Department of Energy Technology

Combining Simulation and Optimisation for Dimensioning Optimal Building Envelopes and HVAC Systems

Mohamed Hamdy Hassan Mohamed

Aalto University

DOCTORAL DISSERTATIONS

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Abstract

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Abstract

Responding to the international calls for high energy performance buildings like nearly-zero energy buildings (nZEB), recent years have seen significant growth in energy-saving and energy-supply measures in the building sector. A detailed look at the possible combinations of measures indicates that there could be a huge number (possibly millions) of candidate designs. In exploring this number of designs, looking for optimal ones is an arduous multi-objective design task. Buildings are required to be not only energy-efficient but also economically feasible and environmentally sound while adhering to an ever-increasing demand for better indoor comfort levels. The current thesis introduces suitable methods and techniques that attempt to carry out time-efficient multivariate explorations and transparent multi-objective analysis for optimizing such complex building design problems. The thesis's experiences can be considered as seeds for developing a generic simulation-based optimisation design tool for high-energy-performance buildings.

Case studies are made to illustrate the effectiveness of the introduced methods and techniques. In all the studies, IDA-ICE is used for simulation and MATLAB is implemented for optimisation as well as supplementary calculations. A new program (IDA-ESBO) is used to simulate renewable energy source systems (RESs). Using detailed simulation programs was important to investigate the impact of the energy-saving measures (ESMs) and the RESs as well as their effects on the thermal and/or energy performance of the studied buildings. The case studies yielded many optimal design concepts (e.g., the type of heating/cooling (H/C) system is a key element to achieve environmentally friendly buildings with minimum life cycle cost. The cost-optimal implementations of ESMs and RESs depend significantly on the installed H/C system). On building regulations, comments are taken. For instance, in line with the cost-optimal methodology framework of the European Energy Performance of Buildings Directive (EPBD-recast 2010), our study showed that the Finnish building regulation D3-2012 specifies minimum energy performance requirements for dwellings, lower than the estimated cost-optimal level by more than 15%. The adaptive thermal comfort criteria of the Finnish Society of Indoor Air Quality (FiSIAQ-2008) are strict and do not allow for energy-efficient solutions in standard office buildings. The thesis shows that it is technically possible to speed up the optimisation resolution of the building and HVAC design problems and to reach an optimal or close-to-optimal solution set. A simulation-based optimisation approach with a suitable problem setup and resolution algorithm can efficiently explore the possible combinations of design options and support informative, optimal results for decision-makers.

Keywords Building, Energy, Simulation, and Optimization

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PREFACE

This thesis is based on research work carried out at the Laboratory of Heating Ventilating and Air Conditioning (HVAC) in the Aalto University Department of Energy Technology during the years 2008-2012. The research work was funded by the Finnish National Technology Agency (TEKES), and five Finnish companies (Optiplan Oy, Pöyry Building Services Oy, Saint-Gobain Isover Oy, Skanska Oy, and YIT Oy), in addition to a two-year scholarship from the Doctoral Programme in the Built Environment (RYM-TO).

I would like to gratefully acknowledge all of the financial supporters. I wish to thank my supervisor Prof. Kai Sirén for his significant direction and encouragement and my instructor Dr. Ala Hasan, whose comments and advices throughout the study were very much appreciated. I would also like to thank my colleague Matti Palonen for his contribution to my paper [Original publication V].

There are no words to express how grateful I am to my dear parents Hamdy Hassan and Malaka El-Nayal. I would like to extend my appreciation to my lovely wife Monia Kandil and my dear sisters Sherien Hamdy and Shaimaa Hamdy. I would like to dedicate this work to my unborn baby, as I hope for a better world environment for him and for humanity.

Finally, and above all, I would like to thank ALLAH (swt) for taking care of me throughout my life. This process would not have been realised without His blessing.

Espoo, May 2012
Mohamed Hamdy

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LIST OF ORIGINAL PUBLICATIONS

I. Mohamed Hamdy, Ala Hasan, Kai Sirén. (2009). Combination of optimization algorithms for a multi-objective building design problem. Building Simulation (BS2009), 11th International IBPSA Conference, Glasgow-UK.
Available at: http://www.ibpsa.org/proceedings/BS2009/BS09_0173_179.pdf

II. Mohamed Hamdy, Ala Hasan, Kai Sirén. (2011). Applying a multi-objective optimization approach for design of low-emission cost-effective dwellings. Building and Environment, 46 (1); pp. 109-123.
Available at: http://dx.doi.org/10.1016/j.buildenv.2010.07.006,

III. Mohamed Hamdy, Ala Hasan, Kai Sirén. (2011). Impact of adaptive thermal comfort criteria on building energy use and cooling equipment size using a multi-objective optimization scheme. Energy and Buildings, 43 (9); pp. 2055–2067.
Available at: http://dx.doi.org/10.1016/j.enbuild.2011.04.006

IV. Mohamed Hamdy, Ala Hasan, Kai Sirén. (2012). A Multi-stage optimization method for cost-optimal nearly-zero-energy building solutions in line with the EPBD-Recast 2010. Energy and Buildings. Energy and Buildings. Available online 29 August 2012.
Available at: http://dx.doi.org/10.1016/j.enbuild.2012.08.023,

V. Mohamed Hamdy, Matti Palonen, Ala Hasan. (2012). Implementation of Pareto-Archive NSGA-II Algorithms to a nearly-Zero-Energy Building Optimization Problem. First Building Simulation and Optimization Conference (BSO12), IBPSA-England, Loughborough University, UK.
http://indoorenvironment.org/implementation-of-pareto-archive-nsga-ii-algorithms-to-a-nearly-zero-energy-building-optimization-problem/

The thesis author, Mohamed Hamdy, is the principal author of the five publications (I-V). All the simulation, optimisation, and analysis works were carried out by him (in I-IV). In (V), the co-author Matti Palonen performed the optimisation work while the simulation and analysis works were carried out by the principal author.

ABBREVIATIONS

aNSGA-II	active-archive elitist Non-dominated Sorting Genetic Algorithm
BPS	Building Performance Simulation
COP	Coefficient of Performance
IC	Investment Cost of the addressed design variables
dLCC	Different in Life Cycle Cost
DH	District Heating
DH_{24}	Degree hours over 24 deg. C
DH_{27}	Degree hours over 27 deg. C
DHW	Domestic Hot Water
DIV	Diversity of solutions in the Pareto optimal-set
EPBD	Energy Performance of Buildings Directive
ESMs	Energy Saving Measures
GD	Generational Distance
Gen	Number of Generations
GSHP	Ground Source Heat Pump
HVAC	Heating, Ventilation, and Air-Conditioning
H/C	Heating/Cooling systems
HU-1	Heating Unit (primary unit)
HU-2	Heating Unit (auxiliary unit)
LCC	Life Cycle Cost
µWT	Micro-wind Turbine (roof-mounted)
NSGA-II	Elitist Non-dominated Sorting Genetic Algorithm
NS	Number of Solutions
nZEB	nearly-Zero-Energy Buildings
ODT	Outdoor-air Temperature
PEC	Primary Energy Consumption
PEM	Polymer Electrolyte Membrane (PEM) fuel cell.
pNSGA-II	passive-archive elitist Non-dominated Sorting Genetic Algorithm
P*	True Pareto-optimal front
Pop	Population size
RESs:	Renewable Energy Sources
RC:	Replacement Cost

1. Introduction

1.1 Background

To put the world on track to reduce global emissions by at least half of 1990 levels by 2050, developed countries will collectively need to cut their emissions to 30% below 1990 levels by 2020 and by 60-80% by 2050 [EU action. 2008]. Europe needs to cut its greenhouse gas emissions to boost economic growth, maintain its technology leadership and keep climate change in check. In Europe, energy performance of buildings is a key element to achieve the Climate and Energy objectives. Buildings are responsible for 36% of EU CO_2 emissions and 40% of energy consumption. Two-thirds of this energy is used for heating and cooling purposes. Simple measures such as better insulation can reduce the heating energy use in European buildings. However, innovative energy-saving measures (ESMs) and renewable energy sources (RESs) should be implemented to achieve further energy reductions and better environmental impact. In Europe, the ambitious target is nearly-Zero-Energy buildings nZEBs [EPBD. 2010].

In response to such environmental target, many ESMs and RESs options have been developed in recent years. A detailed look at the possible combinations of their options would indicate that there could be a huge number (possibly millions) of candidate designs. Seeking for optimal designs, the research has been led into the application of simulation-based optimisation methods that try to identify the Pareto optimum trade-off between conflicting design objectives (e.g., minimum costs and environmental impacts). The current thesis is a part of this research effort. The thesis aims to improve the efficiency and transparency of the building optimization and to reduce the computational effort and time of it.

1.2 The aims of the thesis

The current thesis aims to provide time-efficient optimisation, achieve an optimal or close-to-optimal solution set and support transparent analysis for multi-objective, multivariate high-energy-performance building design problems.

1.3 The content of the thesis

Instead of the time-consuming optimisation methods (like trial-and-error and exhaustive search), the current thesis adopts the simulation-based optimisation approach for optimising multi-objective multivariate energy-performance building design problems. The approach provides

automatic explorations for wide solution spaces. Applying the simulation-based optimisation approach in the early stages of building design is surveyed in section 2.1. Section 2.2 defines the properties of the building and HVAC optimisation problems and shows the most suitable optimisation algorithms for implementation. Section 3 summarises the original publications and presents their new contributions. Optimisation approaches (PR_GA and GA_RF) are proposed to speed up the optimisation process and to reach an optimal or close-to-optimal solution set (section 3.1). The approaches are combined and used for finding cost-effective, low-emission solutions for dwellings in the cold climate of Finland; in addition, bar charts are proposed to visualise and analyse the optimisation results besides the Pareto-optimal front principle (section 3.2). The impact of the Finnish adaptive thermal comfort criteria-2008 (by FiSIAQ) on the energy use of buildings and cooling equipment size is assessed by using a suitable simulation-based optimisation scheme (section 3.3). A multi-stage optimisation method is proposed for efficient, transparent and time-saving optimisation in line with the cost-optimality framework methodology of EPBD-2010 (section 3.4). An active archiving strategy is proposed to improve the performance of the original NSGA-II algorithm (section 3.5). The new contributions of the thesis are summarised in section 4. General conclusions can be found in section 5.

2. Surveys

2.1 Simulation-based optimisation approach

When a huge number of possible designs are offered, a trial and error exploration cannot guarantee finding optimal solutions while an exhaustive search is an inefficient exploration procedure in time and effort. Instead of the above two exploration methods, a simulation-based optimisation approach has been used for finding optimal building design solutions. One or more objective functions, such as the capital cost, energy use, or life-cycle cost of a building can be minimised through the use of simulation-based optimisation in which a simulation is used to evaluate the performance of the building for each trial solution of the optimisation. The approach has been applied to:

(1) Optimisation of building layout [Jo and Gero 1998; Gero and Kazakov 1998; Wang et al. 2006; Kämpf and Robinson. 2010; Turrin et al. 2011],

(2) Geometric optimisation of fenestration [Wright and Mourshed. 2009],

(3) Optimisation of the building envelope/fabric construction [Caldas and Norford 2002, 2003; Wetter and Wright 2004; Wang et al. 2005; Flager et al., 2008; Geyer, 2009; Suga et al. 2010; Rapone and Saro. 2011; Tresidder et al. 2011],

(4) Optimisation of shape and functional structure of buildings as well as heat source utilisation [Jedrzejuk and Marks. 2002],

(5) Sizing of heating, ventilating, and air-conditioning (HVAC) systems [Wright and Hanby 1987; Wright 1996; Asiedu Y. et al. 2000],

(6) Optimisation of HVAC system control parameters and/or strategy [Huang and Lam 1997; Wang and Jin 2000, Chow et al. 2002; Kolokotsa et al. 2002, Fong et al. 2003, Nassif et al. 2004a,b; Nassif et al. 2005; Mossolly et al. 2009. Lee et al. 2011],

(7) Optimisation of HVAC system synthesis [Wright et al. 2008],

(8) Simultaneous optimisation of building construction and HVAC element(s) [Hasan et al. 2008; Palonen et al. 2009: Bichiou and Krarti. 2011],

(9) Simultaneous optimisation of building construction, HVAC-system size, and system supervisory control [Wright and Farmani 2001; Wright et al. 2002],

(10) Optimisation of building construction, HVAC system, and energy supply system including RES [Verbeeck and Hens. 2007; Diakaki et al. 2010].

It is worthwhile to mention that the above simulation-based optimisation studies are significantly variant. Some of them applied multi-objective optimisation while the others performed single objective ones. The implemented optimisation algorithms range from enumerative to stochastic. The size and complexity of the addressed solution spaces are quite different. Some studies used detailed simulation tools while others used simplified ones. In order to reduce the simulation time:

- Custom simplified thermal models are developed and used instead of using pre-existing detailed simulation tools [Nielsen, 2002, Wright, et al., 2008, Congradac and Kulic 2009, Talbourdet et al. 2011],
- Detailed simulation tools are used. However, simplified simulation models are assumed. For instance, single zone represented one floor single family house [Hasan et al. 2008],
- Instead of a one-year simulation, the simulation is performed only for representative days. Three design days are used in [wright et al 2002; Mourshed et al. 2003] to represent summer, intermediate, and winter weather conditions. Two months (February for winter and August for summer) are used as representative periods for the whole year [Obara 2007].

