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Urban systems exploration: A generic process for multi-objective urban planning to support decision making in early design phases

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ABSTRACT

The competition for limited urban spaces due to the growing demand for both living space and green areas causes conflicts in urban development. This paper aims to provide urban planners with a systematic multi-criteria decision making process and a supporting tool-chain. The process uses multi-objective optimization (MOO) to quantify trade-offs, allowing planners to gain a broad perspective on optimal solutions.

The generic process builds an urban simulation model, applies MOO, explores the results in terms of multi-criteria trade-offs, and guides the decision making of urban planners. To enable this process, we present a tool-chain for applying a Gaussian Process Regression based MOO algorithm to a computationally expensive urban simulation model. The tool-chain allows to identify Pareto-optimal solutions and their properties with reasonable computational effort. A case study model is set up in the Grasshopper environment and couples simulation components for outdoor thermal comfort and Life Cycle Assessment. It allows to identify multi-objective trade-offs for a high-dimensional space of urban configuration degrees of freedom such as outdoor vegetation, photovoltaics, and building characteristics. We compare the workflow results to other MOO algorithms and show how it can support decision making in urban planning at early design phases.

In our case study, the tool chain was able to investigate the multi dimensional space of urban configurations. It systematically identified Pareto-optimal solutions therein and reduced the number of model evaluations significantly. The case study results showcase the trade-off between lifecycle-based global warming potential (GWP) and outdoor thermal comfort. We identified the number of trees and the coverage of the east and west façades with photovoltaics as the most important parameters.

The proposed process proves to be a powerful multi-criteria decision support tool for urban planners. It allows to identify and quantify the Pareto Front of competing urban target trade-offs at early design phases. Additionally, it visualizes them according to the boundary conditions of urban development. The input configurations of the obtained Pareto-solutions serve as a base of urban planning recommendations. In our case study, trees and photovoltaics prove to be good levers in the area of GWP optimal solutions. However, urban planners need to carefully coordinate inputs when aiming for a specific trade-off balance. The tool-chain and the simulation model offer further potential for investigating neighborhood typologies. Thereby, applicants can derive scalable guidance to support the sustainable transformation of the urban environment.

1. Background

Rapid population growth and increasing urbanization as a worldwide megatrend have created a rising demand for urban living spaces [1]. The United Nations predicts that by 2050, two-thirds of the world's population will live in urban areas, putting enormous pressure on cities to meet future housing demands [2]. Alongside this development, the increasingly noticeable consequences of climate change and urban heat islands have highlighted the need for intensifying refurbishment and implementing resilience strategies in cities. While flagship projects showed the feasibility of integrated approaches to these challenges, a broad implementation in urban planning has yet to be achieved. Urban planners need to react quickly in this field of rapidly changing requirements where our society cannot afford an unlimited number of time-consuming experiments but needs feasible and optimized solutions for the sustainable transformation of the urban environment.

Simultaneous consideration of climate change mitigation and climate change adaptation and their interactions are gaining attention

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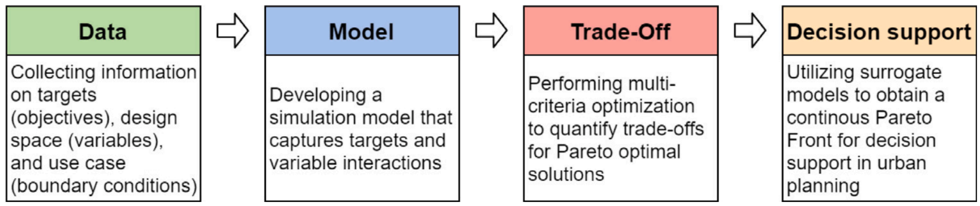

Fig. 1. Main steps of the generic process for multi-criteria decision support in urban planning.

as a necessary part of the urban planning process. Nevertheless, they are sparsely integrated into this process and especially quantification is often missing [3]. While scholars have shown examples of conflicts that might arise from mitigation and adaptation measures [3–5], urban planners need practical advice to develop balanced solutions. Individual cause and effect relationships are well known for both, but the overall effect in such relationships is complex and its consideration often based on experiences [6]. As a result, the individual assessment of related aspects can cause misleading conclusions, as systems may behave other than expected from evaluating their individual components. This is especially true for the urban fabric, where several prevailing characteristics emerge from the dynamic relationships between single parts [7]. Finding an optimal solution for the design of such urban systems is a challenging task in urban planning. Traditional methods often aim to identify a feasible solution that is optimized with respect to single objectives. Additional aspects are considered by setting limits that must not be exceeded or fallen short of, but decision makers expect various possible outcomes to choose from [8]. Thus, exploring the whole space of feasible and optimal solutions is necessary. From this, the extent of competing objectives becomes visible and allows planners and decision makers to balance emerging trade-offs actively.

