MŰEGYETEM 1782

Budapest University of Technology and Economics
Faculty of Architecture
Csonka Pál Doctorate School
Department of Mechanics, Materials and Structures
Faculty of Civil Engineering
Department of Construction Materials and Technologies

Multi-Objective Environmental Optimization of Buildings

Short summary of the dissertation submitted to the
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Benedek György Kiss

Supervisor:
Zsuzsa Szalay, PhD

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ABBREVIATIONS

ADP	Abiotic Depletion Potential
AP	Acidification Potential
BAU	Business as Usual
BIM	Building Information Modelling
CED	Cumulative Energy Demand
DP	Distance to Pareto-front
EEMM	European Electricity Market Model
EP	Eutrophication Potential
GHG	Greenhouse Gas
GWP	Global Warming Potential
IEA	International Energy Agency
IP	Improvement Potential
LCA	Life Cycle Assessment
LCC	Life Cycle Cost
LCIA	Life Cycle Impact Assessment
MOOP	Multi-Objective Optimization Problem
ODP	Stratospheric Ozone Depletion Potential
PPI	Pareto Position Index
PSI	Pareto Spread Indicator

TERMINOLOGY

Business-as-usual (BAU) - cases during the optimization that reflect the current practice in the construction industry. These cases serve as the reference for determining the improvement achieved through optimization. The cases are manifested in specific limited value ranges for the optimization variables.

containerization - software technology that refers to an OS-level virtualization method used to deploy and run distributed applications without launching an entire virtual machine.

decarbonization - the effort to reduce the greenhouse-gas emissions attributed to the electricity production.

dominated solutions - those solutions of a multi-objective optimization, for which at least one other solution exists in the same objective space that is better in *all* objective values.

elitism - a widely used strategy in the selection of good solutions in stochastic multi-objective optimization. Best solutions from a calculated set of solutions (population) are transferred directly to the next generation without further judgement or modification (mutation).

embodied impact - environmental impact that is caused during the production and construction of the building.

Global Warming Potential (GWP) - widely used environmental indicator, that expresses the impact of human emissions on the radiative forcing of the atmosphere and is often referred to as “climate change”. GWP is expressed in kilograms of carbon-dioxide equivalents *(kgCO2-eq.)* by applying characterization factors to certain emitted greenhouse-gases.

Life Cycle Cost (LCC) - widely used economic indicator, often referred to as “global cost”. It means the sum of the present value of the initial investment costs, sum of running costs, and replacement costs (referred to the starting year), as well as disposal costs if applicable.

lifecycle environmental impact and cost - the environmental impact and cost of a product (e.g., the building) considering all life-cycle phases from cradle to grave (e.g., the production of construction materials, the operation, and the decommissioning of the building etc.).

non-dominated solutions - those solutions of a multi-objective optimization that are not dominated by any other solution. Non-dominated solutions are Pareto-optimal within the evaluated set.

NSGA-II - Non-dominated Sorting Genetic Algorithm – a widely used stochastic multi-objective optimization algorithm developed by K. Deb, A. Pratap, S. Agarwal, T. Meyarivan.

objective function, objective (value) - the abstract function that takes the optimization variables as input and returns the target value of the optimization as an output. Objective (value) is the result of the objective function.

Pareto-front - the set of all Pareto-optimal solutions.

Pareto-optimal - solutions in a multi-objective optimization are considered Pareto-optimal if and only if there is no alternative solution that is better in any of the objectives without being worse in another.

quasi-optimal - solutions in a multi-objective optimization that are close to (and including) the Pareto-optimal solutions. Inclusion criteria is the Distance to Pareto-front metric.

trade-off - a compromise between two conflicting objectives.

1. Background and motivation

Buildings are responsible for 36% of the global energy consumption and 39% of the global greenhouse gas (GHG) emissions according to the IEA [1], and for about 40% of total final energy consumption in Europe [2]. The built environment is the largest industrial sector in economic terms, and also the largest in terms of research flow [3]. The improvement of the energy efficiency in both new and existing buildings is crucial to reach climate and energy targets and to increase energy security [4]. The Energy Performance of Buildings Directive, introduced in 2002 [5] and recast in 2010 [6] is one of the most important legislative steps of the European Union for improving the energy performance of the building stock, and the high interest form both research and policy making keeps up the pursuit of increasing energy efficiency of buildings.

On the other hand, researchers show that in modern, energy efficient buildings the embodied GHG emissions – emissions during the production and construction of the buildings – may take about the same amount as the GHG emissions of the operation of the buildings [7]. This is due to the tendency that the reduction of the energy consumption in the use phase is achieved through the massive employment of insulation, and technical equipment [8–10]. As such, the avoided emissions in the use phase are shifted to the construction and demolition phases of the building's life cycle [11–13], thus resulting in a "problem shifting" instead of a solution. The problem may be formulated as the search for the "trade-off" between embodied and operational environmental impacts in the large search space of different combinations of measures, including thermal insulation, high-performing windows, efficient and controllable technical systems and renewable energy sources [14].

Life Cycle Assessment (LCA) is a widely accepted scientific method for evaluating the environmental impact of products throughout their whole life cycle. It is also increasingly applied to buildings [15,16]. Even though the environmental impact has become an acknowledged issue in our society, the application of measures on buildings is still limited by economic conditions. Therefore, life cycle thinking also needs to be applied during the cost calculation of buildings. This concept is manifested in Life Cycle Costing (LCC).

Although policy making and the scientific community agrees in the need for low-impact and economically feasible building design, the steps to achieve it raise several difficulties. This is due to multiple reasons: the wide range of possible measures to achieve energy efficiency; the uniqueness of each building design which implies a modelling approach; the multiple methodological options during the modelling; the conflicting aspects of design choices and the multiple objectives to attain [17]. Summarizing these aspects, the design process becomes a Multi-Objective Optimization Problem (MOOP). If the building design can be optimized using mathematical algorithms, moreover, multiple objectives can be considered at the same time, than the process may be capable of actively supporting the stakeholders (architects, engineers or investors and policy making) during the building design. To achieve this, a wide range of disciplines needs to be combined such as mathematics for optimization, building physics to calculate energy performance, environmental studies to quantify the environmental impacts, etc.

2. Literature review and the state of the art

Derived from the above problem statements, a main goal of my research can be formulated as: **Support the design of efficient, low-impact buildings while maintaining reasonable costs throughout the life cycle through algorithmic optimization**. To achieve this, I reviewed the literature to become familiar with the state of the art of the field.

There is a growing number of publications focusing on building LCA as well as on building optimization according to recent review papers [16,18–20]. The availability of tools, computation capacity, the more and more widely applied methodology of Building Information Modelling (BIM) as well as the increasing interest in designing buildings with low environmental impact results in high quality research all around the scientific community (Figure 1).

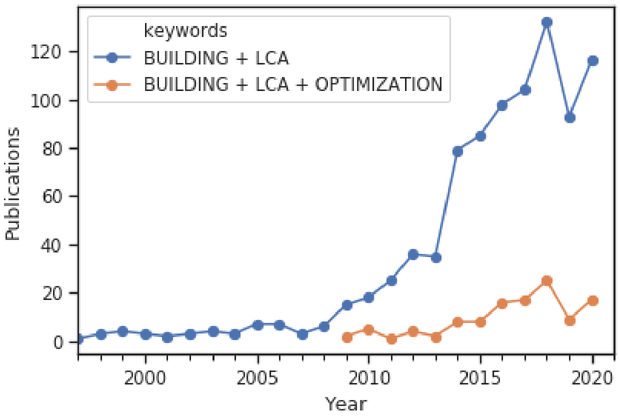

Figure 1. Number of papers published in each year in the building LCA optimization field, based on a metadata-search on Sciencedirect.com using the keywords "BUILDING + LCA" and "BUILDING + LCA + OPTIMIZATION" within the search field "Title, abstract author-specified keywords" (search results revised on June 18, 2021).