Using a detailed simulation, time-efficient multi-objective optimisation, and/or suitable visualization methods are missing from many of the above sources. Although the simulation-

based optimisation approach is one of the most promising exploration methods for finding an optimal solution set among a huge number of possibilities, it is addressed only in a small number of energy and buildings PhD works such as: [Caldas. 2001; Nielsen. 2002; Wetter. 2004; Zhang. Y. 2005; Pedersen. 2007; Verbeeck. 2007; Hopfe. 2009]. In practice, applying simulation-based optimisation (integrated optimisation of parameters, Figure 1) does not meet the satisfaction level of professionals. The growing of the simulation and optimisation building design tools (Figure 2) reflect their importance. Aiming for better satisfaction levels, the current PhD thesis aims to speed up the optimisation process and to provide repeatable and informative results for building and HVAC professionals. The work targets multi-objective multivariate building design problems with constraint functions. The aim and target of the current work has not been widely investigated in the literature.

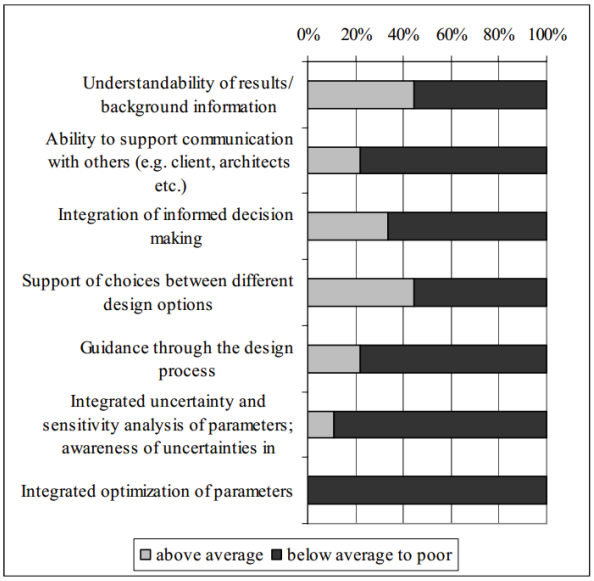


Figure 1. Summary of the current satisfaction level in BPS according to professionals' perception [Hopfe. 2009].

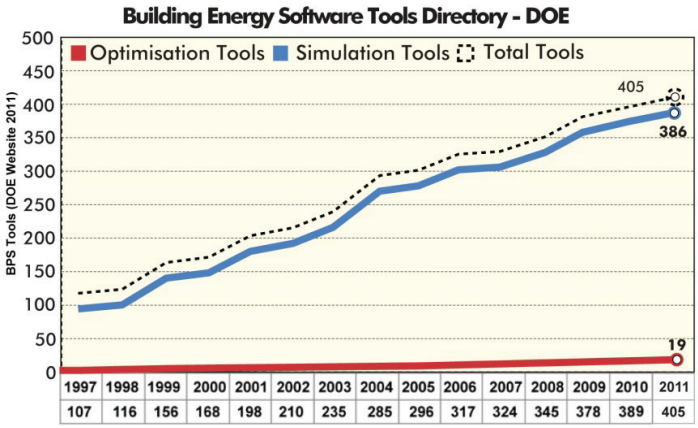


Figure 2, The growth of simulation and optimisation building design tools in the last fifteen years [DOE. 2011].

2.2 Suitable optimisation algorithms

Building design is an inherently multi-objective process, which entails a trade-off being made between two or more conflicting design objectives (such as between minimizing both operating and capital cost). This has led to research into the application of simulation-based multi-objective optimisation methods that try to identify the Pareto optimum trade-off between conflicting design objectives. The current thesis is a part of this research effort.

Optimisation of a building as a whole is a complex problem due to the amount of design variables as well as the discrete, non-linear, and highly constrained characteristics. The popular optimisation methods for solving multi-objective optimisation problems are generally classified into three categories: (1) Enumerative algorithms, (2) deterministic algorithms, and (3) stochastic algorithms. The enumerative methods search in a discrete space. They evaluate all the solutions and choose the best one. These algorithms are computationally expensive and consequently they are not suitable for exploring wide solution spaces. Gradient and gradient-free determinations can be found. The gradient ones use the gradient of the evaluation functions either by going in the direction where the gradient is the smallest or by searching for solutions that have a gradient vector equal to zero. The gradient-free ones such as the Hooke-Jeeves direct search [Hooke and. Jeeves, 1961], constructs a sequence of iterates that converge to a stationary point if the cost function is smooth and coercive. In [Emmerich et al., 2008], the Hooke-Jeeve algorithm is used to minimise energy consumption by considering different building scenarios and characteristics. A gradient-free sequential quadratic programming (SQP) filter algorithm is proposed and tested in

Pedersen's PhD work [Pedersen, 2007]. The algorithm can converge fast and in a stable manner, as long as there are no active domain constraints. Generally, the deterministic algorithms need the evaluation functions to have particular mathematical properties like continuity and derivability [Wetter and Wright, 2003, 2004]. Therefore, they are not the best choice for handling discontinuous building and HVAC problems with highly constrained characteristics and multi-objective functions. The advantage of stochastic algorithms is that they do not have many mathematical requirements about the optimisation problem. The stochastic algorithms: annealing [Kirkpatrick et al. 1983; Cerny 1985], tabu search [Glover 1990], ant colony [Colorni et al. 1991], particle swarm [Eberhart and Kennedy 1995] and genetic algorithms (Holland 1975; Goldberg 1989: Deb et al. 2001], were designed to deal with highly complex optimisation problems [Collet and Rennard. 2006].

A stochastic element was added to the Pattern search algorithm for optimizing the topological design of the bracing system for a free-form building [Baldock et al. 2005]. Pattern search algorithms are guaranteed to converge to a stationary point, even for non-smooth functions; however, the stationary-point may not be the optimum point [Wetter and Wright 2003]. The ant colony optimisation algorithm (ACO) was used to search for a trade-off between light intake, thermal performance, view and cost for a panelled building envelope for a media centre in Paris [Shea et al. 2006]. A strong multi-objective particle-swarm optimisation (S-MOPSO) was used for the optimisation of a heating, ventilation, and air conditioning (HVAC) system in an office building [Andrew et al. 2011]. Instead of the above algorithms, the last ten years have seen an increasing interest in using Genetic Algorithms (GAs) for optimisation of building and HVAC systems. The GAs are the most efficient stochastic algorithms when the optimisation problem is not smooth or when the cost function is noisy [Mitchell, 1997 and Chambers 2001]. The GAs consider many points in the search space simultaneously, rather than a single point, thus they have a reduced chance of converging to a local minimum, in which other algorithms may end up [Congradac and Kulic 2009]. The GAs with the Pareto concept are used widely in energy and buildings context [Wright et al. 2002; Wang et al. 2005; Wang et al. 2006; Charron and Athienitis. 2006; Manzan. et al. 2006; Verbeeck and Hens. 2007; Caldas, 2008; Flager et al. 2008; Geyer, 2009; Magnier and Haghighat. 2010; Turrin et al. 2011]. According to the studies of Zitzler [Zitzler et al. 2000] and Deb [Deb et al. 2002], the elitist Non-dominated Sorting Genetic Algorithm (NSGA-II) seems to be the most efficient of the multi-objective GAs. The NSGA-II is implemented to find trade-off relations between energy consumption and investment cost or the thermal comfort level of buildings [Nassif et al., 2004a,b; Nassif et al.2005; Emmerich

et al. 2008; Hopfe. 2009; Palonen et al. 2009; Hoes et al. 2011; Loonen et al. 2011]. The NSGA-II (Deb et al. 2002) could be one of the most suitable optimisation algorithms to handle multi-objective multivariate building and HVAC design problems with discrete, non-linear, and highly constrained characteristics. However because of its stochastic behaviour, it could occasionally fail to get close to the Pareto-optimal front, particularly if a low number of evaluations is implemented [Palonen et al. 2009]. The high number of iterations is chosen to avoid the early breakdown of the optimisation [Hopfe. 2009]. Since building simulation is often very time-consuming, a large number of iterations would not be practical. In the present thesis, deterministic phases and archive strategies are added to the original NSGA-II in order to perform rapid optimisation –using a low number of simulation runs- and guarantee an optimal or close-to-optimal solution set for building design problems (see the next section).

3. The new contributions applied to the original publications

This section presents the work of the original publications from the point of view of new contributions. The work is done by a computer (Intel® core ™2 Quad CUP 2.40 GHz processor, 3061 MB RAM).

3.1 Proposing approaches for improving the optimisation performance (Original publication I)

As shown in section (2.2), an elitist non-dominated sorting genetic algorithm (NSGA-II, by Deb et al. 2001) has been receiving increasing attention for its potential for solving complex design problems. The algorithm is suitable to solve multi-objective multivariate building and HVAC design problems with discrete, non-linear, and highly constrained characteristics. However it could occasionally fail to get close to the Pareto-optimal front, particularly if a low number of iterations are used. This happens because of the random behaviour of the algorithm and its inability to keep all of the non-dominated solutions through the optimisation process. NSGA-II, a stochastic optimisation algorithm, implements elitism by maintaining two populations of limited size N. The adult population P from the previous generation and the child population Q are generated at the current generation. During each generation, the two populations are combined and sorted according to a non-domination concept. Then N solutions are selected as the next parent population P. The number of non-dominated points available after sorting may be greater than the populations size N, which defines the number of (elite) points that are kept by the algorithm. When the number of available non-dominated points is greater than N, NSGA-II

selects the N least crowded solutions by using a crowding distance measure and rejects the rest of the non-dominated points.

The chances of the above mentioned occasionally failing can be reduced easily by using a large number of iterations. This solution is not time-efficient for building optimisation problems, which often require time-consuming iterations (simulations). In this thesis, iteration often means simulation. In order to improve the optimisation performance, the chances of the above mentioned process failing are reduced by adding deterministic optimisation phases and achieving strategies to the NSGA-II. The proposed phases and strategies reduce the NSGA-II's random behaviour and treat its inability to keep all of the potentially Pareto optimal solutions, because of the limited population size, during the optimisation run, respectively. By combing NSGA-II with the proposed phases and/or strategies, it became applicable to achieve optimal or close-to-optimal solutions using relatively low numbers of iterations. This provides time-efficient optimisation for our building design problems.

Original publication I proposed two optimisation approaches PR_GA and GA_RF. Both combine a controlled elitist genetic algorithm (GA), a variant of NSGA-II [Deb et al. 2001], with deterministic optimisation phase and passive archive strategy. An elitist GA always favours individuals with better fitness value (rank) whereas, a controlled elitist GA also favours individuals that can help increase the diversity of the population even if they have a lower fitness value. It is very important to maintain the diversity of population for convergence to Pareto-optimal front.

3.1.1 PR_GA approach

Deterministic algorithms are considered to be more efficient and precise for local optimisation than stochastic algorithms (GA), while stochastic algorithms are considered to be more reliable in global optimisation and robust to numerical noise [Hopfe. 2009]. Original publication I proposed two-phase optimisation approach (PR_GA) retaining the good features of the above two algorithms. The PR_GA, a two-objective optimisation approach, performs the optimisation in two phases one deterministic and the other stochastic. The role of the first phase (the preparation phase known as PR) is to prepare a good collection of solutions and supply them to the second phase (the genetic algorithm phase GA) as an initial population rather than starting with a random sample. A good collection of solutions is prepared by using Fmincon (a single- objective sequential quadratic programming algorithm from MATLAB 2008b Direct Search Toolbox). The

Fmincon minimises one objective function considering the other as a constraint. Considering different constraint values, the minimisation is repeated three times. According to diverse and non-domination concepts, the minimisation results are sorted and a good collection of solutions is selected. A controlled elitist genetic algorithm (GA), a variant of NSGA-II [Deb et al. 2001], from the MATLAB 2008a genetic optimisation toolbox (GA) is used in the second phase. In order to avoid losing good solutions during the two-phase optimisation, passive archiving is used simply as storage for the evaluated solutions. The major advantage of PR_GA is that it tries to reduce the random behaviour of GA in an attempt to obtain good solutions with a lower number of simulations. In Original publication I, the performance of the proposed approach is tested against the MATLAB 2008b NSGA-II. Original publication I used PR_GA and MATLAB NSGA-II to find the optimal trade-off relation between the additional investment cost (dIC) and the space-heating energy needed for a one-floor single-family house in the cold climate of Finland. Table 1 presents the upper and lower bounds of the addressed design variables. Half a meter is the different between the insulation thickness bounds.

Table 1. Design variables

Design Variables	Type	Nominal value	Lower bounds	Upper bounds
Wall Insulation Thickness (m)	Continuous	0.122	0.122	0.522
Ceiling Insulation Thickness (m)	Continuous	0.299	0.299	0.799
Floor Insulation Thickness (m)	Continuous	0.165	0.165	0.565
U-Values of the Windows (W/m^2K)	Discrete (two options)	1.4	1	1.4
Heat Recovery Efficiency (%)	Discrete (two options)	70	70	80

Figures 3 and 4 show the optimisation problem's brute-force in addition to the PR_GA's Pareto-optimal front (Case 1) and the MATLAB NSGA-II ones (Case 2, 3, 4, and 5). The Brute-force search is an exhaustive search that systematically enumerates all possible candidate solutions. Table 2 and Figure 5 show the number of simulation-runs and the execution time of the five cases, respectively. Figures 4 and 5 show that the proposed optimisation approach (PR_GA) can reduce the optimisation time by more than 50% and achieve a better optimal solution set compared with MATLAB NSGA-II-alone. The simulation time of one simulation run was about 50 Sec.