To quantify trade-offs in urban planning, systemic approaches and complex simulation models are necessary [9,10]. This complexity is, among other things, due to the various scales of urban sustainability aspects. For instance, building energy demand is determined at the building level, whereas summer heat stress can be assessed indoors (building level) and outdoors (neighborhood level). Several practical simulation methods for urban planning exist and are still under development, but they are most often computationally expensive, meaning single evaluations are time-consuming, allowing only for a limited number of simulation runs [11]. Furthermore, such simulation models usually have a large number of inputs and domain-specific outputs. Hence, the possible number of evaluations is limited and requires optimization methods. Translating the results of such approaches into decision support for urban planners is crucial to make the underlying complexity of modeling and optimization accessible in practice.

In summary, the multitude of competing objectives and large decision spaces pose a great challenge to urban planners. Domain-specific simulation models support them, but holistic decision support can hardly be derived from such models, as they only focus on single aspects. Therefore, an approach for the creation and multi-objective optimization of interdisciplinary urban simulation models and the subsequent derivation of multi-criteria decision support is needed. We aim to fill this gap by proposing a generic process that shows which steps to take and how to couple them. Fig. 1 introduces this process's main parts: data collection, simulation model setup, trade-off analysis, and multi-criteria decision support.

2. State of research

First, this section explains the concept of Hyper Space Exploration, which serves as the theoretical foundation for setting up the generic multi-criteria decision making process. The rest of the section is structured along the main parts of the process (Fig. 1) and focuses on the relationship between each of the parts and urban planning.

2.1. *Hyper space exploration for developing multi-criteria decision support processes*

Hyper Space Exploration (HSE) is a systems engineering concept that combines virtual prototyping with statistical learning to explore a vast space of potential solution alternatives in complex environments. We use it as a guiding framework to develop a process for multi-criteria decision support in urban planning. The Hyper Space consists of the changeable variables (Design Space), the system configuration (Use Case), and the target variables (Target Space). HSE allows to explore the effects of inputs and system configurations on target indicators. It quantifies trade-offs and identifies Pareto-solutions. The methodology involves a five-step iterative process of Design Space definition, design of experiments, simulation, surrogate model building, and system and surrogate model optimization. The application of the HSE methodology takes place within a tool-chain together with a simulation model that maps the systemic interactions. All parts need to be coupled with the HSE environment to ensure control and monitoring of inputs and outputs during optimization [12,13]. The generic workflow has been successfully used in various applications, such as battery energy storage systems [14] or decentralized energy systems [15], where it's capabilities and universality were demonstrated.

2.2. *The urban planning process*

Until the beginning of the 20th century, cities were planned based on empirical values from different disciplines. These empirical values were applied mostly regardless of each other, which led to competitions and restrictions in single aspects. It was only then that a cross-disciplinary discourse was integrated into urban planning to generate long-term plans for urban development. However, the focus was primarily on the plan itself, which was usually followed independently of the context. This approach gradually gave way to process-oriented planning, which envisioned not a strict goal but rather the inclusion of context and possibilities [16]. The traditional rational urban planning process consist of four steps: (a) situation analysis, (b) goal establishment, (c) action identification, (d) consequence evaluation and comparison [17]. These have been expanded to more detail in various attempts [18]. Data collection always plays an important role at the beginning of the traditional urban planning process and can be related to the HSE framework as Use Case definition (a, situation analysis), Target Space definition (b, goal establishment), and Design Space definition (c, possible actions). In contrast to the HSE idea of exploring the whole space of possible outcomes, the traditional urban planning process mostly aims to develop individual solutions for the given urban context and task. Thus, urban planning is often limited to iterative scenario work [19], where planners try to achieve an optimum in one aspect (e.g. floor area) while giving several constraints (e.g. minimum number of trees). As urban development is likely to focus on real estate aspects [20], important aspects of sustainability are common objectives for constraint, which leads to non-optimized solutions in this regard [18]. This approach is partly a result of the growing complexity of urban planning, which makes thorough investigation of circumstances difficult, thus leading to scenario work. The evaluation of scenarios in this context is a weakness for several reasons. On the one hand, decision makers cannot be sure to get a set of optimal solutions for their choice, as only a limited number of constrained evaluations is made. On the other hand, there is usually only a small number of evaluated scenarios [21]. These scenarios represent single solutions in an unknown space of possible solutions. Thus, there is no further information on the expected trade-offs and their influencing factors. In consequence, some scholars argue for an update of common urban design and planning processes in order to overcome these shortages [6].