From the mathematical point of view, optimization is the minimization or maximization of one or more objectives that are functions of some variables [21]. In single-objective optimization, there is one objective, while in multi-objective optimization two or more conflicting objectives are optimized simultaneously [22,23]. In the scientific literature focussing on the environmental optimization of buildings often a limited number of design options are compared and this approach is called "optimization" [24–27]. But this does not allow for comprehensive conclusions. On the other hand, there is a growing body of scientific literature on the application of mathematical optimization to building design [17,28,29]. The objectives can be – amongst others – the minimization of costs [30–33], energy use [34,35], the maximization of thermal comfort [36–38], the performance of building elements [39], or the optimal combination of hybrid renewable energy systems [40]. However, there exists a limited number of optimization studies related to the life cycle environmental impact of buildings [17].

These works follow different approaches to assess the problem, such as the integration of LCA with Building Information Modelling (BIM) [41–48], or the definition of a parametric model using mathematical formulae [13,49,50]. The utilization of existing design tools is not only limited to BIM, but often detailed calculation of energy demand with building energy simulation software is included [50,51].

The way how LCA and optimization can support the design decision making is rarely discussed in the literature [52]. Suitable visualizations provide a promising way [53–55] and they can help to achieve significant improvement in the environmental impact [56], and to improve collaboration between design stakeholders [57].

The environmental impact of the electricity supply is one of the key areas that indirectly influence the optimization of buildings. This is due to the high potential and effort in the decarbonization and the increasing dependency of the building sector on electricity [58]. There are many studies in the literature assessing the technical and economic feasibility of different decarbonization pathways (e.g. [59–63]). This aspect becomes especially important if future electricity mix scenarios are considered in building LCA [64–68]. In other cases, it was shown that the detailed hourly resolution modelling of the building's electricity demand and the corresponding environmental impact has significant influence on the LCA results [69,70].

3. Research objectives

Through identifying the gaps in the scientific literature, I set the following research goals:

Objective 1: **Development of a modular framework.** To integrate all aspects discussed in the literature review a new framework should be developed with the following requirements: It should consider all life-cycle stages of the full building including embodied and operational impacts and costs. It should apply a parametric building model that is the basis of the algorithmic definition of certain design options and so automated optimization procedures can be applied to it. Finally, it should be modular, meaning that the specific calculation steps can be easily replaced with a module corresponding to another methodology.

Objective 2: **Definition of multi-criteria analysis.** As the goal of the optimization is to support design decision making, it is crucial to discuss how the optimization results are evaluated. As the goal of the study is not only to minimize the environmental impacts but to do that at reasonable costs, the method should consider both objectives at the same time. The results should focus on both the achievable saving through the optimization as well as the recommendations regarding design choices on how to achieve it.

Objective 3: **Application of optimization to a case study building design.** Through application of a suitable optimization algorithm, the potential savings regarding environmental impact and cost should be quantified. Furthermore, information should be provided on the optimal design variables for low-impact buildings at reasonable costs. Suitable visualization techniques should be applied to support the broad understanding of the multi-objective optimization results.

Objective 4: **Evaluate the choice of heating system.** The choice of the heating system determines the fuel used to heat the building. Depending on the share of operational and embodied impacts as well as the conversion factor of a heating fuel, the optimization may significantly differ. The effect of applying different types of fuels (such as biomass, fossil, or electricity) should be investigated.

Objective 5: **Evaluate the decarbonization of the electricity mix.** In case of a heating, where electricity is used as the main fuel and the demand is covered through the grid supply, the decarbonization of the electricity production can similarly influence the optimization results as the discussed in objective 4. Therefore, this effect should be analysed using different scenarios.

Objective 6: **Evaluate the climatic and economic conditions.** As the energy consumption of the building depends on the climate, furthermore, the life-cycle costs as well as the embodied impacts are influenced by local economic and technological conditions, results of the optimization may significantly depend on the location of the building. The extent of the difference should be investigated through applying the optimization in different locations.

4. Methods used in the study

To quantify the environmental impacts of a building design, I applied the standardized methodology of LCA [71,72]. The standard EN 15978 [73] defines six most important environmental indicators that is supported by a consistent and widely accepted scientific background applicable to buildings. Among them Global Warming Potential (GWP) [74] is the most widely applied indicator. GWP expresses the impact of human emissions on the radiative forcing of the atmosphere and is often referred to as "climate change". GWP is expressed in kilograms of carbon-dioxide equivalents ($kgCO_2$*-eq.*) by applying characterization factors to certain emitted GHGs. As a conflicting objective I choose the *global* cost to quantify the economic aspects of the design. According to the EU regulation [75] supporting the EPBD, "*global cost means the sum of the present value of the initial investment costs, sum of running costs, and replacement costs (referred to the starting year), as well as disposal costs if applicable*". To calculate the global cost, the methodology of LCC is used, and the result is referred to as Life Cycle Cost.

For the application of optimization to the building design, I followed the parametric approach. I defined a hierarchical building data model that contains all necessary information to conduct LCA and LCC. Based on the data model I created templates where the background data can be matched with all construction materials and systems contained in the building design. I applied the most well-known generic database, *ecoinvent* – version 3.6, Cut-Off system model [76] – to generate the required Life Cycle Impact Assessment (LCIA) data. To adapt the datasets, I defined a localization process, which changes the electricity and gas providers in the product system from the original location to specific for the new location. This way the LCIA values are adapted to the local production conditions. Considered system boundaries include the product stages (A1-3), the construction process (A4-5), the use stage (B4 replacement and B6 operational energy use), and the end-of-life (C2-C4) according to the standard EN 15978 [73]. For each life cycle stage, the corresponding environmental impact is calculated based on the background data and the amounts derived from the building data model.

Cost data was collected from a year-by-year published collection of manufacturer-specific and average data for construction costs [77]. For materials that were not available in the collection, manufacturer and market values were collected. Installation costs are based on standard hourly wage in the construction sector specific to different working types, and the standard installation time extracted from an online construction budgeting platform [78]. Energy prices are based on statistical data for natural gas [79] and electricity[80], and market analysis for pellet. Cost calculation is similar to the environmental impact calculation including the stages of production, installation, replacement and operation based on the building model and the background data. A discounting rate of 3% was applied in all cases.

I integrated and tested three different energy performance calculation options, namely dynamic energy simulation with the EnergyPlus [81], the monthly steady-state calculation according to

EN ISO 52016 [82] or seasonal method according to the Hungarian energy performance regulation [83]. From the three options, dynamic energy simulation proved to be the most adequate to deliver detailed results.

As part of an international collaboration, I reviewed several visualization techniques and adopted the most relevant types for the analysis of multi-objective optimization results. Findings show that scatter plots and parallel coordinates plots are appropriate for displaying and comparing a high number of solutions while pie chart is the most common option for visualizing parts-to-whole comparison (e. g., the share of life cycle stages). Bar chart is the most often used option for comparing design options with each other.

I reviewed the multi-objective techniques applicable for building performance optimization, and concluded that the NSGA-II algorithm [84] is the most widely used and the most appropriate choice for my purpose. The most important properties of NSGA-II are that it is very efficient in sorting the non-dominated solutions in a MOOP, it converges very quickly through the application of elitism and gives a set of Pareto-optimal solutions that are well distributed along the Pareto-front. Additionally, I tested two other algorithms, such as Direct Multi-Search (DMS) [85] and Strength Pareto Evolutionary Algorithm (SPEA2) [86] to justify my choice. While the former failed to extend the optimized solutions from some of the found local optima, the latter was significantly slower than NSGA-II due to the lack of support for parallel computing.