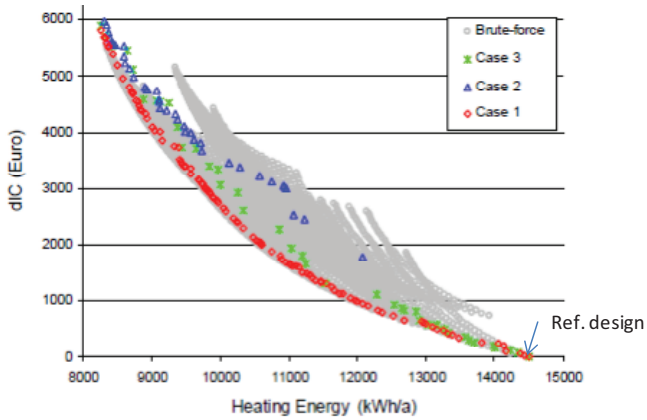


Figure 3. PR_GA results compared with MATLAB NSGA-II ones using a close number of simulation runs (see Figure 5 and Table 2) [Original publication I].

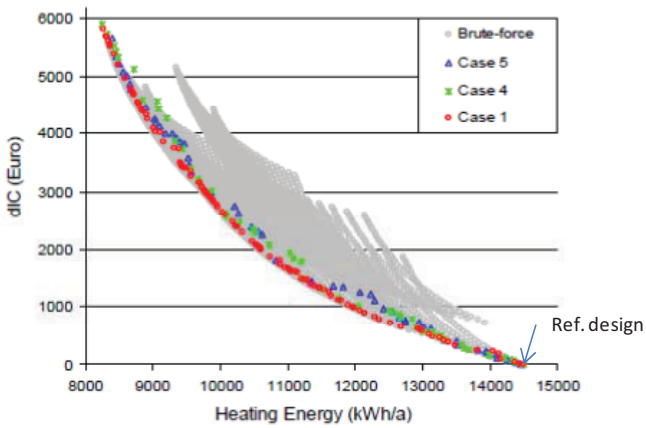


Figure 4. PR_GA results compared with MATLAB NSGA-II results using higher number of simulation-runs [Original publication I].

Table 2 the settings of the optimisation cases

Case	Algorithm	No. Pre Run	Size Pop	No. Gen	Number of Simulation Runs*
1	PR_GA	207	36	10	567
2	MATLAB NSGA-II	0	36	16	576
3	MATLAB NSGA-II	0	20	30	600
4	MATLAB NSGA-II	0	20	55	1100
5	MATLAB NSGA-II	0	25	50	1250

**Number of Simulation Runs = Pre + (Pop X Gen)*

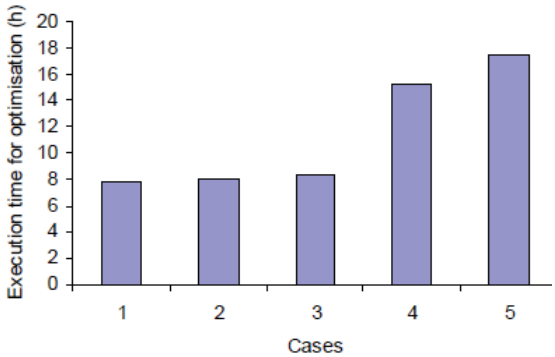


Figure 5. Execution time required for cases 1, 2, 3, 4 and 5 (in hours).

3.1.2 GA_RF approach

The second optimisation approach, proposed in Original publication I (GA_RF) is also a combination of deterministic and stochastic algorithms from MATLAB 2008b toolboxes (Fminmax and NSGA-II, respectively). GA denotes a genetic algorithm while RF denotes refine the GA results. The GA_RF is a two-objective, two-phase (hybrid) optimisation approach. In the first phase (GA), MATLAB NSGA-II performs a low number of generations. In the second phase (refinement phase RF), the deterministic algorithm (Fminmax) attempts to yield optimal results, picked out from the GA phase, to the utopia point. The refine phase (RF) is used to efficiently replace a larger number of inefficient GA generations. The GA convergence rate slows down after a certain number of generations [Caldas and Norford 2003]. The main advantage of GA_RF is that it provides trusted results by using a deterministic stopping criterion (TolFun). After a successful poll by Fminmax, if the difference between the function value at the previous best point and function value at the current best point is less than the value of function tolerance (TolFun), the algorithm halts. Using a suitable value of TolFun can avoid many of useless simulations-runs (i.e., it is evident that improving the results by saving 1 Euro or 1 kWh/a of heating energy does not merit consuming much long time. Many of simulation-runs were saved by using TolFun ≤ 1 through employing the refine phase PR after the GA). The second GA_RF's advantage is that it provides a larger number of optimal solutions compared with NSGA-II alone. Using nearly the same number of simulations, GA_RF (Case 6: 400 simulations using NSGA-II followed by 821ones using Fminimax) provided a better and more optimal solution set than NSGA-II-alone (Case 7: 1250 simulations using MATLAB NSGA-II-alone), as illustrated in Figure 6. The figure presents the brute-force and GA_RF and MATLAB NSGA-II-alone results

for the optimisation problem mentioned in section 3.1.1: exploring possible combinations of five design variables (Table 1) seeking a minimum of additional investment cost (dIC) and space-heating energy needed for a single-family house in the cold climate of Finland (original publication I). A fixed population size (20 individuals) is used in the two cases 6 and 7.

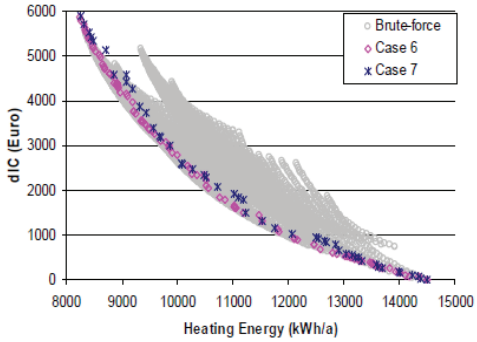


Figure 6. Comparison of the results of cases 6 (NSGA-II alone) and 7 (GA_RF).

3.2 Applying a simulation-based optimisation approach for design of low-emission, cost-effective dwellings (Original publication II)

3.2.1 Proposing an efficient optimisation approach (PR_GA_RF approach)

In Original publication II, the two previous optimisation approaches are combined to find low-emission cost-effective solutions for a two-story house in Finland (Figure 7). The combination is called PR_GA_RF approach. The PR_GA_RF is a three-phase optimisation approach with passive archive stores all the evaluated solutions. The archive avoids losing potential Pareto-optimal front solutions, as mentioned before, during the optimisation phases. The approach could be time-consuming. However, it is recommended for achieving high quality results, particularly for high-constraint optimisation problems. In the preparation (PR) and refine (RF) phases, the constraint functions are handled by deterministic approach (fmincon Trust Region Reflective Algorithm, MATLAB R2008b) rather than the penalty function approach which is used in the GA phase. If sufficient number of simulations is given, the refine phase can guarantee good convergence to the true Pareto-optimal front. The refine phase halts when there is no potential for further convergence. This provides high quality results.

In original publication II, the optimisation approach is combined with IDA-ICE (Figure 8) to explore a wide solution space consisting of eight design variables: three continuous and five discrete variables (Tables 3, 4, and 5): the insulations have prices of 56.3, 32.5, and 100 €/m^3, and thermal conductivity of 0.035, 0.05, and 0.026 W/m^2 K, respectively. A simulation run took on average 2.5 min. The PR_GA_RF is employed to minimise two objective functions: the CO_2-eq emissions related to the space-heating and DHW of the predefined house and the investment costs of the addressed design variables. The minimisation task is performed for three cases. Case 1 does not consider the risk of overheating in summer, which could happen due to the implementation of a building envelope with a low U-value and/or the use of an improper shading method. In terms of degree-hour $DH_{24,}$ Case 2 and 3 considered constraint functions ($DH_{24} \leq 2400$ ^{o}C h and $DH_{24} \leq 1000$ ^{o}C h, respectively) on the summer overheating hours. The degree-hour DH_{24} is the summation of the operative temperature degrees higher than 24 ^{o}C at the warmest zone during a one-year simulation period (8760 h)

$$DH_{24} = \sum_{i=1}^{i=8760} dH_{24}$$

$$dH_{24} = (T_i - 24)\Delta t \qquad \text{when } T_i - 24 > 0$$

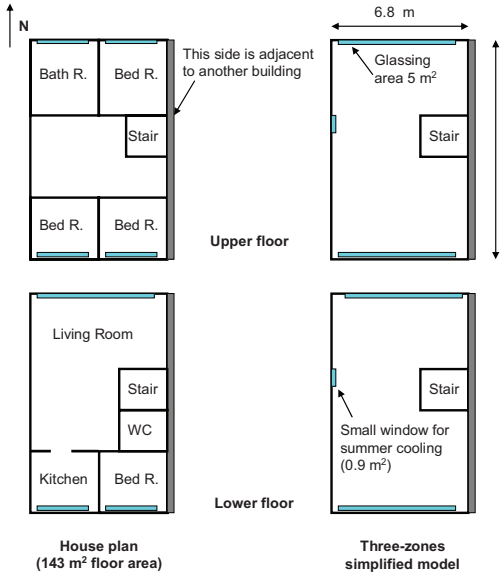
$$dH_{24} = 0 \qquad \text{when } T_i - 24 \leq 0 \qquad (1)$$

where T_i is the operative temperature [^{o}C] at the centre of the warmest zone (upper floor) and dt is a one-hour time period [h].

Figure 9 shows the Pareto-optimal fronts of the three studied cases. The fronts consist of 41, 64, and 58 optimal solutions for Cases 1, 2, and 3, respectively. A higher number of simulations was required to solve the most complex constrained optimisation case (Case 3). In the three cases, the PR_GA_RF performed 1310, 2787, and 3500 simulations: 290, 297 and 325 for the preparation phase (PR), 720, 1200, 1600 for the NSGA-II phase (GA), and 300, 1290 and 1575 for the refine phase (PR), respectively. The preparation and refine phases are halted according to the predefined stopping criterion (TolFun), while a maximum number of generations is used to stop the NSGA-II phase (GA). The PR_GA_RF could achieve a sufficient number of optimal or close-to-optimal solutions using a lower number of simulations. However, high quality results were desired. It is worthwhile to mention that in order to evaluate the impact of changing the heating system type; many simulations were carried out with the same building envelope structure. The time of such a

simulation would be saved if there was availability for post-processing the pre-simulated results. This is considered in original publications IV and V.

Figure 9 shows that at the value of CO_2-eq emissions (50 kg CO_2-eq/m^2.a), a higher investment cost was needed in Case 2 compared with Case 1 in order to achieve a better thermal comfort level (lower overheated hours DH_{24}). This can be shown by points (*A*) and (*B*). Point (*A*) has DH_{24} of 5400 C. h, which is higher than that of point (*B*), which is 2200 C. h. For the latter, a lower building tightness, a weaker shading method and relatively thin insulation were implemented to decrease the amount of summer overheating. However, this required a lot of space-heating energy (points A and B have space-heating energies of 70 and 130 kWh/m^2.a, respectively). To keep the same level of CO_2-eq emissions (equal environmental impact), the optimisation solver selected the Oil Fire Boiler system (*Sys.*2) which has a lower emission factor (*EF* = 0.267 kg/kWh) for point *B* instead of the Electrical Radiator (*Sys.*1 with *EF* = 0.459 kg/kWh) which was the selection of point (*A*). This required an additional investment cost of 9150 € (the price difference between heating systems 1 and 2). Furthermore, the shading method costs of point *B* entail an additional 4000 € to decrease direct solar radiation. However, a 3150 € investment cost was saved by using less insulation and less efficient building tightness. As a result, an additional cost (10 000 €) was needed for higher thermal comfort conditions (point *B*) to maintain the same impact on the environment (50 kg CO_2eq/m^2.a). This is a very expensive solution. Cheaper solutions would be found if wider solution space or was suggested (i.e., fixed size of operable windows was considered as conceptual design. Using larger sizes of operable windows for natural cooling was not suggested as inexpensive solution for avoiding summer overheating). Finally, it is worthwhile to mention that, on average, Case 1 used lower U_{bldg} (average U_{bldg} = 0.24 W/m^2 K) to attain minimum amounts of heating energy (and consequently CO_2-eq emissions). However, Case 2 implemented higher U_{bldg} (average U_{bldg} = 0.38 W/m^2 K) for fewer summer overheating solutions ($DH_{24} \leq 2400$ ^oC. h) with and without a cooling method. The intermediate values of U_{bldg} (average U_{bldg} = 0.3 W/m^2 K) with the cooling method are selected in Case 3.



a- Original floor plan b- Three zones simplified model

Figure 7. A two-story house (143 m^2) in the cold climate of Finland [Original publication II].

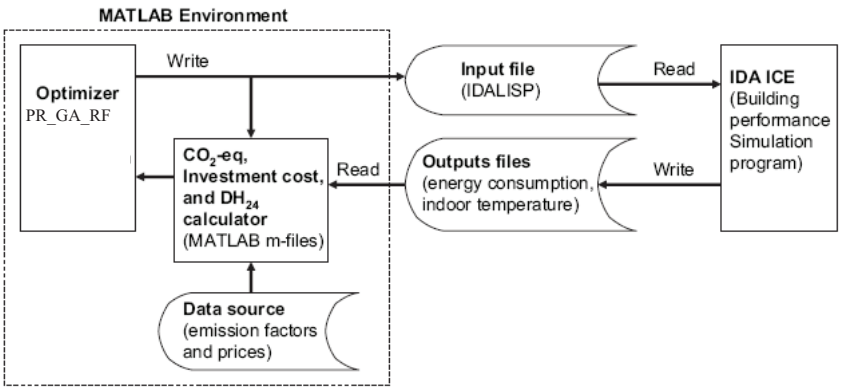


Figure 8. Simulation-based optimisation scheme (IDA_ICE for simulation and PR_GA_RF for optimisation) [Original publication II].