2.3. Simulation of urban interactions

The building sector faces a multitude of interactions, which result in numerous multi-criteria issues that should be considered in the planning process. Interactions exist both within building systems [22] and between buildings at the neighborhood level [23]. These indoor–outdoor interactions have been intensively studied in research [24]. Liu et al. develop a parameterized Grasshopper model to investigate the effects of neighborhood shading on the energy demand of buildings. Thereby, they show that heating and cooling loads are heavily influenced by the urban context [25]. Löffler et al. take a similar approach to investigate the effect of urban density on energy demand and find a comparable effect of insulation and density on heating demand [26]. Naboni et al. show how outdoor and building simulation can be combined into a holistic model. They utilize existing plugins in the Grasshopper environment to determine daylight availability, outdoor thermal comfort, and energy demand of design variations [27]. While most of these studies focus on building-related parameters, Zheng et al. integrate street trees into the assessment of energy efficiency and outdoor thermal comfort. Furthermore, they emphasize the trade-off between these two aspects [28]. However, the aforementioned studies mainly focus on the interactive effect in terms of energy demand. Lifecycle-based approaches are rarely found in the context of complex urban simulation models. Another significant challenge are the extensive simulation times required for outdoor comfort [29], wind [30], or energy consumption [31]. Obviously, simulation times increase further with parallel investigation of these aspects. In addition, such sophisticated simulation models are difficult to use for decision makers, making it necessary to derive easily communicable decision support.

2.4. Multi-objective optimization of urban simulation models

The application of multi-objective optimization (MOO) methods in the building sector has been a growing research interest in recent years [32]. These methods allow decision makers to identify optimal (in mathematical terms, non-dominated or Pareto-optimal) solutions to complex design problems by considering multiple performance criteria simultaneously. Pareto-optimal solutions (or Pareto-points) generalize the concept of mathematical minimum to multiple dimensions. Roughly speaking, a Pareto-optimal solution is a solution such that no other solutions are better in every component [33]. In the setup described here, this translates to solutions where minor lifecycle-based global warming potential (GWP) is only possible by worsened outdoor thermal comfort or vice versa. Consequently, there is more than one Pareto-solution for such problems. Getting a broad spectrum of possible Pareto-solutions allows to start a discussion on the prevailing trade-offs and how to balance them [12].

Several methods for MOO exist, but only a few are suitable for computationally expensive urban simulation models. This limits the applicability of MOO algorithms as optimization quality decreases with a smaller number of evaluations [34]. Brute Force methods evaluate all input configurations sequentially but are only appropriate for finite or discretized parameters [35]. Gradient-based methods are sensitive to local extremes and are therefore not suitable for nonlinear building simulations [36]. Hence, global optimization approaches are required. These can be divided into direct search and surrogate model-based search. Only a few direct search algorithms are available, as they often can only work with a limited number of inputs and mathematical guarantees for a global optimum are difficult to provide [37]. Model-based algorithms, on the other hand, generate surrogate models for the simulation to be optimized. Evolutionary algorithms and particle swarm optimization have proven to be suitable for building optimization in this context [34,37]. In practice, however, there are often uncertainties in dealing with such algorithms, and computationally intensive models are investigated with unsuitable methods and too short optimization runtimes [38]. Wortmann compares several optimization algorithms in a trade-off analysis of daylight and glare and states that the application of model-based MOO in architecture is highly suitable for computationally expensive architectural simulation models [39]. Zhang et al. show how model-based MOO can be used to achieve significant improvements in energy usage and building structure while facing a trade-off with solar availability. They also highlight the importance of optimization approaches for decision making in early design phases [40]. However, many MOO algorithms do not guarantee complete coverage of the Pareto Front (PF), which is necessary for a holistic representation of the decision space of urban planners [41]. For instance, Zhao et al. use a genetic algorithm to optimize daylight performance and energy demand. Although, the optimization converges to the final PF, there are still gaps in the results [42].

2.5. Multi-criteria decision support in urban planning

In the building sector, Kiss et al. demonstrate how MOO can support decision making by balancing environmental indicators from building operation and construction. The HypE algorithm, proposed by Bader et al. [43], is utilized to identify competing impact categories. They highlight the potential of such approaches to reveal the decision space for designers [44]. Schuler et al. use linear equations to investigate planning options and trade-offs for decision makers at both the individual building and the urban scale. They note that detailed dynamic simulations may require significant effort to represent a complete picture of the decision space [11]. Abdollahzadeh et al. demonstrate the use of coupled indoor and outdoor simulations in a parametric approach for simultaneously evaluating building energy demand and outdoor thermal comfort. They discuss the revelation of the decision space and the selection of the optimal design outcome. However, increasing simulation time poses a significant challenge for a more detailed simulation model [45]. Mukkavaara and Shadram show how sensitivity analysis can be used to support decision making in the context of Life Cycle Energy Analysis. They apply MOO and select Pareto-optimal solutions based on obtained sensitivity by utilizing the Method of Morris [46]. The use of surrogate models for deriving the Design Space of Pareto-solutions is shown by Li et al.. They set up a surrogate model for a single simulation tool and use this model to optimize for the PF. By obtaining a distribution of the Design Space parameters, they derive recommendations for the input ranges. In their outlook they mention the integration of further aspects in order to enforce a systemic perspective in the urban environment [47].