Finally, I implemented the framework in a "service-based" containerized computer environment using existing software tools such as DesignBuilder, EnergyPlus, OpenLCA for the calculation; Jupyter, Pandas, Matplotlib, Seaborn, Plotly for the evaluation of results, PostgreSQL and Redis for the data storage; and Flask with Docker for the containerization. By focusing on the parallelization, I achieved a significant reduction in calculation time compared to single-threaded calculation workflows.

Table 1. Design parameters used as variables of the optimization with their limits and the values representing the "Business As Usual" case

Design parameter		**Value limits / options**	**Business As Usual (BAU) values**
Fenestration ratio	N	1 - 80 %	13 - 24 %
	W	1 - 80 %	23 - 34 %
	S	1 - 80 %	33 - 44 %
	E	1 - 80 %	23 - 34 %
Glazing type	N	double / triple	double / triple
	W		
	S		
	E		
Shading	N	yes / no	yes / no
	W		
	S		
	E		
Frame type		plastic / wooden	plastic / wooden
Roof insulation	material	EPS white / EPS graphite / PUR / rock wool / wood wool / ICB	EPS white / EPS graphite / PUR / rock wool
	thickness	1 - 80 cm	20 - 25 cm
Wall insulation	material		EPS white / EPS graphite
	thickness		10 - 15 cm
Floor insulation	material		EPS white / EPS graphite / rock wool
	thickness		4 - 10 cm

To apply the framework, I established a parametric building model of a typical multi-apartment building of the Hungarian building stock. Design parameters include building envelope characteristics such as window ratio, glazing and frame type, shading, insulation type and thickness. The 19 design parameters serve as the variables for the optimization. To quantify the potential of improvement in both environmental impact and life cycle cost, I identified a reference design, which serves as the "business as usual" (BAU) case. The parametric building definition is the same as for the optimization case, but the parameter values are limited to express a design corresponding to the current practice (Table 1).

5. Outline of the thesis

The research steps and the assessment cases through which I provide an answer to the research objectives are outlined on Figure 2. The literature review includes five relevant topics such as: the LCA of buildings; building performance optimization; LCA of the electricity mix (and its application to buildings); workflows and design tools; and LCA result visualization.

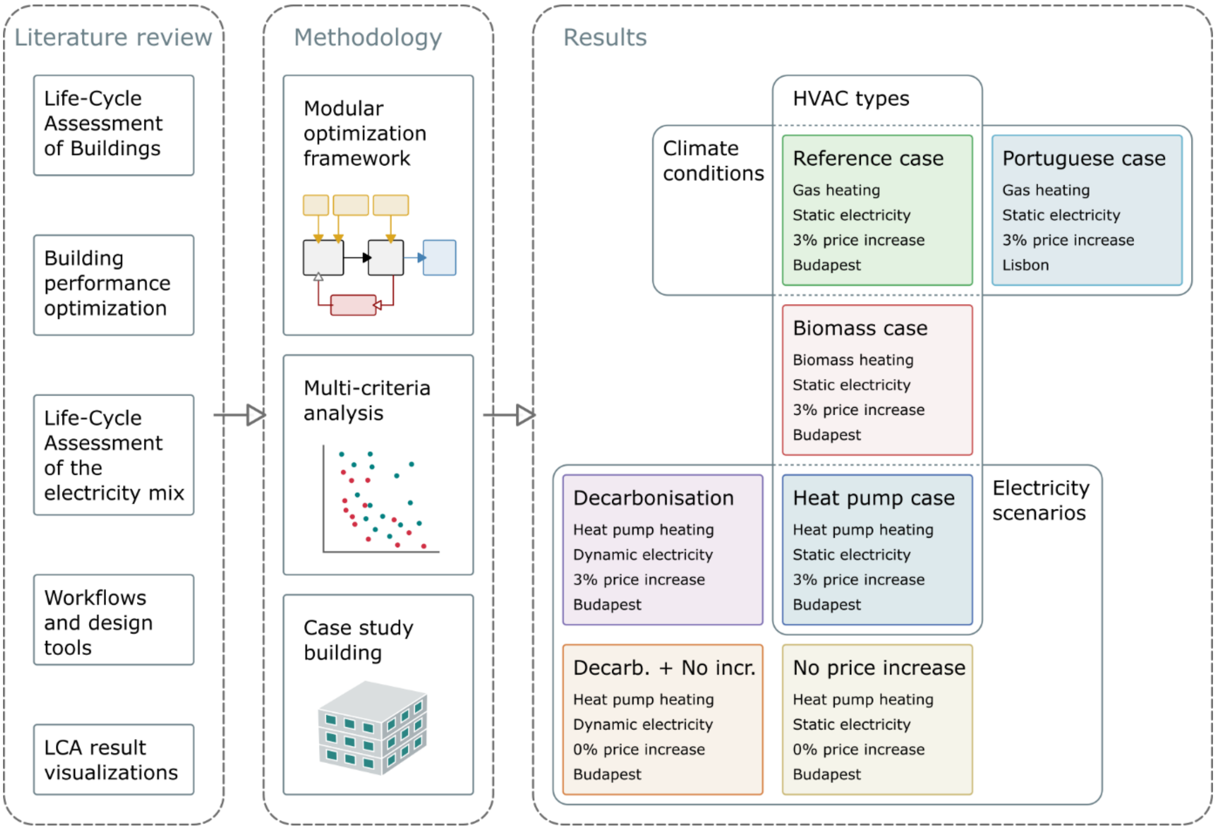

Figure 2. Structure of the research and the interrelation of the analysed cases.

The methodology consists of the thorough definition and justification of the developed framework including the discussion of LCA and LCC calculations as well as the actual implementation of the system (**Main Result I**). Furthermore, the analysis of the multi-objective optimization results and the corresponding metrics are defined (**Main Result II**), then the case study building that is targeted by the optimization is introduced. The different aspects of the optimization are evaluated through the application of the optimization framework and methodology on the case study building. The *Reference case* serves as the basis of the comparison (**Main Result IV**) and the for the verification of the methodology (**Main Result III**). Comparing the *Biomass case* and the *Heat pump case* with the reference, the effect of using different heating fuels is evaluated (**Main Result V**). The further analysis with various electricity mix scenarios supports the assessment of *decarbonisation* and *price increase* influence on the optimization results (**Main Result VI**). Finally, comparing the reference with a case reflecting the *Portuguese* environmental and economic context, the location-dependency of the optima are presented (**Main Result VII**).

6. Main results

Main Result I

on the definition of the modular framework for building optimization using life cycle assessment

Through the analysis of design tools as well as the scientific literature on building optimization and life-cycle assessment I concluded that there is no tool that can integrate existing software solutions in a modular way and is capable of calculating the life cycle environmental impacts and costs in an automated workflow.