Table 3 Design variables

	Variables	Type	Initial designs	Lower bound	Upper bound
1	Insulation thickness of external wall [m]	Continuous	0.124	0.024	0.424
2	Insulation thickness of roof [m]	Continuous	0.21	0.11	0.51
3	Insulation thickness of floor [m]	Continuous	0.14	0.04	0.44
4	Shading type	Discrete	1	shading	no shading
5	Window type	Discrete	1	1	5
6	Heat recovery	Discrete	2	1	3
7	Building tightness type	Discrete	1	1	5
8	Heating/cooling system type	Discrete	From 1 to 5	1	5

Variables no. 5, 6, and 7 are described in Table 4. Variables no. 8 is described in Table 5

Table 4: Window, building tightness, and air handling unit types

Type	Window				Building tightness		Air-handling unit (AHU)	
	U-Value [W/m^2.K]	T [%]	SC	Price [€/m^2]	n_{50} [1/h]	Cost * [€/m^2]	η of heat recovery	Price [€]
1	1.4	44	0.656	180	4	0	60	3172
2	1.1	44	0.656	185	3	5	70	3443
3	1	34	0.53	205	2	12	80	3715
4	0.85	29	0.482	240	1	22	-	-
5	1.1	28	0.437	210	0.5	30	-	-

T: Total solar transmission. SC: Shading Coefficient factor**.** n50: the number of air changes per hour equivalent to an air leakage rate with a 50-Pa pressure difference between the indoors and outdoors
*The Building tightness cost is for the additional work by a one-square-meter floor area.

Table 5: Heating/cooling system types

Type	Type	Price [€/m^2]	EF/ η [kg CO_2eq/kWh]
1	Direct electric radiator*	30	0.459 / 1
2	Oil fire boiler*	94	0.267 / 0.9
3	District heating*	101	0.226 / 1
4	GSHP *	126	0.459 / 3 #
5	GSHP with free cooling	133	0.459 / 3 #

EF: Emission Factor
* Without cooling system
# η = COP in case of GSHP system

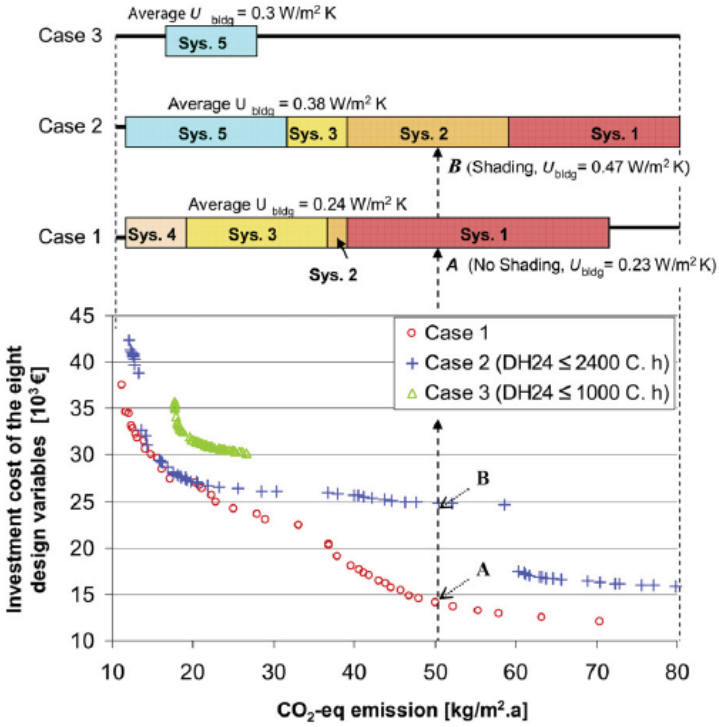


Figure 9. Pareto-optimal fronts of the three studied cases (1, 2, and 3) and contribution of the heating/cooling system types (Table 5) in each case [Original publication II].

3.2.2 Proposing a transparent analysis method: Visualising the optimisation results by Pareto-optimal front and bar chart with double arrow.

The benefit of the optimisation process can only be realised if the results of the optimisation can be analysed in a way that aids the decision-making process and the selection of the final design solution. The analysis of multi-objective optimisation results is non-trivial, in that the problem is multi-dimensional with several interacting relationships being of interest. Brownlee and Wright [2012] have reviewed existing approaches to visualise/analysis the building optimisation results.

In Original publication II, Pareto-optimal fronts (Figure 10a) are used to visualise the optimal trade-off between the two objective functions (IC of the design variables and CO_2-eq emissions) addressed for the predefined two-story house (Figure 7). In order to systematically identify the

impact of the design variables on the trade-off, the Pareto set is sorted by one of the objectives (CO_2-eq emission) and bar charts and double arrow are proposed to present the values of each variable among the Pareto set. The design variables which have the same impact on the Pareto set are aggregated and presented by one value. For instance one U-value (U_{bldg}) is used to present the impact of the wall, roof, floor, and window U-values on the heating demand and consequently on the CO_2-eq emissions according to the installed heating/cooling system. The bar chart (Figure 10b), used double arrow to present the design-variables (e.g., the heating/cooling system and the shading option) which have constant values among a portion of the Pareto set. In the same way, the values of the rest of the design variables (building tightness, window types and heat recovery methods, Table 4) are presented (Figure 11). The values of the constraint function (degree hours $DH_{24,}$ equation 1) among the Pareto set is also presented by a bar chart, Figure 10c. Figures 10 and 11 present the results of Case 2. Cases 1 and 3 results are also presented using Pareto-optimal fronts and bar charts with double arrow (see Original publication II).

From the optimisation results, it is concluded that: (1) compared with the initial design, 32% less CO_2-eq emissions and a 26% lower investment cost solution could be achieved; (2) the type of heating energy source has a marked influence on the optimal solutions; (3) the influence of the external wall, roof and floor insulation thickness as well as the window U-value on the energy consumption and thermal comfort level can be reduced into an overall building U-value; and (4) to avoid much of summer overheating, dwellings which have insufficient natural ventilation measures could require less insulation than the standard (inconsistent with energy-saving requirements) and/or additional cost for the shading method.

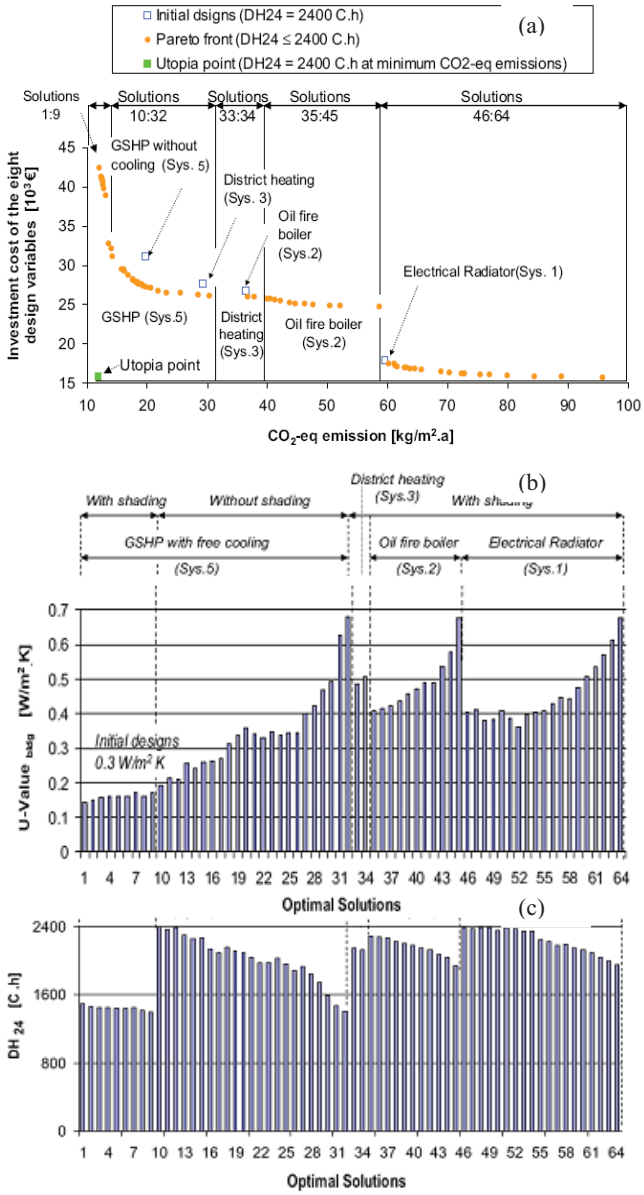


Figure 10. the overall building U-value (U_{bldg}) (b), the constraint function value (DH_{24}) and (c) among the Prato-optimal 64 solutions (a), Case study 2 [original publication II].

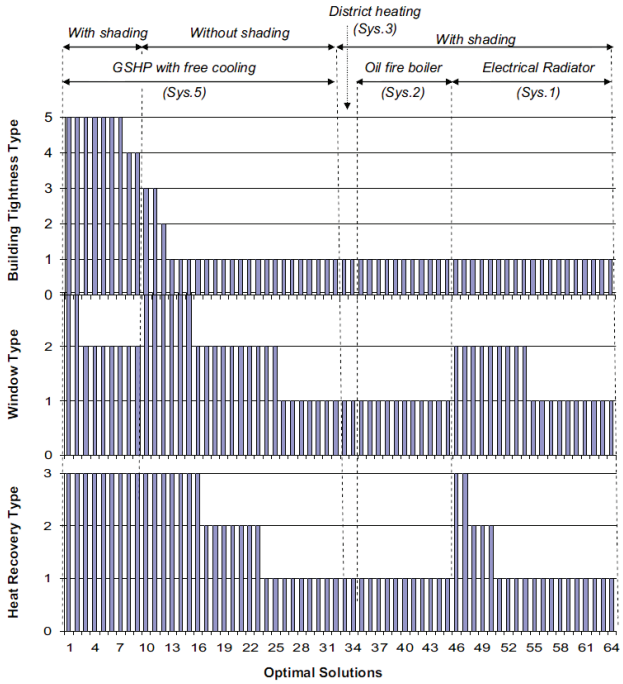


Figure 11 the building tightness, window, and heat recovery types among the Prato-optimal 64 solutions [Original publication II].

3.3 Assessing the impact of the Finnish adaptive thermal comfort criteria-2008 on building energy use and cooling equipment size using simulation-based optimisation scheme (Original publication III)

Recently adaptive thermal-comfort criteria have been introduced in the international indoor-climate standards to reduce heating/cooling energy requirements. In 2008, the Finnish Society of Indoor Air Quality (FiSIAQ) developed the national adaptive thermal-comfort criteria of Finland. The FiSIAQ categorised the indoor comfort level into three classes (S1, S2, and S3). S1 is the highest comfort class. The classification defines the indoor operative temperature set points as a function of the 24-hour mean average outdoor air temperature (ODT_{24} hour average). Figure 12 shows the set-point profiles, the allowable set-point deviation bands and the maximum/minimum temperature limitations of the S1 and S2 classes. It is important to note that S1 and S2 classes have the same set-point temperature profile. The S1 class stipulates that the operative temperature (T_{op}) should be kept at the set-point with acceptable deviations of ±0.5 for 95% of the occupied hours. However, S2 class requires keeping the T_{op} at the set-point with acceptable deviation ±1 ◦C, 90% of the occupied hours. The criterion proposes 20 ◦C and 23 ◦C as the minimum and

maximum temperature limits in the cold season. For summer, the maximum temperature limits (26 ◦C and 27 ◦C) are used for S1 and S2, respectively.

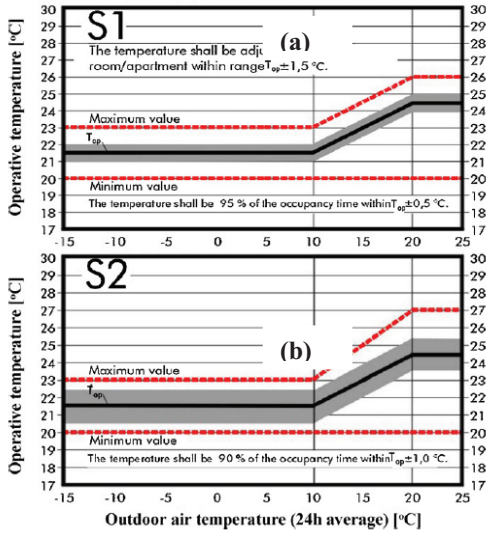


Figure. 12. The set-point profile, minimum and maximum limits according to the Finnish Classification of Indoor Climate 2008 [FiSIAQ. 2008].

