clo, a winter clothing resistance of 1.0 clo, an air velocity of 0.1 m/s, a relative humidity of 50% and an external work set at zero met. The boundary temperatures of the comfort range were calculated in compliance with the Category II of EN 15251 suitable for new buildings mechanically conditioned (Figure 5.16).

Color Figs.: 5.15 and 5.16

5.4 Application of optimization: a comfortable net-zero energy house

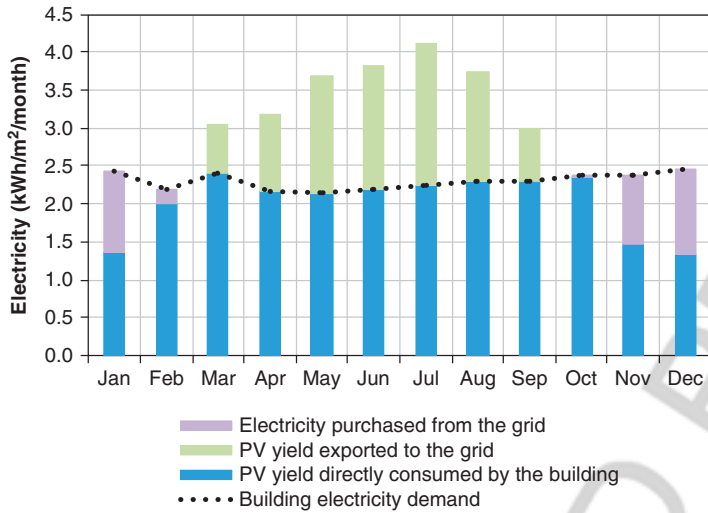


Fig. 5.15 Electricity balance of the home including PV yield

According to this scenario, the building is all-electric and delivered energy is alternative to primary energy to express the breakdown of energy uses. Annual delivered electric energy for space heating amounts to $7.3 \text{ kWh}/(\text{m}^2 \text{ a})$ and annual delivered electric energy for space cooling (sensible plus latent) is $9.5 \text{ kWh}/(\text{m}^2 \text{ a})$. Thus, the overall

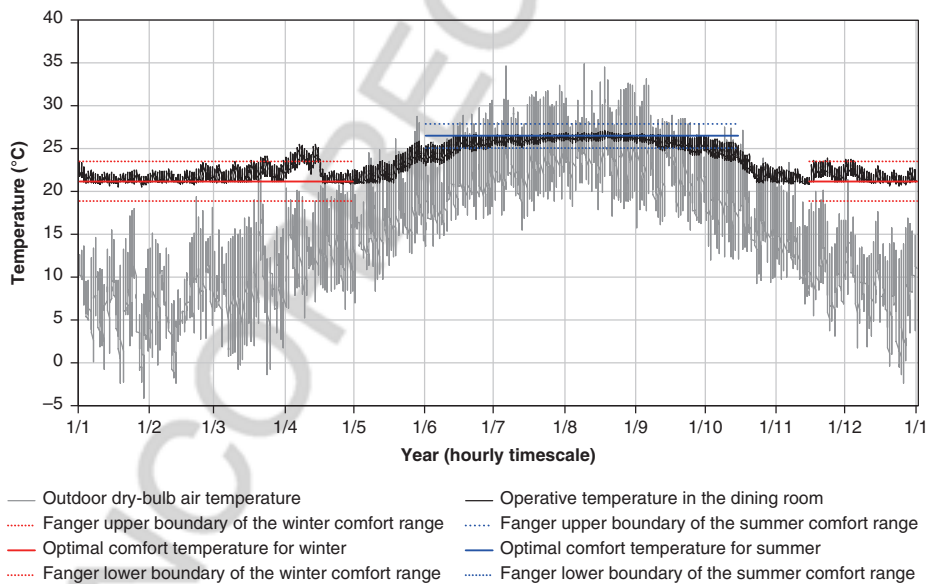


Fig. 5.16 Operative temperature profiles inside the living room in conditioned mode compared with the Category II range of the Fanger model

electricity demand is 7253 kWh per year, that is, 48.8 kWh/(m² a). Therefore, using the previous assumptions about the PV array, 20 PV panels are sufficient to cover the whole electricity demand of this scenario. The PV array is characterized by a nominal peak power of 6.0 kW_p and covering an area of 32.6 m². The expected annual PV yield is 7580 kWh per year, hence the building, also in this scenario, is expected to produce (over a year) more electricity than it requires.

5.4.4 Final considerations

A novel optimization procedure aiming at minimizing two seasonal long-term discomfort indices in a free-floating building is presented and it was used to support the design of a real building. This procedure identified an optimal building variant, which, in free-floating mode, offers indoor operative temperatures compatible with the 80% acceptability class of the Standard ASHRAE 55 with only few deviations outside such comfort zone.

If such optimal building variant is equipped with a heating and cooling system, its primary energy for space conditioning is much lower than primary energy for lighting, electrical appliances, DHW production, and ventilation. Finally, since annual primary energy required by the house amounts to 108 kWh/(m² a), the optimized building fulfills also the *Passivhaus* certification criteria of having a primary energy requirement lower than 120 kWh/(m² a). It should be noted that the modeling and the optimization approach outlined here can be applied to any residential or commercial building prototype.

5.5 Conclusion

Building simulation is becoming a major tool in the building design process. At present, any increase in the use of optimization will be driven by the extent to which it aids design decision-making, particularly for large projects. In this respect, one of the most powerful forms is multiobjective optimization, since it provides a set of solutions and presents a trade-off between two or more possibly conflicting objectives. For instance, the trade-off can be used to explore the impact of lower capital investment on the increase in carbon emissions. Optimization can facilitate a multidisciplinary design process by addressing all building design aspects in a holistic approach. This will enhance fully integrated Net ZEB designs where the building designers can act to influence the direction of the optimization.

Despite the potential of building performance optimization, decision support, time, knowledge, lack of tools, and uncertainty are the themes that need to be addressed for enhanced market penetration of optimization in the AEC industry. The factors that inhibit the uptake of BPO are not only related to the optimization techniques or the tools themselves, but also to the simulation models inputs, causing significant restraint in the AEC industry take-up. From the evidence available and the presented case studies, the optimization process has generally been shown to be applicable to real design practice. For policymakers, it can facilitate development of incentive measures and policies that integrate many objectives, such as integration of renewables with energy efficiency measures, as well as optimized operation that reduces and shifts peak electricity demand while enhancing comfort in high-performance buildings.

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1. Please provide the first name initial of the author (Rudolf) in ref. (Köppen, 1930).

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