I established a modular framework that is able to assess the most important building parameters that influence the environmental impact and cost such as geometry, material usage and thermal properties; covers the whole life cycle "from cradle to grave"; includes the whole building in the calculation not only parts of it; and is capable of algorithmic optimization, meaning that the model can be altered automatically, and the calculation procedure is fully integrated (Figure 3)**.**

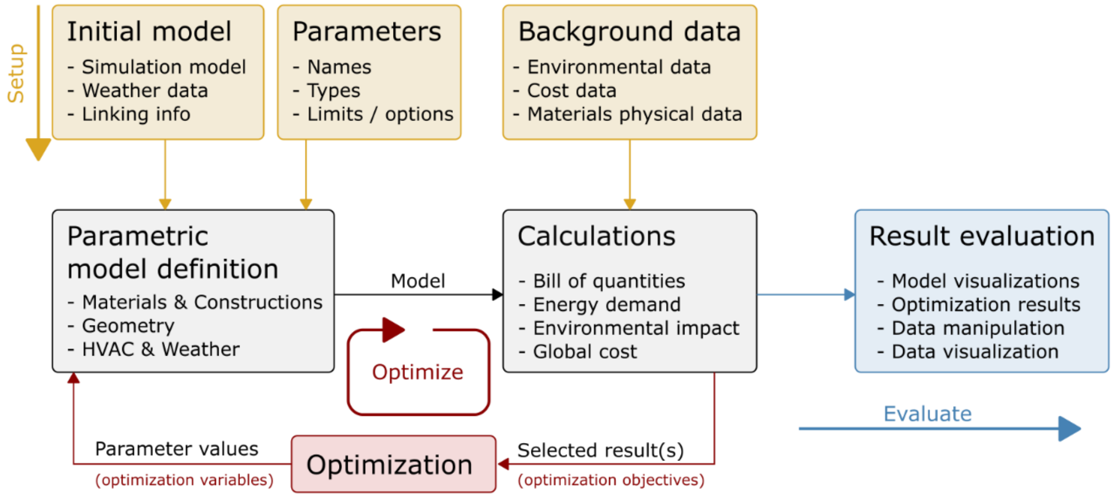

Figure 3. Structure of the calculation framework and illustration of the workflow steps

Publications supporting this main result: [P1, P2, P3]

Main Result II

on the definition of new metrics to support design optimization using multi-objective optimization results

I reviewed the literature regarding the analysis of multi-objective optimization results. The high number of Pareto-optimal solutions makes it difficult for stakeholders in the design process to derive the right consequences without explicitly articulating any preference over the objectives. To support design decision making based on the results of the optimization I defined new metrics to analyse the full set of Pareto-optimal solutions in a bi-objective problem. The metrics support the understanding of optimal design parameters from an engineering perspective without judging between the objectives.

II.1 Distance to Pareto-front

I introduced the metric *Distance to Pareto-front* (*DP*) to determine the quasi-optimal region in the objective space (Figure 4)**. Using DP_{max} as a criterion I determined the quasi-optimal solutions of each optimization case. The inclusion of close-to-optimal solutions in the analysis significantly improves the design flexibility as well as the robustness of the optimized solutions without drastically reducing the potential improvement in the objective values.**

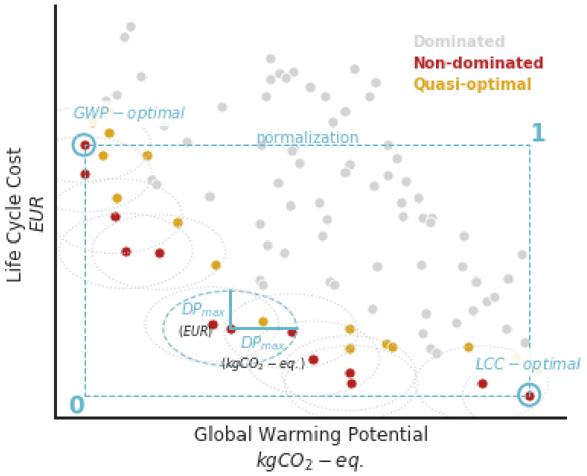

Figure 4. Determination of quasi-optimal solutions using the distance to pareto-front (DP_{max})

DP_{max} values were adjusted in each case separately to reflect a maximum of ca. 1% of the total GWP and LCC of the Pareto-optimal (non-dominated) solutions.

II.2. Pareto Position Index, Improvement Potential and Pareto Spread Indicator

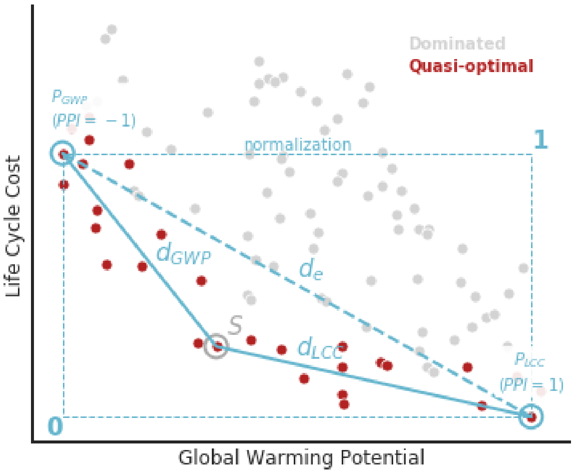

Figure 5. Calculation of the Pareto Position Index for a given point (S) in the objective space: $PPI(S) = \frac{d_{GWP}-d_{LCC}}{d_e}$.

I introduced a set of metrics to characterize and compare a full set of quasi-optimal solutions: the *Pareto Position Index* (*PPI*) to express the weight of the objectives in a specific solution (Figure 5)**; the *Improvement Potential* (*IP*) to show how much a solution has been improved through optimization compared to a reference point; the Strict improvement Potential ($IP_{max,S}$) to show the maximum of *IP* for each objective with the**

other objective value not worse than the reference (Figure 6); **finally, the *Pareto Spread Indicator* (*PSI*) to express the strength of the trade-off between the objectives in a particular set of quasi-optimal solutions** (Figure 7)**. Using IP_{max}, IP_{min}, $IP_{max,S}$ and PSI I was able to compare multi-objective optimization cases and express their characteristics depending on the evaluated assumptions.**

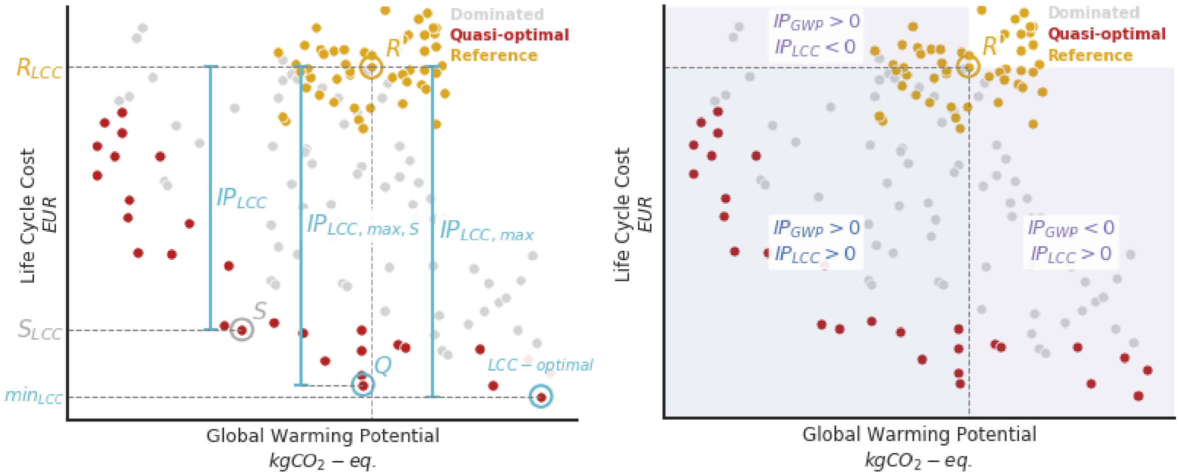

Figure 6. Improvement potential in case of LCC (left), and regions defined by IP with different signs.