Original publication III proposed a suitable simulation-based optimisation scheme to assess the impact of applying the Finnish thermal-comfort criteria on the total primary energy consumption and the cooling equipment size of office buildings located in Helsinki, Finland. The scheme is a combination of IDA-ICE 4.0 for simulation, MATLAB-2008a m.files for supplementary calculations, and a multi-objective genetic-algorithm (variant of NSGA-II) from MATLAB-2008a for optimisation, Figure 13. The applicability of implementing energy-saving measures (ESMs) such as night ventilation, night temperature set-back, day lighting as well as optimal building envelope and optimal HVAC settings and sizes are considered by investigating 24 design variables (Table 6) via a two-step optimisation process. Each step employed about 2000 simulation-runs. The first step addressed the 24 design variables. From the first optimisation step, it is concluded that not all of the 24 design variables have equally significant influence on the results. Some of the design variables (X_4, X_6, X_7, X_8, X_{10}, X_{11}, X_{13}, X_{14}, X_{18}, X_{19}, X_{21}, and X_{22}) have little or no influence on the results in some areas of the solution space. Aiming to improve the quality of the optimisation results, an extended optimisation step (a second step) is implemented considering constant values for those variables. The second step focused only on the 10 variables which have a considerable impact on the three objective functions: minimum percent of set-point deviations based on the S1 definition (Figure 12a), minimum total primary energy demand (summations of heating, cooling,

fan, pump, and artificial lighting energies), and minimum room-cooling equipment size. Constraint function was used to avoid violating the S2 maximum and minimum temperature limits (Figure 12b). Like the concept of PR_GA approach (section 3.1.1), the optimal solutions of the first optimisation step are determined and used to support the initial population of the second optimisation step with good (near-to-optimal) individuals rather than starting with completely random ones. The different between PR_GA and the two-step optimization scheme implemented here is that the later used variant of NSGA-II from MATLAB-2008 in the two optimization steps. PR_GA uses deterministic algorithm in the first optimization step and variant of NSGA-II in the second step.

The design variables can be categorized as the following. Eight design variables for the centralized AHU: two (X_1 and X_2) to define the optimal supply air temperature profile as a function of the outdoor air temperature (ODT); six (from X_3 to X_8) to describe the optimal control strategy for night ventilation (i.e., the night ventilation is enabled only if X_3, X_4, and X_5 conditions are achieved during the period defined by X_7 and X_8). In addition, eight design variables are taken for each of the two representative zones: three (X_9 to X_{11} for the north zone and X_{17} to X_{19} for the south zone) as selection parameters for a suitable cooling beam; three (X_{12} to X_{14} for the north zone and X_{20} to X_{22} for the south zone) to determine the optimal settings for the water radiator; and two (X_{15} and X_{16} for the north zone and X_{23} and X_{24} for the south zone) to specify the window and shading properties. The internal shading type (from light to dark) is considered. The shading type affects the window properties (U-value, solar heat gain coefficient SHGC value, and solar transmittance T-value) by the multiplier factors presented in Figure 14.

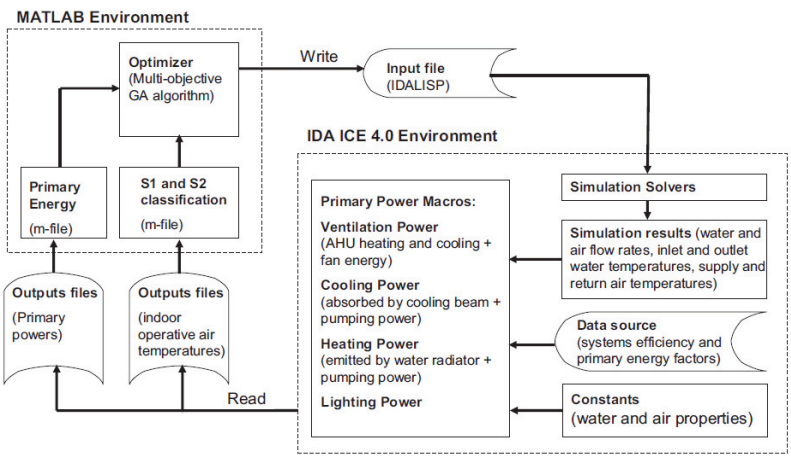


Figure 13. The simulation-based optimisation scheme proposed in Original publication III.

Table 6. Design variables and their lower and upper bounds (LB , UB) in the two-step optimisations

Design variable		X	Description	S1-optimal	S2-optimal	ISO-case
AHU	Supply air temp. profile	X_1	T_s at ODT $\leq$ 16 [°C][a]	16.52	16	16
		X_2	T_s at ODT $\geq$ 24 [°C][a]	18.5	21.5	21.5
	Night ventilation control strategy	X_3	NV is enabled if ODT $\geq X_3$ [°C]	7.75	12	10
		X_4	NV is enabled if T_{exh} – ODT $\geq X_4$ [°C]	2	2	2
		X_5	NV is enabled if $T_{exh} \geq X_5$ [°C]	26.77	23.03	22
		X_6	T_s drop X_6 degree during NV [°C]	10	10	10
		X_7	NV is not enabled X_7 [h] before the occupation	4	4	4
		X_8	NV is not enabled X_8 [h] after the occupation	4	4	4
North Office	Cooling beam	X_9	Max. power of the cooling beam [W]	215	130	160
		X_{10}	dT(coolant) at max power [°C]	3	3	3
		X_{11}	dT(zone air – coolant) at max power [°C]	7	7	7
	Water radiator	X_{12}	Night set-back temperature [°C]	20.07	19.02	18
		X_{13}	Set-point temperature [°C]	21	21	20.5
		X_{14}	Control band [°C]	1	1	1
	Window	X_{15}	Window U-value [W/(m^2 K)]	1.43	1.4	1.5
		X_{16}	Internal shading darkness	Light	Light	Light
South Office	Cooling beam	X_{17}	Max. power of the cooling beam [W]	393	235	280
		X_{18}	dT(coolant) at max power [°C]	3	3	3
		X_{19}	dT(zone air – coolant) at max power [°C]	7	7	7
	Water radiator	X_{20}	Night set-back temperature [°C]	19.87	18.9	18
		X_{21}	Set-point temperature [°C]	21	21	20.5
		X_{22}	Control band [°C]	1	1	1
	Window	X_{23}	Window U-value [W/(m^2 K)]	1.56	1.48	1.50
		X_{24}	Internal shading darkness	Light	Light	Light

[a] A linear relationship is assumed between the supply air temperature (Ts) and the outdoor temperature (ODT), while 16 ≤ ODT ≤ 24.

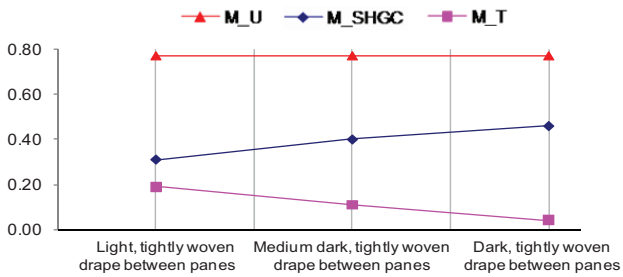


Figure. 14. The assumed multiplier factors of shading type.
Parameters for internal shading (woven drape between panes)
M_U: multiplier for U-value of window glass
M_SHGC: multiplier for solar heat gain coefficient of window glass
M_T: multiplier for solar transmittance of window glass

Two fully mechanically air-conditioned single offices (north and south zones in Figure 15) are taken as representative zones for the one floor studied of a given office building. A detailed simulation model is used to calculate the operative temperature (the measure of the FiSIAQ S1 and S2 definitions) and the energy requirements in the two representative zones during the simulated period (from February 1 to July 31). The six month period was sufficient to assess the indoor operative temperature at different whole-year outdoor conditions. Running the six-month simulation instead of the twelve-month one reduced the simulation time and consequently the optimisation time by about 40%. The execution time of one simulation run was between 11 and 17 min, depending on the design variable combination.

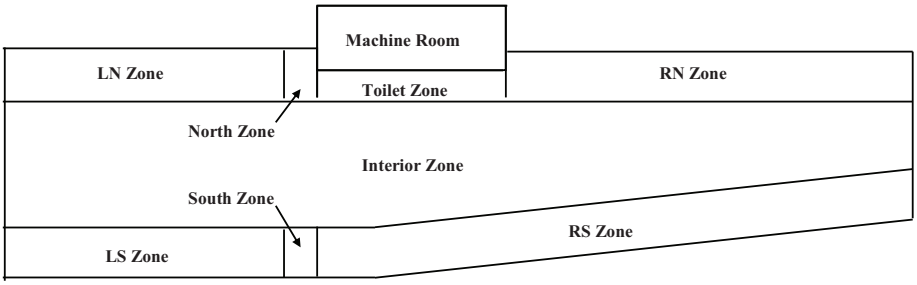


Figure. 15. North and south representative zones for a one-story office building.

Taking into account the possible implementations of ESMs, the simulation-based optimisation scheme succeeded in determining the optimal trade-offs between the objective functions: 1 and 2 (Figure 16a) as well as 1 and 3 (Figure 16b). Although there was no obvious trade-off between the second and third objectives, it was important to consider them as objectives to be minimized against minimizing the discomfort sensation (objective 3). The solutions that satisfy the minimum thermal comfort requirements of S1 and S2 classes with minimum energy demand and minimum room cooling-equipment size are selected as S1 and S2 unique solutions, respectively. The solutions show that, on average, an additional 10 kWh/(m^2 a) primary energy demand and a larger 10 W/m^2 room-cooling equipment size are required to improve the thermal comfort from the medium (S2) to the high-quality (S1) class; higher thermal comfort levels limit the use of night ventilation and water radiator night temperature set-back options. Compared with the ISO EN 7730-2005 standard, the Finnish criterion could reduce the heating/cooling equipment size slightly. However, it significantly increases both the heating and cooling energy demand; the results show a 32.8% increase in the primary energy demand (Table 7). It is concluded that the Finnish classification-2008 is strict and does not allow for energy-efficient solutions in office buildings with standard heat surges and a tight building envelope, particularly if a free cooling option is not applicable. The S1 class limits the applicability of night ventilation and the night set-back temperature as energy-saving measures (small early morning overcooling due to the use of night ventilation and/or night temperature set-back is inconsistent with the strict S1 requirements). Moreover, maintaining a narrow temperature range (S1) requires more accurate control instruments than maintaining a broad range (S2). This invites questions. Is the so-called S1-class thermal environment worth its inherent energy penalty and its inherent control complexity? Is it even more comfortable than S2-class in a realistic environment?

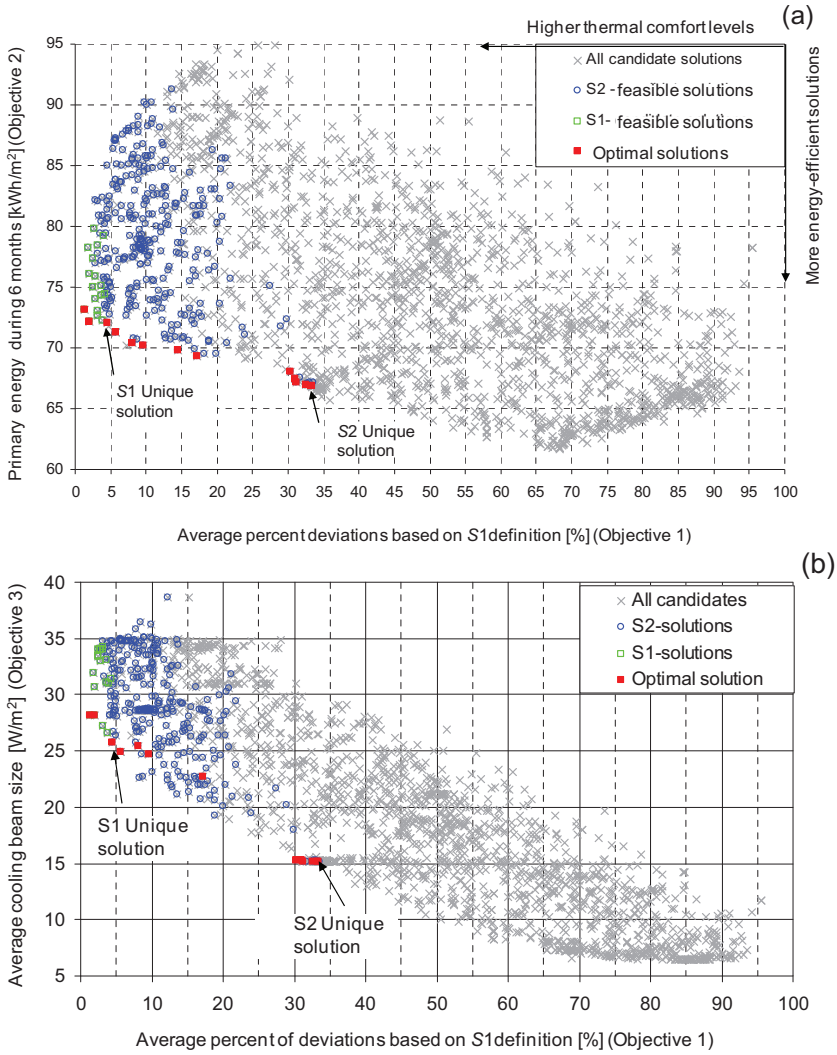


Figure. 16. The optimal trade-off relations between the thermal comfort level (average percent deviations based on the FiSIAQ S1-definition) and the total primary energy consumption (a) and the room-cooling equipment size (b). The S1 and S2 unique solutions are the ones which achieve the S1 and S2 definitions (Figure 12 a and b, respectively) with minimum energy requirements.