3. Methodology

This section describes the generic process for multi-criteria decision support in urban planning. Alongside, we provide examples of methods and tools that can be used to implement the process. Fig. 2 shows the individual steps of the proposed process, which we explain in the following.

(1) *Target Space definition:* The targeted objectives of urban development are defined. These may include a variety of aspects from the fields of ecology, economy, and society. In order to allow for the optimization, all the defined objectives need to be quantifiable, i.e. they need to be real numbers. Therefore, the focus is on defining the Key Performance Indicators (KPIs) that shall be included in the following optimization to ensure a measurable outcome of the design process. A possible way to derive these KPIs is through public discussion and

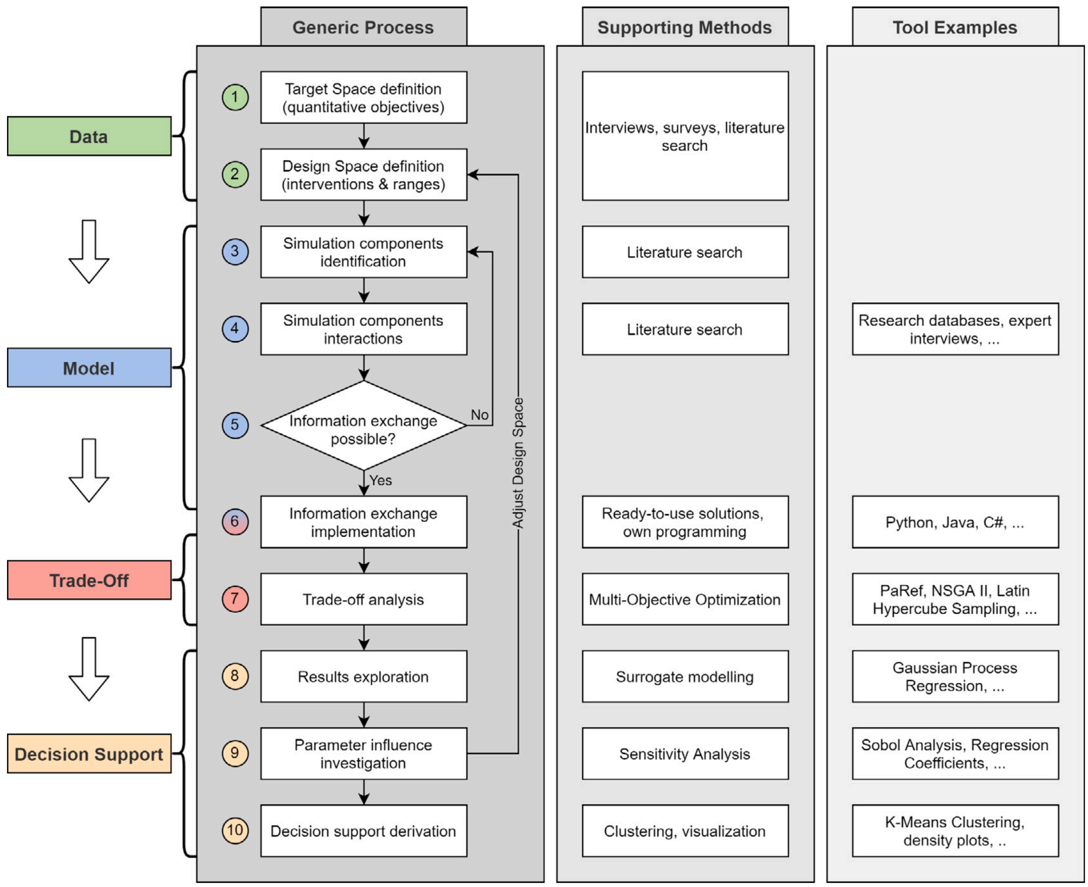

Fig. 2. The generic process of Urban Systems Exploration for multi-criteria decision support in urban planning with supporting methods and tool examples.

orienting the selection on the city council's published intentions for future development.

(2) *Design Space definition:* Defining possible interventions depends on the context of the project and whether it is a new or existing development. After defining the relevant interventions, their boundary conditions are assigned. These conditions may include ranges for specific variables or constraints. For instance, urban density can be limited by regulations and thus should not take a value outside a certain range. Discussion within project groups or former experience are possible ways to identify these. The interventions and their ranges make up the Design Space of the project.