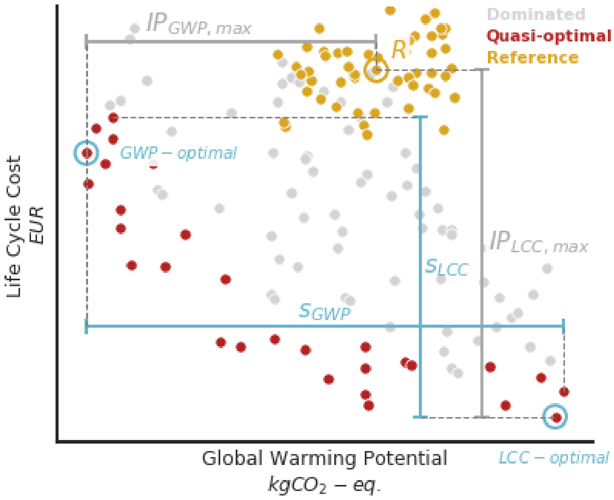

Figure 7. Calculation of the Pareto Spread Indicator for each objective o: $PSI_o(s) = \frac{s_o}{IP_{o,max}}$

II.3. Distance to Ideal Point

I introduced the normalized *Distance to the Ideal Point* (*DI*) to express how close a solution is in the objective space to the theoretical point where the single-objective optima are united. Using the IP_{max} values for the normalization of DI I determined the "trade-off" solution at DI_{min}, in each optimisation case (Figure 8)**.**

The advantage of this method compared to other methods in the literature is that the unit of the objective values does not need to be comparable, still the improvement potential regarding both objectives is treated with equal weights.

Publications supporting this main result: [P7]

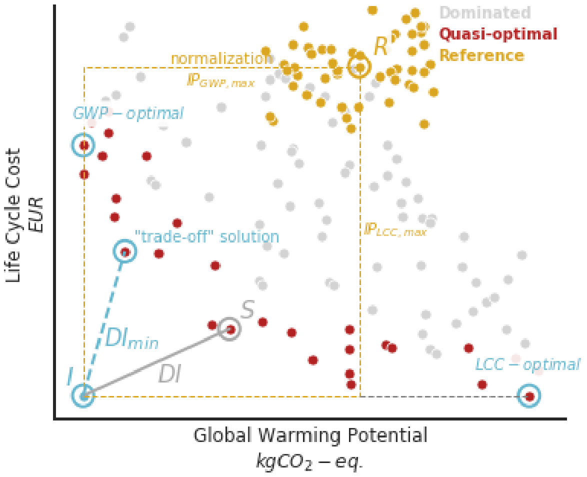

Figure 8. Determination of the trade-off solutions using DI_{min}

Main Result III

on the evaluation of design variables and optimization objectives to support optimization

To justify the design variables of the parametric building model, I analysed the options for the wall insulation materials, as well as the individual influence of other variables and the conflict of the objectives in more detail.

III.1 Unitized environmental impact and cost value of insulation materials

I introduced the unitized environmental impact and cost value of insulation materials. This metric is suitable for a quick preliminary comparison of different thermal insulation materials considering environmental and cost properties on top of the most important thermophysical attributes.

The metric can be calculated using the following equation:

$$\hat{I}_m = \frac{I_m \cdot \rho_m \cdot \lambda_m}{t_m}$$

$$\hat{C}_m = \frac{C_m \cdot \lambda_m}{t_m}$$

where $\hat{I}_m$ is the unitized impact of material m in $\left[\frac{kgCO_2eq \cdot \frac{W}{mK}}{m^3 \cdot year}\right]$ for GWP, $\hat{C}_m$ is the unitized cost of material m in $\left[\frac{EUR \cdot \frac{W}{mK}}{m^3 \cdot year}\right]$, I_m is the impact of material m in $\left[\frac{kgCO_2eq}{kg}\right]$ contained in the life cycle database, C_m is the cost of material m in $\left[\frac{EUR}{m^3}\right]$ contained in the cost database, ρ_m is the density of the material in $\left[\frac{kg}{m^3}\right]$, λ_m is the thermal conductivity of material m in $\left[\frac{W}{mK}\right]$, t_m is the expected lifetime of material m in $[years]$,

By calculating the unitized GWP and cost value for the Hungarian context, I compared seven insulation materials applicable in an external thermal insulation composite system. I concluded that white and graphite EPS perform better than rockwool, XPS, insulation cork board and PUR both in unitized GWP and unitized cost value. Wood wool proved to be the best performing material in terms of unitized GWP, while white EPS is the best option in terms of unitized cost (Figure 9).

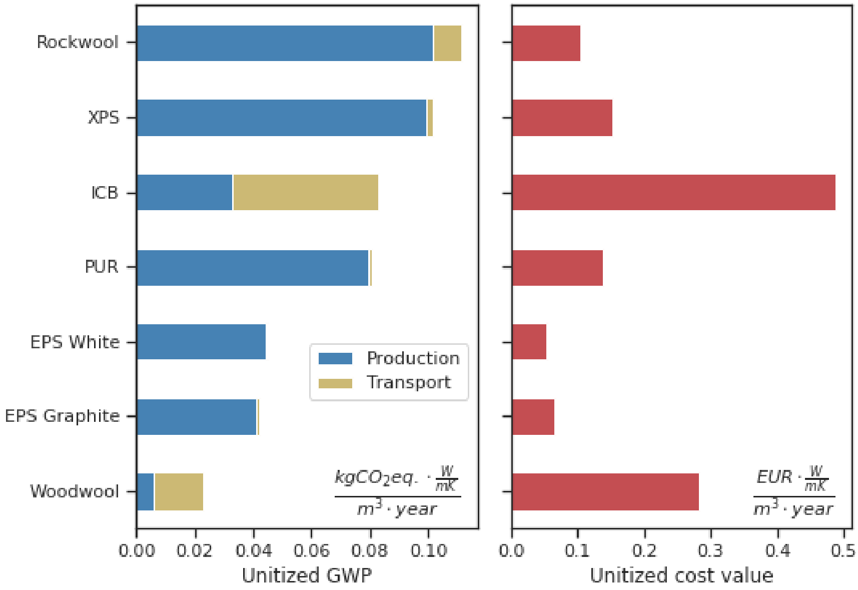

Figure 9. Unitized GWP and cost values of the insulation material options applicable in an ETICS.

These findings are also supported by the results of the optimization cases. Among the seven insulation materials only white and graphite EPS and wood wool appeared within the quasi-optimal solutions of the Hungarian cases.

III.2 Interdependency of optimization variables

Using a Monte-Carlo simulation with all possible value combinations of the variables I created a set of 20 000 solutions to cover the search space of the optimization. By filtering the solutions for each specific value of each variable I compared the shift in the mean of the filtered solutions from the mean of all solutions in the optimization space. I concluded that none of the variables can cause alone large deviation in any of the objectives, therefore all variables must be optimized at the same time.

III.3 Conflicting objectives in the environmental optimization of buildings

I calculated the seven most important environmental indicators according to the EN 15978 standard [73] within the Monte-Carlo simulation. By calculating the PSI values using the range of all solutions as a reference I compared all indicators pairwise to each other. Conflicting indicators are indicated by high PSI values for both objectives at the same time in the bivariate comparison.

I showed that none of the environmental indicators are strictly conflicting in case of a typical multi-apartment building of the Hungarian building stock. Furthermore, high positive correlation is observed between GWP, CED and ODP as well as AP and EP. By calculating the PSI values for the target objectives, I proved that GWP and LCC are valid conflicting objectives in the proposed optimization case.

PSI values for the indicator pairs are 29% to 11% (ADP-ODP), 29% to 6% (ADP-GWP), and 26% to 6% (ADP-CED). PSI values for the target objectives (GWP-LCC) are 28% to 44%.

Publications supporting this main result: [P4]

Main Result IV

on the optimization of a typical multi-apartment building of the Hungarian building stock

By applying the NSGA-II multi-objective optimization algorithm [84] I optimized the parametric building model of the case study building. Additionally, through a Monte-Carlo simulation using the BAU limits for each variable I established a set of solutions that represent the current practice in construction.