Table 7. The annual primary energy demand

Design	Thermal comfort Criterion	The annual primary energy demand [kWh/m^2]							
		Cooling			Heating			Electricity	Total
		Space	AHU	Total	Space	AHU	Total	Fan	HVAC
ISO-case	ISO EN 7730-2005 (Category B)	8.4	2.7	11.1	10.8	10.6	21.4	22.6	55.1
*S2-optimal unique solution**	Finnish adaptive criterion-2008 (Class *S*2)	22.1	2.6	24.7	15.4	11.8	27.2	21.4	73.3
Percentage of energy increase [%] ISO-case 100%		163	-3	122	42	11	27	-6	33

* S2-optimal unique solution (Figure 16) is the solution that achieves the S2-definition (Figure 12b) with minimum primary energy consumption and room-cooling equipment size.

3.4 Proposing an optimisation method for a cost-optimality calculation in line with the framework of EPBD-recast 2010 (Original publication IV)

According to the European Energy Performance of Buildings Directive (EPBD 2010/31/EU), 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. Higher energy performance requirements (like nearly-zero-energy building nZEBs requirements) should also be economically feasible. The EPBD indicates that all new buildings should be nZEBs by the end of 2020, and two years prior to that all pre-existing public buildings should be as well. Finding cost-optimal solutions for minimum energy performance and nearly-zero-energy buildings is an arduous task. According to the EPBD, the cost-optimal solutions should be found among ranges of combinations of compatible energy efficiency and energy supply measures. These combinations should range from those in compliance with the current regulations to combinations that realise nZEBs. Those should also include various options for renewable energy generation. Finding optimal solutions requires assessing the environmental and economic viabilities of all possible compatible designs. Figure 17 shows the cost-optimal curve that would be found from the assessment where the environmental and economic viabilities are presented in terms of PEC (Primary Energy Consumption) and dLCC (Difference in Life Cycle Cost) per one square meter of a building, respectively. The dLCC is the difference between the LCC for any design and that for the reference one. The lowest part of the curve (the economic optimum) is the cost-optimal solution. 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 towards nearly-zero energy buildings, where the extreme left of the curve is the nZEB optimal solution.

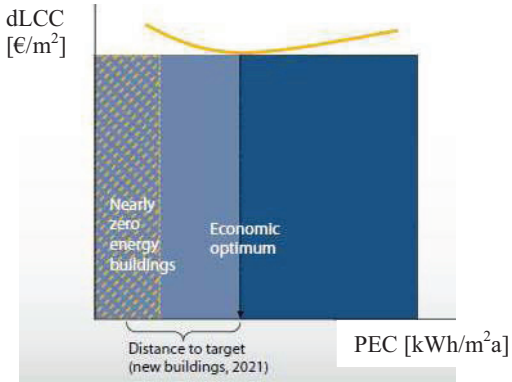


Figure 17. Cost-optimal curve

One of the main challenges of the EBPD-2010 calculation methodology is ensuring that on the one hand, all ESMs with a possible impact on the primary or final energy use of a building are considered, whilst, on the other hand, the calculation exercise remains manageable and proportionate [EC. 2011]. Applying several options for many variants could offer millions of design solutions. In order to limit the number of solutions, the guideline of the EBPD draft [EC. 2011] proposes to address a matrix of energy efficiency packages, which rules out mutually exclusive technologies. For instance, a heat pump for space heating (*SH*) does not have to be assessed in combination with a high-efficiency boiler for space heating as the options are mutually exclusive and do not complement each other. The possible energy efficiency measures and measures based on RES (and packages/variants thereof) can be presented in a matrix, with unfeasible combinations eliminated. This approach cannot guarantee global cost-optimal solutions because it explores only some of the available combinations of design options. Furthermore, considerable effort and experience are needed to determine correctly which options to rule out. To establish a comprehensive overview, all combinations of commonly used and advanced measures should be considered. Stochastic methods are a promising means of investigating a huge number of combinations. However, they should be employed under a suitable scheme. The aim of Original publication IV is to introduce a suitable optimisation methodology which provides efficient, transparent and time-saving explorations in line with the EPBD-recast 2010.

Efficient exploration is performed by combining efficient optimisation approach (PR_GA) and detailed simulation programs.

- **Transparent exploration** is presented via multi-stage optimisation showing the effect of the design-variable combinations.
- **Time-saving exploration** is achieved via speeding up the exploration by avoiding the unrealistic/unfeasible design-variable combinations and using pre-simulated results instead of running time-consuming simulation (when possible).

3.4.1 A multi-stage optimisation method for efficient, transparent, and time-saving explorations

In order to find a cost-optimal curve (an optimal trade-off relation between PEC and dLCC, Figure 17) for a single-family house in Finland, a multi-stage optimisation 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). 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 realise nZEBs (e.g., passive house U-values [RIL. 2009], photovoltaic and solar thermal collectors). The variables include a number of external wall, roof, and floor 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 Original publication IV. According to the National Building Code of Finland C3-2010, a reference design is built. The life cycle costs of the candidate solutions are calculated relative to the reference design one using the term of dLCC.

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 which influence the thermal performance (heating, cooling and comfort) of the house, i.e., building envelope parameters and a heat recovery unit.
- ***Stage* 2** assesses the economic and environmental viability of implementing the offered primary heating/cooling systems to the optimal combinations (packages) found in *Stage* 1.
- ***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 RESs as supplementary systems.

Table 5. Design variables

	DESIGN VARIABLE	DESCRIPTION	OPTIONS
1	U-value of the external wall [W/m^2.K]	From 0.17 to 0.07	16
2	U-value of the ceiling [W/m^2.K]	From 0.09 to 0.07	8
3	U-value of the floor [W/m^2.K]	From 0.17 to 0.08	13
4	Building tightness levels [1/h]	2, 1, 0.5	3
5	Window type (all with Wood-aluminium frames)	Triple-Laminated glass (Air gas), Triple-Laminated glass (Argon gas), or Quadruple Laminated (Argon gas)	3
6	Shading type	External blind, horizontal laths, Blind between the outer panes, horizontal laths, Blind between the inner panes, horizontal laths, or Internal blind, 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 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

The aim of *Stage* 1 is to find representative energy-efficient building designs, disregarding 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) of the influencing measures (insulation, building tightness, window type, shading method and heat recovery type) are minimised, while a penalty function is applied when the summer-comfort criterion ($DH_{27} \geq 150$ ^oC h) is violated. The minimisation work is performed by the proposed PR_GA optimisation approach (section 3.1.1). Thermal demand is minimized because it is the major demand in residential buildings, particularly in the cold-climate EU countries [Bianchi et al. 2011]. The PW presents the initial and replacement costs (IC and RC) of the addressed measures

$$\text{PW}=\sum_{i=1}^{5} IC_i + \sum_{i=1}^{5} RC_i \qquad (2)$$

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

$$DH_{27} = \sum_{i=1}^{i=8760} dT_{27}\Delta t$$

$$dT_{27} = (T_i - 27) \qquad T_i - 27 > 0$$

$$dT_{27} = 0 \qquad \text{when } T_i - 27 \leq 0 \qquad (3)$$

where T_i is the mean air temperature [°C] at the warmest zone (upper floor) and Δt is a one-hour time period [h].

Figure 18 presents the optimisation 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 above influencing ESMs. Group 1 presents the optimal building designs which satisfy the summer overheating criterion (equation 3), while Group 2 presents the ones that do not fulfil the criterion. Groups 1 and 2 consist of 19 and 13 solutions, respectively. Group 2 packages are not eliminated as non-comfort solutions, because they could be feasible when the mechanical cooling method is added. In term of LCC, implementing RES (e.g., photovoltaic) could improve the economical 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 optimisation stages 2 and 3, respectively.

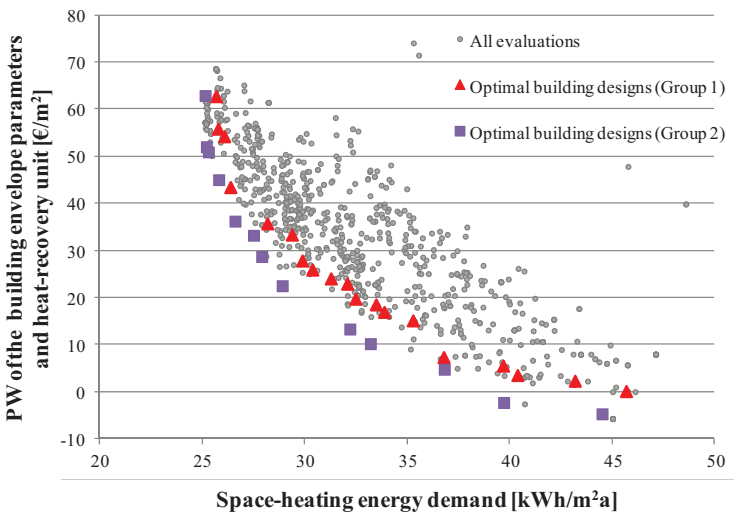


Figure 18 *Stage* 1 optimisation results [Original publication IV]

Figure 19 presents the results of *Stage* 2. The results are the dLCC and PEC of *Stage* 1 optimal solutions (Group 1 and 2; Figure 18) when the offered primary heating systems (direct electrical, district heating, oil fire boiler, and GSHP) are installed. In line with the draft's cost-optimal regulation [EC. 2011], 3% real interest rate (r) and 2% energy price escalation rate (e) are used. Primary energy factors, efficiencies, capital and service costs, subscription fees, and energy prices (Table 6) are used to calculate *Stage*-2's results. 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 ^{o}C indoor temperature set point, reduced the DH_{27} (equation 3) of the Group 2 solutions from > 150 ^{o}C.h to zero.

Table 6. Primary heating systems [original publication IV]

System	Capital Cost [€]	Service cost [€/a]	Subscrip-tion fee [€/a]	Energy Price [c/kWh]	η_{SHS} [%]	η_{DHWS} [%]	η_{dist} [%]	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 c/kW) on weekdays, from Monday to Friday, 7 am. - 8 pm. The price of night-time electricity (10.9 c/kW) at other times
b) Beside the 83 € annual fee of electrical connection, 321 € is added for district heating connection

Figure 20 presents improving the environmental viability of *Stage*-2 building envelope and HVAC-system optimal solutions (Figure 19, front 1 and 2) by implementing optimal sizes of RES systems (Solar-thermal and Photovoltaic collector areas). A simulation-based optimisation model is developed, using MATLAB 2008b and IDA ESBO (a building performance simulation program which 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 m^2 solar-thermal collector areas and from 0 to 71 m^2 Photovoltaic module areas). The optimisation is performed by PR_GA approach introduced in section 3.1.1.

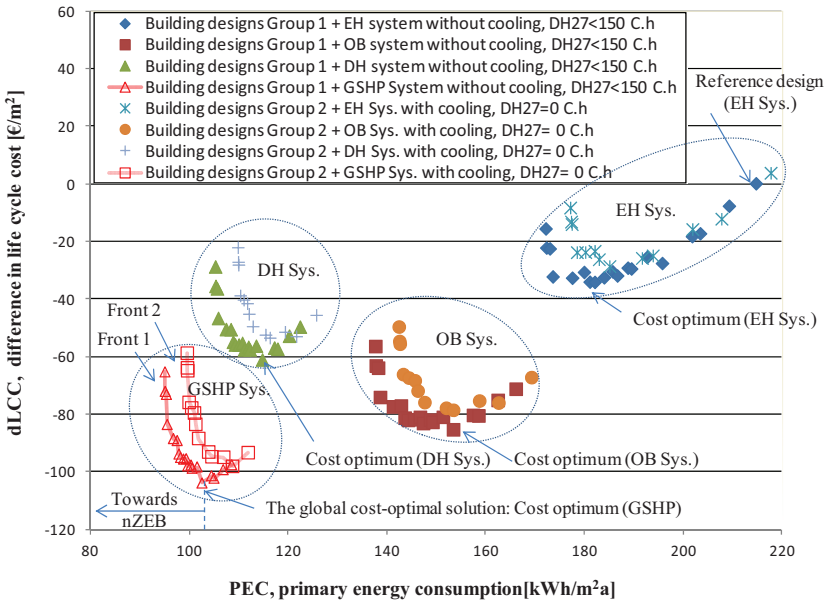


Figure 19 Stage-2 post-processing results [Original publication IV].

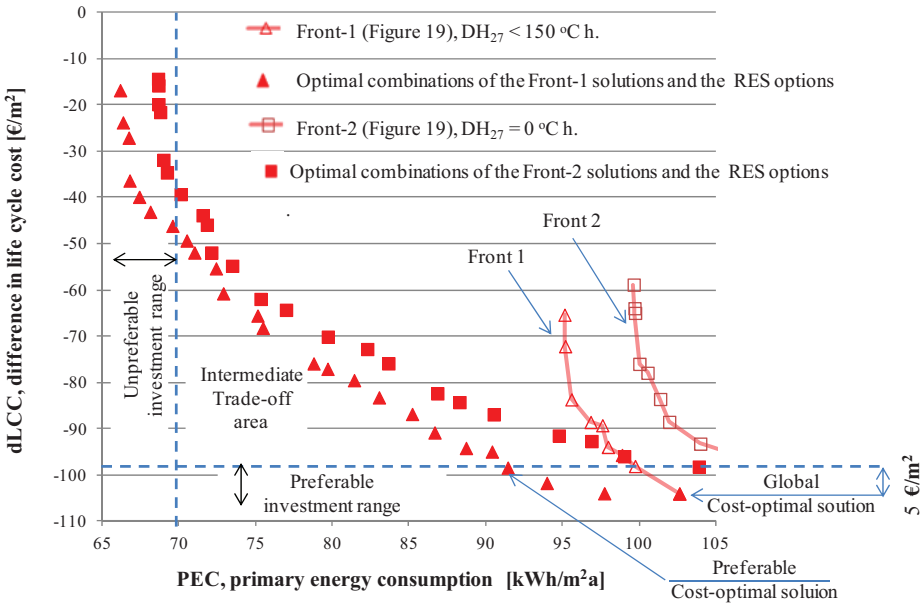


Figure 20 *Stage*-3 optimisation results [Original publication IV].