(3) *Simulation components identification:* After defining Design and Target Space, the necessary simulation components that integrate the interventions and evaluations must be identified. The process described in this paper also applies to computationally expensive simulation models. Thus, users can select from a wide variety of simulation components in their field, as this selection is not limited to fast-running simulations like many MOO applications.

(4) *Simulation components interactions:* While each of the simulation components is capable of the KPI it was selected for, this step ensures a systemic consideration of the urban fabric. Therefore, interactions of the single components need to be identified. In this context, we define two kinds of interactions. On the one hand, the results of one process may serve as input for another. On the other hand, several processes may refer to the same input. Additionally, the influence of interactions should be investigated, as some might only have a minor impact on the results. Consulting literature or experts on a specific nexus can support this step. Excluding known interactions should be done carefully, as systemic behavior may be very different from single considerations and thus neglect significant interactive effects.

(5) *Check information exchange:* As methodologies for obtaining the identified KPIs vary in terms of model type (physical simulation, artificial intelligence models, stochastic models), sufficient possibilities for implementing the identified interactions in the overall model need to be ensured. This may be done by passing on outputs from one simulation component to another component where it serves as an input, or by using the same inputs for several model components. If there are components that do not share any connection with the others or where information exchange is technically not possible, a different simulation component needs to be found.

(6) *Information exchange implementation:* The implementation of information exchange often utilizes one single platform, where all identified simulation components can be connected. This may be an existing software, such as Grasshopper [48], where several simulation plugins operate. Another way is to develop one's own methodology for this information exchange based on programming languages such as Python. Finally, this step leads to an interconnected simulation model, which can be used for the following trade-off analysis.

(7) *Trade-off analysis:* It is not possible to determine Pareto-points theoretically. Hence, an algorithm is necessary. For the trade-off analysis, an MOO algorithm is selected and applied to the model. This MOO algorithm must be effective by identifying points that represent an optimal trade-off, and efficient by using few computational resources. After selecting an appropriate option, it needs to be coupled with the simulation model. Some algorithms provide ready-to-use interfaces, whereas in some cases, users need to define their own exchange methodology for the MOO and the simulation model. After this step, a first impression of the general trade-offs and their properties is possible. This may already be useful for decision making and can guide further investigation.

(8) *Results exploration:* In order to allow a detailed exploration of the resulting trade-offs, the discontinuous results from the MOO are transferred into a continuous space using surrogate modeling. The

simulation results and the corresponding inputs are used to train these models. As the number of available training points limits this process, Gaussian Process Regression (GPR) is suitable for this step. GPR is a highly flexible modeling approach that has empirically proven to be a good choice for regression problems with few data [47,49]. The validity of the model training must also be ensured, as inaccurate training of the surrogate model would cause misleading results in the next step and, therefore, wrong conclusions regarding decision support.

(9) *Parameter influence investigation:* Two crucial aspects are covered by determining the influence of the Design Space parameters. First, it allows to reduce the number of inputs to the process in step (2). This leads to reduced computational effort and more efficient process use. However, it should be noted that these parameters still give valuable information about their value ranges. Low sensitivities reveal that changes in these variables will not lead to high uncertainties in the results, and their value can be narrowed down to a small range. Second, parameters with a high sensitivity are well usable as steering inputs. Their influence and control options should be further evaluated. This is especially useful in high dimensional Design Spaces, where only a limited number of inputs can be visualized and discussed.

(10) *Decision support derivation:* In the final step, decision support is derived from the immediate outputs of the MOO process (7) as well as from the surrogate model (8). One possibility to make the results more accessible is to cluster certain areas of the Pareto-optimal solutions and show the corresponding input values. By obtaining an equally spaced distribution of Pareto-points, density plots allow insights into the steering of trade-offs by the selection of certain input combinations.

We propose to implement the process of Urban Systems Exploration in urban development projects as early as possible. Although little information is available at this point, simulation models designed for this purpose can contribute to the early assessment of the prevailing trade-offs. Additionally, repetitive application of the process improves the results' reliability when conditions become more explicit. In this iterative process, targets and objectives may be refined, and the generic process can be applied several times.

4. Case study description

In this study, the generic process is exemplary applied to a case study neighborhood in Munich, Germany. We give an impression of the trade-off between lifecycle-based GWP and outdoor thermal comfort (Section 4.1). In Section 4.2, the KPIs for evaluating this trade-off are identified, and a simulation model is set up as described in the process steps (1) – (6). For the application of steps (7) – (10), we set up a toolchain suitable for the MOO of urban neighborhoods. Finally, we present the case study neighborhood for implementation in Section 4.3.