IV.1 Improvement potential

By comparing the mean of the BAU case with the optimized solutions I identified that the GWP of the case study building can be reduced by 9% (LCC-optimal solutions) to 26% (GWP-optimal solutions). A maximum of 14% reduction can be achieved in LCC (LCC-optimal solutions), but the GWP-optimal solutions have 22% higher LCC compared to the BAU. The maximum improvement potential corresponds to 5.39 *kgCO₂-eq./m²a* in terms of GWP and 2.98 *EUR/m²a* for LCC (Figure 10)**.**

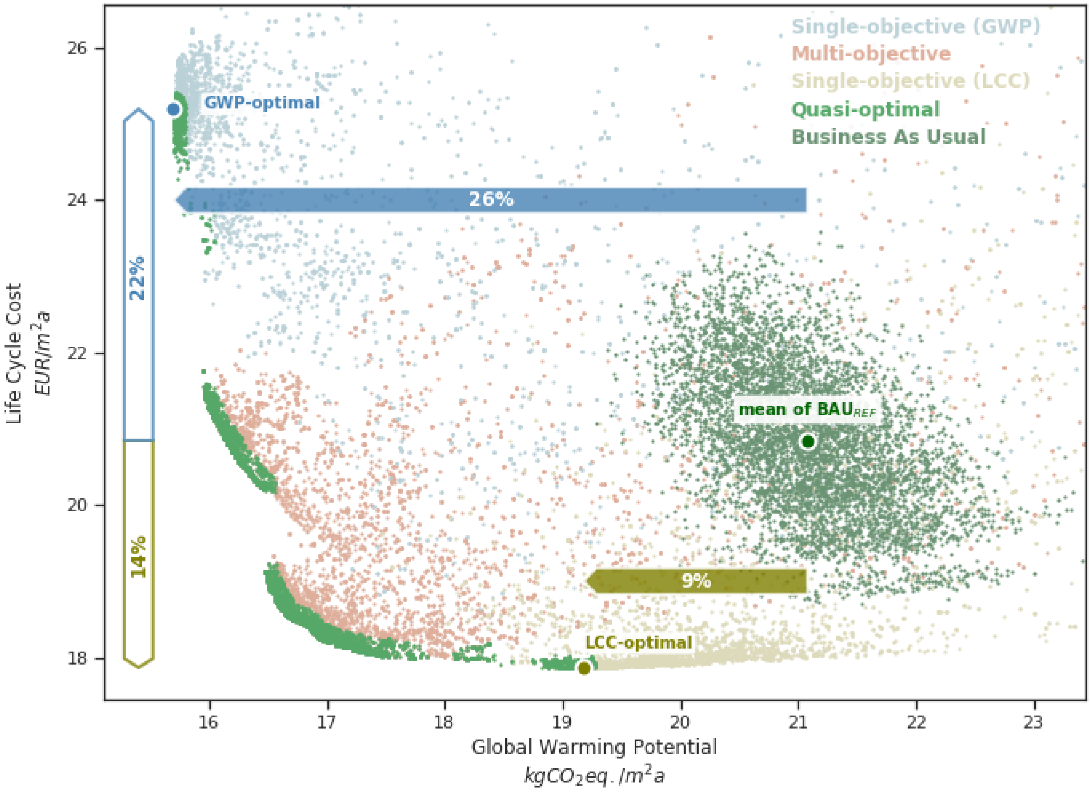

Figure 10. Results of the optimization (Reference case) in the objective space.

IV.2 Optimal design parameters

I classified optimization variables into *synergy*, *trade-off* and *neutral* to evaluate their conflict within the quasi-optimal solutions. While *synergy* variables take a similar value within all quasi-optimal solutions, *trade-off* variables take specific values depending on the preference between the objectives. *Neutral* variables may take any value within quasi-optimal solutions regardless of the preference between objectives. Additionally, I introduced the term *distinguishing* variable for those variables that are responsible for the largest visual separation of clusters within the objective space.

I applied this classification to the variables of the quasi-optimal solutions. Fenestration ratio on the North, West, and East façade as well as the glazing type of the South façade were classified as *synergy* variables. Variables reflecting properties of the fenestration on these façades are *neutral* variables, while frame type, fenestration ratio and shading on the South façade, as well as insulation material and thickness are *trade-off* variables in the reference optimization of the Hungarian case study building. After clustering the quasi-optimal solutions based on the distinguishing variables (glazing type on South façade, shading, frame type and wall insulation material) I analysed the design parameter characteristics of each cluster.

I showed that an extreme level of the insulation ($U_{flat\,roof} = 0.06 \pm 0.01\ W/m^2K$, $U_{wall} = 0.06 \pm 0.01\ W/m^2K$ and $U_{floor} = 0.10 \pm 0.01\ W/m^2K$), large, shaded fenestration (75 ± 3 %) on the South façade, low-impact materials (wooden window frame and wood wool insulation) are preferred in case of a GWP-optimal design. At the same time, the LCC-optimal design has an EPS insulation with $U_{wall} = 0.17 \pm 0.02\ W/m^2K$, $U_{flat\,roof} = 0.19 \pm 0.03\ W/m^2K$ and minimal insulation ($U_{floor} = 0.79 \pm 0.18\ W/m^2K$) on the floor, as well as unshaded small windows (23 ± 3 % fenestration ratio) with plastic frame and double glazing on the South façade, which is close to the requirements of the current national building energy regulation.

IV.3. Embodied impacts

While the operational GWP is being regulated through building energy performance policy measures, the embodied GWP of buildings is not considered in current policy making. In case of the optimized building design the share of embodied GWP is a notable 60% for GWP-optimal solutions, but even the LCC-optimal solutions comprise about 42% embodied GWP. On the other hand, operational costs only contribute to 3-8% to the life cycle costs, while investment costs may take up to 80-83% within the optimized solutions.

By evaluating the quasi-optimal solutions, I showed that increasing the energy performance of the LCC-optimal design increases the share of embodied GWP from 42% up to 60% in the life cycle GWP of the optimal building design. However, despite of the high share of embodied GWP the increased energy performance is still beneficial from the environmental point of view and up to 16% additional improvement can be realized in GWP compared to the LCC-optimal solutions.

Publications supporting this main result: [P4, P5]

Main Result V

on the influence of the heating fuel on the optimized building parameters

To evaluate how much the choice of heating fuel influences the optimal building design as well as the improvement potential, I applied the optimization to three cases with different heating systems: a gas boiler; a pellet boiler and an air-to-water heat pump.

V.1 Optimality with different heating systems

I showed that the pellet boiler case outperforms the other two cases in terms of GWP by an average of 15% compared to the heat pump case and 22% compared to the gas boiler case. In terms of LCC the pellet boiler case is better than the heat-pump by an average of 7% and is close to the gas boiler case (Figure 11)**. Furthermore, I demonstrated that in**

case of choosing a pellet boiler for heating, GWP and LCC are significantly less conflicting in an optimal building design.