According to the Directive 2010/31/EU, the minimum LCC solution (global cost-optimal solution) determines the minimum energy performance requirements. However, a slightly higher LCC solution could be preferable if it reduces the PEC significantly. Figure 20 shows the global and preferable cost-optimal designs. The difference between the LCC of the cost-optimal solutions is 5 €/m^2. Based on the resulted global and preferable cost-optimal solutions, the minimum energy performance level should be 103 or 92 kWh/m^{2}a of primary energy, respectively. The cost-optimal levels are respectively 40% and 47% lower than the 172 kWh/m^{2}a (372 -1.4 × $Area_{house}$) level, which was implemented this year by the Finnish code D3-2012 [D3. 2011].

3.4.2 Proposing a transparent analysis method: visualising the optimisation results by Pareto-optimal front and scatter plot with common x-axis

In order to analyse the integrated optimal solutions (optimal combinations of the Front-1 solutions and the RES options, Figure 20), a Pareto-optimal front and scatter plot is used to visualise the influence of the design variables on the objective functions (dLCC and PEC), Figure 21. The optimisation history and the Pareto-optimal front are shown in Figure 21a. The values of the design variables among the Pareto-set are shown by scatter plot Figure 21b. The plot presents the Front-1 solutions by their space-heating energy-saving percentage relative to the reference design [%] and the RES options (solar-thermal and photovoltaic area) by their sizes [m^2]. The same approach is used to present the preferable cost-optimal integrations of ESMs and RES options at different energy price escalation rates (Figure 22). Figure 22 is produced by running the proposed three optimisation stages assuming different energy price escalation rates (from 1 to 15%).

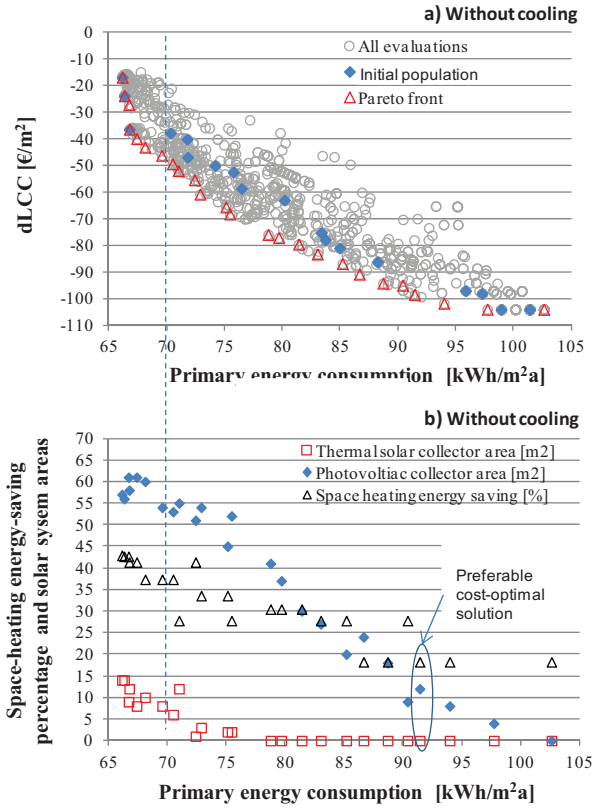


Figure 21 Pareto-optimal front (a) scatter plot (b), [Original publication IV].

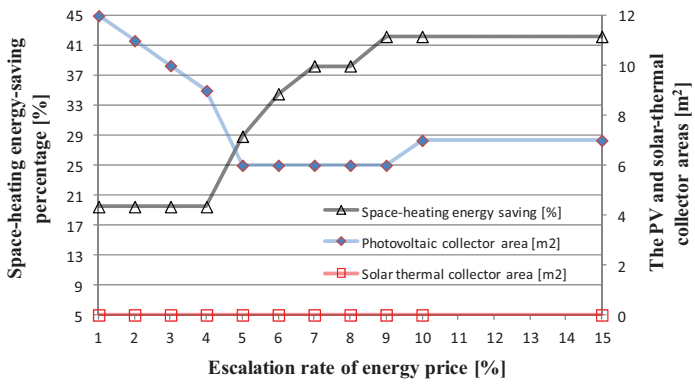


Figure 22 Preferable cost-optimal integrations of ESMs and RES options at different energy price escalation rates [Original publication IV].

3.4.3 Concluding cost-optimal solutions for high-energy-performance dwellings located in Finland

Publication IV's results show that for a single-family house in the cold climate of Finland:

• The financial and the environmental aims do not necessarily contradict each other. The achieved preferable cost-optimal solutions, at different energy price escalation rates (from 2 to 15%) and a calculation period of 30 years, have primary-energy consumption around 47% lower than the D3-2012 standard value (172 kWh/m^{2}a).

• The cost-optimal implementations of ESMs and RES methods depend on the installed heating/cooling system and its energy-price escalation rate. For a cost-optimal operation, a building with a fully electrical heating system requires more ESMs (e.g., additional insulation) than a building heated by a GSHP or fuel-based heating systems (e.g., OB and DH). PV sizes up to 20 sq.m. and 15 sq.m. are preferable cost-optimal options for houses with high electrical energy demands: houses with a mechanical cooling option and a direct or indirect electrical heating system (EH and GSHP), respectively. Smaller PV sizes (up to 5 sq.m.) are economically feasible for houses without a mechanical cooling implementation and fuel-based heating systems. Solar-thermal system is not a cost-optimal solution, particularly for houses heated by fuel-based heating systems. The solar-thermal system has a lower economic viability than the PV system because the latter reduces the most expensive energy source (electrical energy). The solar-thermal system not only increases the investment cost but also the replacement one. The life-span of a solar-thermal collector is often shorter than that of a PV one. For nZEB solutions, a solar-thermal system with collector up to 15 sq.m is economically feasible.

• The cost-optimal combinations of space-heating ESMs depend on their influence on summer overheating. Measures which significantly increase summer overheating (e.g., inefficient shading methods) are not preferable from an economic point of view because they could lead to a need for mechanical cooling.

• Mechanical cooling is not a cost-optimal option. It increases not only the investment cost but also the operating cost. Proper shading and building tightness as well as natural cooling via operable windows can eliminate the summer overheating risk. The economical feasibility of the mechanical cooling option becomes close to optimal when it is integrated with a sufficient size of PV for free electricity from solar panels.

• Higher energy-price escalation rates encourage investments in RES and/or ESMs options. This is limited by the energy-saving potential of the options. For instance, increasing insulation to ''the

passive house U-values'' is not a cost-optimal option because it has a limited influence on the space-heating energy saving. A lower insulation level is the cost-optimal one.

• Currently, on-site solar systems cannot contribute as a part of a global cost-optimal solution because of their expensive capital costs. However, small PV sizes can compete with the ESMs for achieving energy performance levels higher than the global cost-optimal one, with a slight increase in the LCC.

• From the economic point of view, it is viable to achieve nZEB with primary-energy consumption up to 70 kWh/m^{2}a. Economical and environmental incentives/credits are required to improve the economic feasibility of solutions towards net-zero-energy building.

3.5 Proposing an algorithm for improving the optimisation performance of building design: aNSGA-II (Original publication V)

As mentioned in section 3.1, the original NSGA-II does not keep all potentially Pareto-optimal solutions during the optimisation process because of its limited population size. In order to avoid this, Original publication V combined the original NSGA-II with an active archiving strategy. The combination is called aNSGA-II. The active archive strategy not only keeps all the non-dominated points that would be rejected by the original NSGA-II, but also participates in the solution generation procedure. The saved non-dominated points supplement the diversity and allow the use of a small parent population size (e.g., 6 individuals). When the size of the parent population is small, high-quality (non-dominated) solutions are used more frequently than dominated solutions. This is expected to increase the rate of convergence of the true Pareto-optimal solutions. The other advantage of the proposed active archiving strategy is that it reduces the random behaviour of the original NSGA-II. The strategy increases the repeatability of the optimisation results, particularly in cases in which only low numbers of iterations are allowed. Building simulation is often time-consuming. Therefore, a large number of iterations (simulations) is not practically feasible for building design.

Compared with the original NSGA-II and pNSGA-II (original NSGA-II with passive archive that only keeps all the evaluated solutions), the performance of the aNSGA-II is evaluated in terms of

- Convergence to the Pareto-optimal set (Generational Distance), denoted by the GD,
- Diversity of solutions in the Pareto-optimal set, denoted by DIV, and
- Number of solutions on the Pareto-optimal set, denoted by NS.

The Generational Distance GD [Deb, 2001] is used as the convergence metric. The metric finds an average Euclidean distance between the true Pareto-optimal front P* and the solution set *S* obtained by each algorithm and as follows:

$$\text{GD} = \sum_{i=1}^{|S|} d_i \frac{1}{|S|} \qquad (4)$$

where d_i is the Euclidean distance (in the objective space) between the solution $i \in S$ and the nearest member of P^*.

The Diversity of the solution set returned by the algorithm *DIV* is measured using a diversity metric from [Deb et al, 2002]:

$$\text{DIV} = \frac{d_f + d_l + \sum_{i=1}^{N-1} | d_i - \bar{d} |}{d_f + d_l + (N-1)\bar{d}} \qquad (5)$$

where d_i is the Euclidean distance between the consecutive solutions in the obtained non-dominated set of solutions and $\bar{d}$ is the average of all distances d_i (i=1,..,N), assuming there are N solutions in the obtained non-dominated set. The parameters d_f and d_l are the Euclidean distances between the extreme and the boundary solutions. This metric gives smaller values to the better distributions. The number of the obtained non-dominated solutions (P^* members) are denoted by *NS*.

The three algorithms (original NSGA-II, pNSGA-II, and aNSGA-II) are tested in a problem to find the optimal trade-off relationships between the difference in life cycle cost (dLCC) and the primary energy consumption (PEC) of a single-family house located in Finland (Figure 23). The objective functions (dLCC and PEC) comply with the European Energy Performance of Buildings Directive (EPBD, 2010), see Figure 17. Table 7 presents the upper and lower bounds of the addressed design variables. The problem is performed by using the simulation-based optimisation scheme shown in Figure 24. The energy performance of the integrated solutions is evaluated by a simple simulation model which is developed using MATLAB R2008b. The MATLAB model has a simple one-node water storage tank. The model is based on pre-simulated results of the three designs of the building envelope and pre-evaluated performances of the energy source systems. The simulation is kept relatively simple in order to speed up the comprehensive analysis process. The aim of the Original publication V is to test aNSGA-II algorithm, rather than to answer particular questions about building design. The simplified model provides very fast

simulations (< 2 sec per simulation) and allows a comprehensive search for the true-Pareto-optimal front, which will be used for the validation of the results of the three tested algorithms. The true Pareto-optimal front is found by an exhaustive search evaluating 1,306,368 (3×4×2×4×3×21×6×6×6) combinations of the design-variable options.

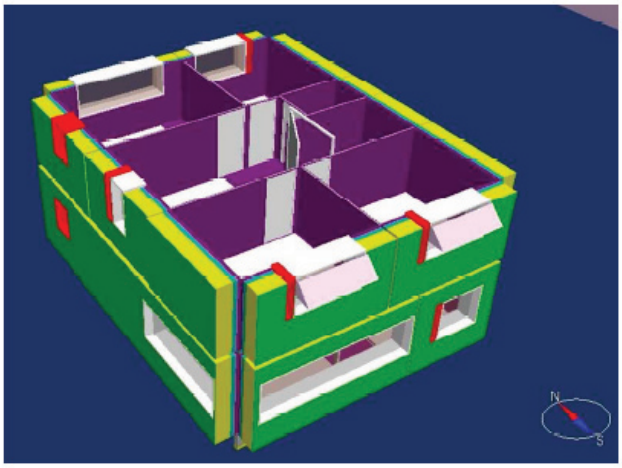


Figure 23. The studied single-family house in cold climate of Finland (156 m^2 total floor area).

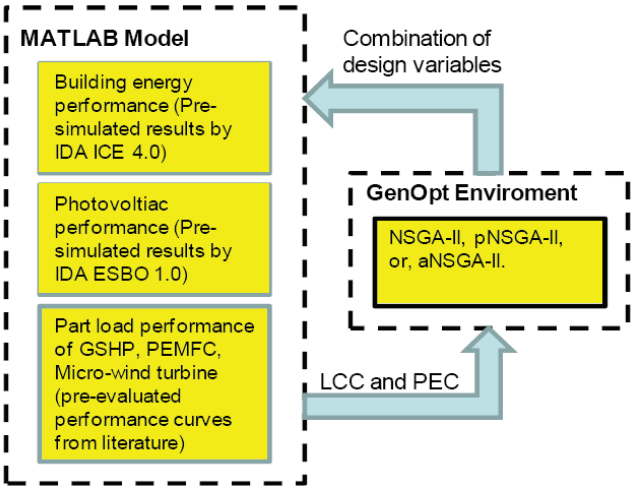


Figure 24. Simulation-based optimisation scheme.

Table 7. The Design variables.