4.1. Trade-off under consideration

Urban green spaces provide various benefits, such as reducing urban heat island effects, reducing building cooling energy demands, and enhancing outdoor thermal comfort [50]. Additionally, urban green infrastructure supplies several cultural ecosystem benefits, including health, social cohesion, and local identity [51]. However, increasing urbanization causes competition for limited space in cities, raising the question of whether to use available areas for new buildings or green spaces. This creates challenges for the urban planning process, such as balancing outdoor thermal comfort with heating energy demand and greenhouse gas emissions [52]. Considering this fact, it is crucial to make trade-offs easily usable for strategic planning at the neighborhood level, as co-benefits from mitigation and adaptation decrease the later the related measures are scheduled [3]. Research has pointed out several relevant effects when it comes to building-green interactions. Darvish et al. showed that urban trees can have a considerable effect on buildings' heating and cooling energy demand [53]. Hamin and Gurran elaborate on the competing requirements for climate change mitigation and adaptation. Densely built areas contribute to mitigation, whereas open and green spaces improve adaptation [4]. However, research rarely considers the combined effects of technological measures, such as refurbishment, and green measures, such as tree coverage and tree shapes [54].

Table 1
Design Space for the multi-objective optimization.

Simulation parameter	Unit	Input range
Tree percentage	[%]	[0, 100]
Tree crown diameter	[m]	[2, 10]
Tree height from ground	[m]	[6, 10]
Tree crown transparency summer	[%]	[10, 30]
Tree crown transparency winter	[%]	[45, 80]
PV roof percentage	[%]	[0, 100]
PV south façade percentage	[%]	[0, 100]
PV east – west façade percentage	[%]	[0, 100]
PV battery capacity	[kWh]	[0, 80]
Green roof soil thickness	[m]	[0, 0.25]
Window-to-Wall Ratio all orientations	[%]	[10, 50]
Window solar heat gain coefficient	[–]	[0.4, 0.85]
Albedo façade	[–]	[0.1, 0.7]
Street width	[m]	[3, 9]

4.2. Process application in a case study

4.2.1. Data and inputs

As a first step of the generic process, suitable KPIs need to be identified (1). The goal of this case study is to investigate the trade-off between climate change mitigation and climate change adaptation. Therefore, we implement two main aspects into the simulation model: climate change contribution and outdoor thermal comfort. These are represented by the indicators lifecycle-based GWP and Universal Thermal Climate Index (UTCI). In the following step, intended interventions and their representation in the simulation model are determined (2). The aim is to identify configurations of outdoor space and building interventions that lead to Pareto-optimal solutions for the neighborhood. Table 1 shows the considered ranges for the 14 selected model inputs. Tree percentage represents the proportion of possible tree locations around the buildings that are occupied by trees. Photovoltaic (PV) percentages refer to the corresponding occupied proportion of the building surfaces. Tree crown transparency indicates the foliage condition over the year, with low transparency representing dense foliage. The street width between buildings is included, as wider streets reduce the number of possible tree locations.

4.2.2. Simulation model

The simulation model developed for this study is based on the parametric Grasshopper environment in Rhinoceros 3D [48]. The available plugins enable coupled workflows to evaluate our chosen KPIs. The main parts of the simulation model considered in step (3) are:

- Outdoor thermal comfort simulation [55]
- Wind simulation with Fast-Fluid-Dynamics [56]
- Building energy simulation [57]
- Life Cycle Assessment [58]
- Photovoltaics simulation [59]

As several simulation cores are involved, a coupling approach within the Grasshopper environment is necessary. However, both KPIs are not independent but dynamically exchanging and partly based on identical inputs. The qualitative search for interactions between the simulation components revealed a strong connection between urban vegetation, its potential cooling effect for urban heat islands, and buildings' energy demand [60,61]. To integrate this interaction, we decided to implement another simulation component into the model, the Urban Weather Generator [62] (4). As mentioned, the Grasshopper

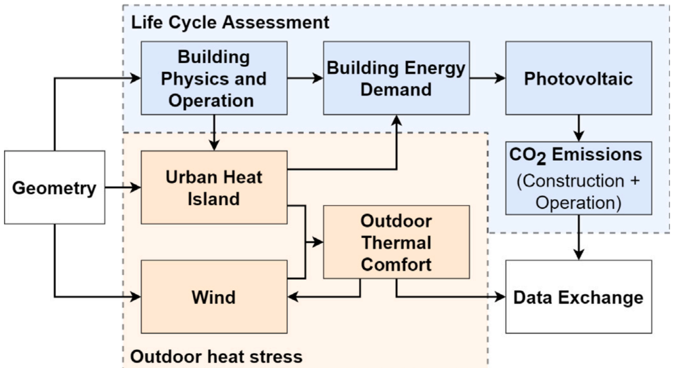

Fig. 3. Simplified representation of the information flows within the Grasshopper model.