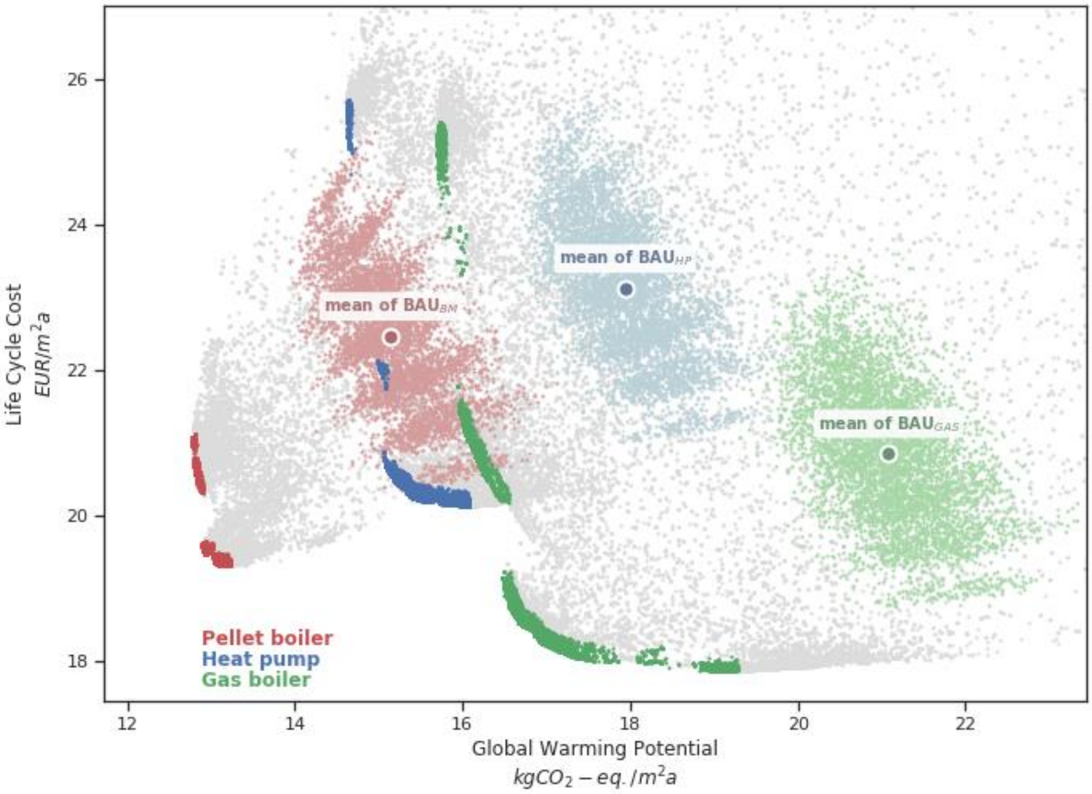

Figure 11. Results of the three optimization cases in the objective space. Quasi-optimal solutions are depicted by saturated colours, BAU cases are shown in light colours. The mean of each BAU case serves as a reference.

I quantified the conflict between GWP and LCC using PSI values. While the trade-off between GWP and LCC is larger in case of heat pump ($PSI_{GWP} = 0.67$, $PSI_{LCC} = 2.53$) and gas boiler ($PSI_{GWP} = 0.44$, $PSI_{LCC} = 1.87$), it is significantly less for pellet boiler ($PSI_{GWP} = 0.19$, $PSI_{LCC} = 0.57$).

V.2 Optimized solutions and the regulation

By comparing the envelope U values of the optimized solutions, I showed that the type of the heating system may determine the optimal insulation level of the envelope. However, the requirements for the envelope U-values are determined independently from the heating system according to the current building energy regulation. Additionally, I showed that instead of improving the energy performance of the envelope to extreme levels, a change in the heating system from gas boiler to a pellet boiler is a more adequate choice when considering GWP in a design optimization.

Cost-optimal U-values are higher in case of a gas boiler and a heat pump (0.19 W/m^2K on the wall and $0.20 - 0.21$ W/m^2K on the flat roof), and are lower in case of a pellet boiler (0.13 W/m^2K on the wall and 0.15 W/m^2K on the flat roof). GWP-optimal U-values range from 0.05 W/m^2K (gas boiler) to 0.11 W/m^2K (pellet poiler) for the wall, and from 0.06 W/m^2K (gas boiler) to 0.12 W/m^2K (pellet boiler) for the flat roof. The current requirements for the U-values are 0.24 W/m^2K on the wall and 0.17 W/m^2K on the flat roof.

Publications supporting this main result: [P4]

Main Result VI

on the influence of electricity decarbonization on the optimized building parameters

Using the "*Decarbon*" scenario of the European Electricity Market Model (EEMM) developed in the South East Europe Electricity Roadmap (SEERMAP) project [87], I developed three additional optimization cases using a heat pump for heating to evaluate the impact of future electricity mix decarbonization on the optimized design. Although the decarbonization of the electricity mix reduces both the operational and the embodied impacts, I applied the effect only in the operational phase as most of the embodied impacts occur at the beginning of the life cycle, when the effect of decarbonization is still negligible.

VI.1

I proved that the decarbonization of the electricity mix is a key factor in the optimal design as well as the lifecycle emissions of the buildings. Using a dynamic electricity mix (with continuous improvement until 2050 in terms of emissions) based on the EEMM model, I showed that 25 – 26% reduction in GWP can be observed between the mean of the optimized building solutions compared to the static mix.

While the difference in total GWP is significant, the improvement potential is lower if dynamic mix is applied which means 10% (1.2 kgCO_2-eq./m^2a) compared to 18% (3.3 kgCO_2-eq./m^2a) in case of static mix. The minimum improvement in LCC within optimized solutions turns to be positive (5 – 6%) in case of dynamic mix instead of negative (-11 to -14%) when using static mix.

VI.2

I demonstrated that if the electricity mix is decarbonized, GWP and LCC are much less conflicting than without decarbonization. I showed that in case of dynamic electricity mix an optimal energy efficiency level can be identified in the case study building (with $U_{flat\,roof} = 0.19 \pm 0.04\ W/m^2K$ and $U_{wall} = 0.18 \pm 0.03\ W/m^2K$ and fenestration ratio of 23 ± 4% on the South façade with double glazing and no shading) regardless of the preference between GWP and LCC.

The preference between GWP and LCC is only reflected in the material usage, as more expensive, but less impacting materials are applied with a higher preference for GWP.

VI.3

I showed that the decarbonization of the electricity mix results in a 30% mean improvement in terms of GWP without optimizing the building design, which is more than the 18% that can be achieved through design optimization. When applying optimization on the decarbonized scenario, an additional 7% improvement can be achieved compared to the BAU case with a heat pump and static electricity mix (Figure 12)**.**

Publications supporting this main result: [P6, P7]

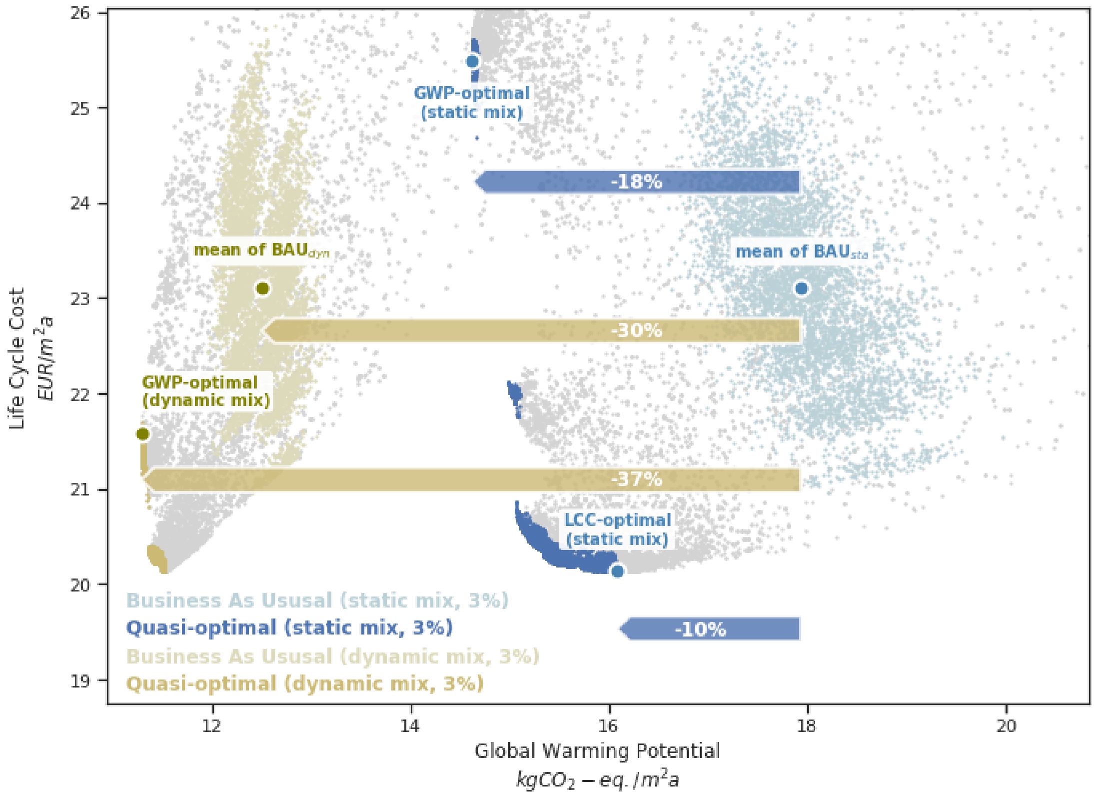

Figure 12. Illustration of the improvement that can be achieved through optimization of the building design, decarbonization of the electricity mix or the combination of them.