DESIGN VARIABLES	OPTIONS
Building envelope	C3-2010, low energy, or passive house
Type of primary heating unit (HU-1)	Indirect electrical heating, District heating, GSHP, or PEM fuel cell
Type of auxiliary heating unit (HU-2)	Electric heater or gas boiler
Size of μWT [W]	0, 120, 400, or 950
Heat recovery efficiency η	60, 70, or 80 %
Photovoltaic area [m^2]	From 0 to 60 m^2(3 m^2step)
T_{out} from HU-1 [^oC]	40, 44, 48, 52, 58 or 60 ^oC
Size of the heating coil of the DHW tank (% of the max. size)	50, 60, 70, 80, 90, or 100 %
Size of HU-1 (% of the peak heating load)	50, 60, 70, 80, 90, or 100 %

In terms of GD, Figure 25 shows that aNSGA-II has better repeatability to converge to a close-to-optimal solution set than original NSGA-II and pNSGA-II, using a low number of simulations (180). A smaller GD value yields better convergence to the true Pareto-optimal front. Figure 26 presents the best and worst convergence cases of 100 optimisation runs, which were achieved by using the three optimisation algorithms. The figure shows that at the two cases aNSGA-II achieve a better solution set than the two others. Table 8 presents the divergence DIV and the number of solutions NS on the Pareto-optimal front in the best and worst convergence runs. These results show that pNSGA-II and aNSGA-II produce a larger number of solutions on the Pareto-optimal front NS than the original NSGA-II. Hence, it is not fair to compare GD and DIV of NSGA-II with those of the other two algorithms. However, pNSGA-II and aNSGA-II can be compared with each other because they have a close number of solutions. It worthwhile to mention that aNSGA-II finds a denser Pareto-optimal front than NSGA-II. However it is likely to more computationally expensive. It deals with a larger number of solutions (the archive as well as the new population members). Hence all computations for domination check and crowding distance would be more expensive.

From Figures 25 and 26, we can conclude that aNSGA-II has better convergence. This is because aNSGA-II continues to converge during the optimisation process while NSGA-II and pNSGA-II create oscillating estimates of the true Pareto-optimal front. The diversity of the two algorithms with the archive strategies is quite close (Table 8). The diversity metric DIV is affected by NS, the number of solutions obtained on the non-dominated front, because DIV gives lower values for lower numbers of NS. This can be seen in Table 8, where the original NSGA-II algorithm yielded the lowest value with six points and aNSGA-II got the highest value with 22 points. Besides, the shape of the true Pareto-optimal front in

the optimisation problem is disconnected and the distribution of the disconnected regions is not uniform, which affects the diversity metric as well. The influence of increasing the number of the generations on the convergence is shown in Figure 27. Assuming a fixed population size (six individuals), 100 optimization runs are repeated at different number of generations. It is clear that generational Distance (GD) for the three algorithms is decreasing with increasing the number of the generations. However, the performance of the aNSGA-II is progressively improving with increasing the number of the generations, while the other two algorithms appear to be unstable in this respect. Because of the limited population size, the original NSGA-II could loss potential Pareto-optimal solutions during the optimization runs. Increasing the number of generations could not resolve this problem. Using a large number of generations increases the pNSGA's solutions. This could lead to deceptive large value of average-GD. The advantage of aNSGA-II algorithm is confirmed using complex Bi-objective benchmark test problems (ZDT2 and ZDT3) created by Zitzler, Deb and Thiele (Deb. 2001). Further work is required to compare aNSGA-II with the other optimisation approaches (PR_GA, GA_RF, and PR_GA_RF) introduced in this thesis.

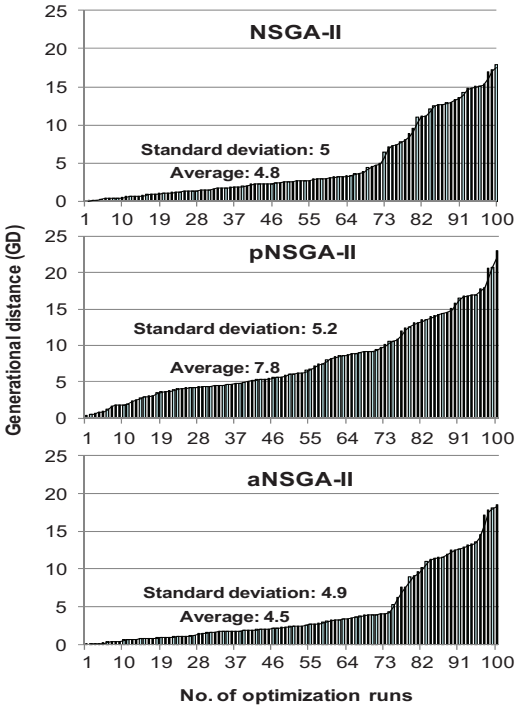


Figure 25 Convergence metric (GD) for 100 optimisation runs, implementing 180 simulations in each run (Original publication V).

Table 8 DIV and NS achieved in the best and worst convergence runs using 180 simulations in each run (Original publication V).

ALGORITHM	*BEST RUN*		*WORST RUN*	
	DIV	*NS*	*DIV*	*NS*
NSGA-II	0.55	6	0.81	6
pNSGA-II	1.27	22	1.31	18
aNSGA-II	1.35	24	1.07	22

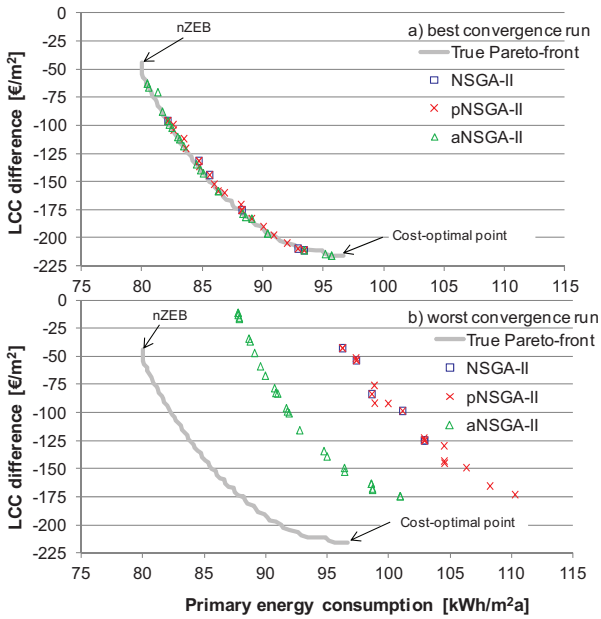


Figure 26. True Pareto-optimal front and found solutions at (a) the best and (b) the worst convergence runs in 100 optimisation runs [Original publication V].

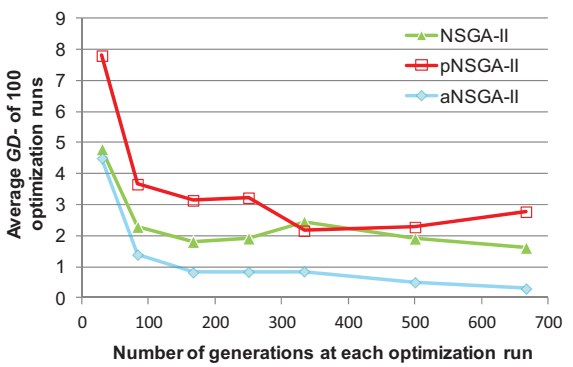


Figure. 27. Average GD of 100 optimisation runs applying different number generations [Original Publication V].

4. Summary of the new contributions

This section summarises the new contributions introduced in our original publications (I, II, III, IV, and V). In general, four multi-objective multivariate approaches (PR_GA: section 3.1.1, GA_RF: section 3.1.2, PR_GA_RF: section 3.2.1, and aNSGA-II: section 3.5) are proposed for improving the optimisation performance (speed and quality) of building design. Two approaches (Pareto-optimal front and bar chart with double arrow: section 3.2.2, and Pareto-optimal front and scatter plot with common x-axis: section 3.4.2) are introduced for visualising and analysing the optimisation results. The feasibility of applying the approaches is demonstrated by five case studies (original publications I, II, III, IV, and V) addressing several objective functions, different levels of constraint functions: section 3.2, and a large number of design variables. The case studies succeeded in finding the optimal trade-off relations between conflicting objective functions such as ‘‘energy consumption, net primary energy consumption, or CO_2-equivelient emission’’, ‘‘initial cost or life cycle cost’’, ‘’equipment size’’, and ‘’thermal comfort level’’. The solution-space of the case studies includes a wide range of discrete and continuous design variables (e.g., wall, roof, floor insulation thickness, window type, building tightness level, shading type, equipment size, night ventilation control strategy, HVAC settings, and energy supply systems including renewable energy sources). The use of a simulation-based optimisation approach is extended from just finding optimal solutions to assessing the impact of different thermal comfort levels on building energy use and cooling equipment size: section 3.3. This section addresses new adaptive thermal comfort criteria for fully mechanical buildings in Finland. One of the most important contributing factors of this thesis is introducing an efficient, transparent, and time-saving multi-stage optimisation method in line with the cost-optimality framework calculation of the EPBD 2010/31/EU: section 3.4. The above contributions can be considered as seeds for developing a generic simulation-based optimisation design tool for solving building design problems.

5. Conclusions

The potential of multi-objective simulation-based optimisation approach is not sufficiently exploited in current building design practice. The thesis argues that this field of engineering requires a special setup of the optimisation model that considers the uniqueness of buildings and HVAC, and allows the designer to trust an analysis of the optimisation results. Evolutionary algorithms such as (NSGA-II) are efficient to handle multi-criteria multivariate building design problems. However, there is a potential for improving their performance (speed and results quality) by combining them with deterministic algorithms and/or suitable archiving strategies (Original publications I, II, V). Exploring all of the design variables in a single optimisation step could lead to running unrealistic/incompatible solutions (Original publication II, III). This extends the optimisation time and increases the analysis effort. Multi-stage optimisation can reduce the computational effort and provide a transparent analysis (Original publication III, IV). In publication IV, a multi-stage simulation-based optimisation method is introduced for efficient, transparent and time-saving explorations. With such an optimisation method, a huge solution space with more than 3×10^9 possible design solutions are explored efficiently and transparently by only about 3000 evaluations. The method combines parametric modelling, performance simulation software, and deterministic and genetic algorithms, together with archive to store and retrieve the solutions for subsequent exploration. Combining NSGA-II with an active archive strategy (aNSGA-II) is a promising algorithm for time-efficient building optimisation (Original publication V). The algorithm has a high repeatability rate to converge to optimal or close-to-optimal solutions using relatively a small number of iterations.

The new contributions of the thesis (improving the optimisation performance and proposing transparent analysis methods) are required to reduce the computational effort needed for exploring the economic and environmental viabilities of the growing number of ESMs and RESs seeking optimal high-energy-performance buildings.

6. Future research

Building design is an inherently multi-objective process, there being a trade-off to be made between two or more conflicting design objectives (such as minimizing both life cycle cost and primary energy consumption). Evolutionary algorithms such as (NSGA-II) seem to be efficient for such optimization tasks. However, research (e.g., this thesis) shows potential for improvement. The most suitable multi-objective optimization algorithms for solving multi-criteria multivariate building design problems have not been determined yet. Our future research will compare between existing optimization algorithms/approaches such as: Strength Pareto Evolutionary Algorithm (SPEA-2 [Zitzler et al., 2001]), Multi-Objective Particle Swarm Optimization (MOPSO [Coello, 2002]), MOEA/D [Zhang and LI 2007], a two-step (deterministic then stochastic) optimization approach (PR_GA [Hamdy et al., 2009]), Elitist Non-Dominated Sorting Genetic Algorithms - based on NSGA-II by [Deb et al. 2001] - with passive and active archives (pNSGA-II and aNSGA-II [Hamdy et al., 2012], respectively), and Many-Objective NSGA-II (MO-NSGA-II [Deb 2012]) in terms of

1- Computation time,
2- Solution repeatability,
3- Number of non-dominated solutions,
4- Convergence to Pareto front (Generational distance), and
5- Size of the explored solution-space (Hyper-volume).

The comparisons will address complex building design problems with large solution spaces consist of different energy generation systems (e.g., micro combined heat and power systems, roof-mounted wind turbine, photovoltaic PV, solar thermal collectors), control strategies (e.g., thermal tracing, electrical tracing, and constant operation, seasonal operation), and energy saving measures (e.g., heat recovery units, LED lighting, better building envelops). Multi-criteria Decision Making (MCDM) techniques will also be investigated. A two-stage approach (optimization first, decision making next) may not always be a computationally fast approach. Since building design considerations are bound to have some uncertain parameters (fluctuations in wall thickness, energy costs, etc.) which should be better treated as non-deterministic variables or parameters. Stochastic Optimization methods that handle such uncertainties (aleatory or epistemic) are in the plan to handle such cases for a more robust building design task.

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Responding to the international calls for high energy performance buildings like nearly-zero-energy buildings (nZEB), recent years have seen significant growth in energy-saving and energy-supply measures in the building sector. A detailed look at the possible combinations of measures indicates that there could be a huge number (possibly millions) of candidate designs. In exploring this number of designs, looking for optimal ones is an arduous multi-objective design task. Buildings are required to be not only energy-efficient but also economically feasible and environmentally sound while adhering to an ever-increasing demand for better indoor comfort levels. The current thesis introduces suitable methods and techniques that attempt to carry out time-efficient multivariate explorations and transparent multi-objective analysis for optimizing such complex building design problems. The thesis's experiences can be considered as seeds for developing a generic simulation-based optimisation design tool for high-energy-performance buildings.

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