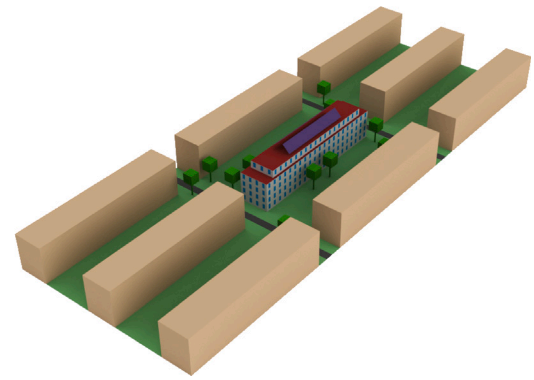

Fig. 4. Representation of the Grasshopper model with the central building for energy simulation and neighboring buildings with trees as context shading.

environment offers a ready-to-use solution to exchange information between simulation components. By applying Python programming and native tools, it is possible to transform data from one simulation output into the correct format for the following components (5).

The next step (6) in the generic process covers the implementation of information exchange in the simulation model. Fig. 3 illustrates the simplified information flow within the simulation model. Firstly, the geometries of the considered buildings within the neighborhood are created, including the buildings themselves, streets, lawns, and trees (Fig. 4). After generating the base geometry, inputs for incorporating the Urban Heat Island (UHI) effect are extracted from this model using the Dragonfly implementation of the Urban Weather Generator [55]. Although the model itself only covers an area of 210 × 72 m, the inputs for the UHI simulation remain constant within the considered typology of row housing and are thus usable for the Urban Weather Generator. This step generates a locally adapted weather file, considering the information on building materials and operational configurations. The local weather file is the basis for the central building's subsequent energy simulation in Energy Plus [63]. This energy simulation considers the previously specified materials and usage profiles. The neighboring buildings represent opaque surfaces in the energy simulation, while trees receive transparency over the year, according to their leaf state. The resulting energy demand of the buildings is transferred to the PV component of Climate Studio [59] as a load profile on an hourly basis, determining the proportion of self-consumed and exported energy. Buildings and trees are considered as shading objects in the PV simulation. Finally, the calculation of GWP over the 50-year lifecycle is performed based on component values (for the construction phase) and emission factors (for the operational phase). For the so-called grey emissions (GWP from material consumption), insulation material, changing Window-to-Wall ratio (WWR), the exchange of existing building components, and disposal after 50 years are considered. This is especially important for evaluating intense refurbishment scenarios, such as the Passive House standard, where grey emissions may take large shares of the total impact [64]. The resulting KPI of CO_2-equivalent per gross floor area is passed on to the data storage. Detailed information on the applied boundary conditions for the LCA of the case study are given in Section 4.3.

To assess outdoor heat stress, we first select a particularly heat-intensive hour. Heat stress is not only determined by air temperature and relative humidity but also by, e.g., radiation and local wind speed. Thus, the UTCI is appropriate for this assessment, as it includes these influences [65]. Due to the computationally expensive wind simulation, evaluating numerous hours is hardly feasible. To overcome this, we implement a pre-selection approach to identify the hour with maximum thermal heat stress for further wind analysis. Outdoor thermal comfort is usually determined for single positions in the model and is thus highly susceptible to fluctuations due to local conditions. In order to minimize the effects of locally cast shadows on outdoor heat stress during specific hours, 15 grid points are regularly distributed within a radius of 50 m around the central building at the height of 1.2 m. Thereby, we cover the outdoor area where tree placement around the central building may influence UTCI. Firstly, the geometrically relevant parameters, such as sky view factor, are determined for each of the grid points. Subsequently, we calculate Mean Radiant Temperature, and finally, the UTCI is determined for each grid point at every daytime hour between May and August using Ladybug Tools [55]. The results for the grid points are then averaged, resulting in one UTCI value for each hour. The hour with the maximum area-averaged UTCI value is filtered and further analyzed from this set. This hour's wind speed and direction are extracted from the weather data. They serve as inputs for the wind simulation, in which we use Fast-Fluid-Dynamics [56]. From the results, we extract the local wind speed and combine it with the other parameters from the local weather file (air temperature, radiation temperatures, relative humidity). This leads to the final UTCI results for each of the 15 grid points in the area. After averaging over the grid points, we obtain the outdoor thermal comfort KPI for data storage.

Another important aspect of setting up the coupled simulation model is the scale at which each of the involved simulation cores operates. Energy simulation can be conducted for individual buildings as well as for entire neighborhoods. In contrast, obtaining outdoor thermal comfort KPIs is mostly done at the neighborhood scale. Hence, the neighborhood scale is chosen for the entire model. Due to the repetitive character of the central building in our case study, energy simulation and LCA are conducted only for this building to reduce simulation time. In this regard, all the surrounding elements (buildings, trees) serve as shading objects. Specific inputs and boundary conditions for the case study are presented in Section 4.3 and are summarized in Table 2.