Main Result VII

on the influence on climatic and economic conditions on the optimized building parameters

Portugal is a good example for an economy with higher energy and labour costs, while significantly lower heating demand than in Hungary. I established an optimization case reflecting the Portuguese climatic and economic conditions by adapting the background data on cost and environmental impacts, changing the weather data to Lisbon, and determining the BAU case corresponding to the Portuguese building energy regulation and construction practice.

VII.1

I showed that in a "business as usual" case the building related life cycle GWP is 37.8% lower, while the LCC is 8.5% higher in Portugal on average than in Hungary. After optimization, GWP can be reduced by up to 24% and LCC up to 17%, while in a trade-off situation, 23% and 17% can be achieved at the same time in terms of GWP and LCC, respectively in the Portuguese context (Figure 13)**.**

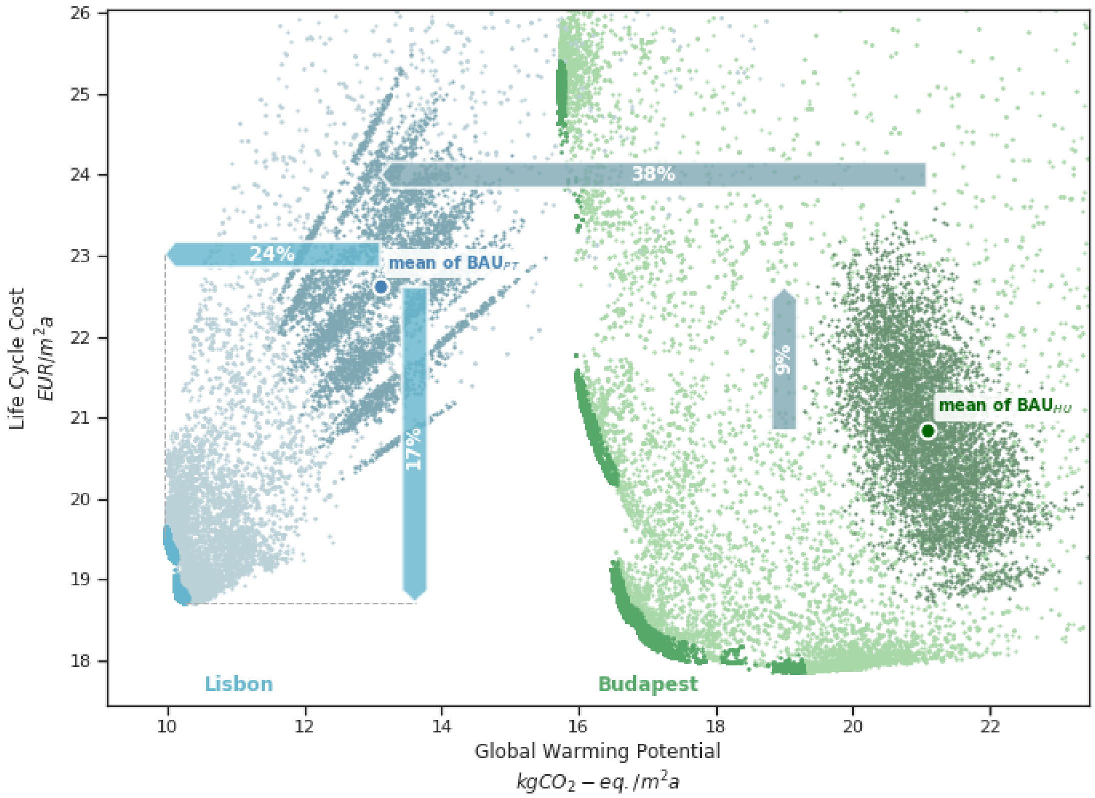

Figure 13. Results of the optimization as well as the BAU cases in both the Hungarian and the Portuguese context. (Pareto front and near optimal solutions depicted by saturated colours).

Optimized solutions cover a much smaller area in the objective-space in the Portuguese case. By expressing the spread with the PSI values, I showed that the trade-off between the objectives is much stronger in the Hungarian case ($PSI_{GWP} = 0.67$, $PSI_{LCC} = 2.53$), than in Portugal ($PSI_{GWP} = 0.11$, $PSI_{LCC} = 0.24$).

VII.2

I concluded that most of the design parameters can be classified as *synergy* and an optimal insulation level of $\boldsymbol{U_{flat\,roof} = 0.26 \pm 0.03\ W/m^2K}$ and $\boldsymbol{U_{wall} = 0.33 \pm 0.04\ W/m^2K}$, as well as an optimal fenestration ratio of 22 ± 2% could be determined for the location of Lisbon regardless of the preference between the objectives. The optimization also showed that insulation is not needed in the floor construction and shading is not required on the windows if the optimal fenestration ratio is kept.

VII.3

I showed that the share of operational GWP against embodied GWP within the optimized solutions in the Portuguese case is much less (19%) than in the Hungarian case (40-58%). Finally, I showed that in Portugal the lighting energy takes the highest share (54-66%) in the net energy demand of the optimized buildings, while in Hungary heating is the major contributor (with 58-79%).

This result – together with the share of operational costs being low (4%) in the optimized cases – further explains why the trade-off between LCC and GWP is much weaker in Portugal than in Hungary. Savings in the operational energy in Portugal have much lower influence on the lifecycle impacts and costs as well.

Publications supporting this main result: [P8, P9]

7. Summary and further research

With my PhD research summarized in this booklet I gave a consistent overview on how multi-objective optimization can support the design of buildings with low environmental impact at reasonable costs. Building on top of existing research I could answer new questions formulated in the objectives adding significant knowledge to the field.

I developed a building optimization framework based on a parametric building model, detailed energy, LCA and LCC calculations. I introduced a comprehensive methodology to evaluate the results of the multi-objective optimization including the definition of new metrics that support the understanding of such a design problem. Through the optimization of a multi-apartment building case study, I showed how the findings can support the design decision making and how much the design can be improved in terms of GHG emissions and global cost. Finally, I evaluated the influence of certain parameters on the optimal design such as the choice of the heating system, the decarbonisation of the electricity mix and the climatic and economic conditions.

The findings of my research may serve as guidance on how the environmental impacts can be considered in a design process from two different perspectives. First, the optimization process can be adapted to any building design, especially in early design stages, where major parameters of the building are not yet fixed. Second, the optimised values can support the development of the national requirements within the building energy regulation.

As future directions to my work I would like to emphasize two options. First, the optimizations could be extended to other building types including both residential and commercial buildings. Through the optimization of characteristic types defined by a building typology the potential improvement of a building stock regarding its environmental impact could be quantified. Second, building-integrated renewable plants could be incorporated in the design parameters and the optimization to extend the variability of the optimal design.

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