4.2.3. Tool chain for multi-objective optimization

The simulation model and the optimization environment are linked via an independent control interface for data exchange. A data storage holds the results for further evaluation upon completion of the optimization process (Fig. 5).

Following the simulation model setup, the trade-off analysis involves the MOO of the black-box model (7). As the simulation model is classified as computationally expensive, only a few evaluations are possible. Therefore, we choose GPR-based Multi-Objective Optimization, as it can effectively and efficiently identify Pareto-points in the Target Space [75]. Starting from an initial Latin Hypercube Sampling (LHS), this methodology combines surrogate models based on GPR for each of the considered outputs and maximizes the Expected Hypervolume Improvement. The approach has recently been updated to the Paref algorithm library. Paref allows to identify Pareto-points and additionally to require some properties of these points (e.g., evenly distributed,

Table 2
Fixed inputs for the Grasshopper simulation model.

Simulation parameter	Input	Source
U-Values [W/m^2·K]	Status Quo: 1.6, 1.0, 1.0, 2.6	[66]
wall, roof, ground, window	Scenario 1 (GEG): 0.24, 0.2, 0.3, 1.3	[67]
	Scenario 2 (PH): 0.15, 0.15, 0.15, 0.7	[68]
Weather data	Retrieved from Meteonorm for Munich airport, 2020	[69]
Heating setpoint	20 °C	[70]
Internal loads [people/m^2]	0.025	[70]
Internal loads lighting [W/m^2]	2	–
Occupancy schedule	weekdays: 17–7 h, weekend: full day	–
Infiltration [m^3/s per m^2 façade]	Scenario 1 (GEG): 0.0003, Scenario 2 (PH): 0.0001	[55]
PV efficiency [%]	22	[71]
PV battery efficiency [%]	70	–
LCA insulation material [–]	eco standard	[72]
Tree transparency months	summer: May – October, winter: November – April	–
Tree crown transparency [%]	summer: 10, winter: 55	[73]
Plant height roof vegetation [m]	0.2	–
Anthropogenic heat $Q_{f,max}$ [W/m^2]	summer: 34.64, winter: 57.5	[74]

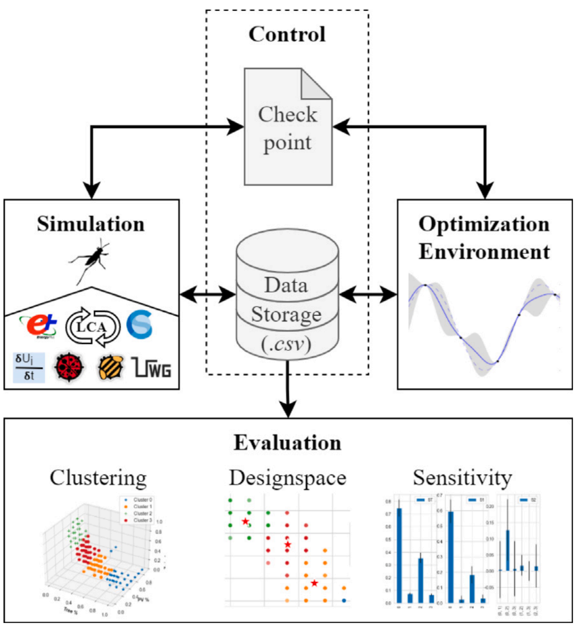

Fig. 5. Tool-chain for coupling the optimization and the simulation environment.

located in a specific target range, being an edge point). Paref provides ready-to-use algorithms that allow one to search explicitly after those properties with theoretical guarantees [76,77]. Through this, Paref can identify Pareto-solutions in certain areas of the PF with a small number of model evaluations. Thereby, it meets our defined requirement of efficient determination of evenly distributed Pareto-points in a complex environment.

For the application in our case study, we generate 15 initial samples using LHS and simulate them with the Grasshopper model. With this initial evaluations, the first GPR models are fitted. In the first step, we choose a configuration for searching edge points of the PF. Thereby, the algorithm weights the two competing KPIs (lifecycle-based GWP and average UTCI) to both extremes to identify the maximum Target Space span. Due to the small number of samples for training the surrogate models, uncertainty in these edge-areas of the PF is initially high. Therefore, the Paref framework allows for multiple runs per point. For each edge point, three iterations are permitted. The search is terminated if the algorithm identifies a point very close to an already evaluated solution. Once the two edge points are identified, we apply the evenly-scanned search algorithm to reveal the rough shape of the PF. After completing this step, the fill-gaps search algorithm is applied. This involves calculating the normalized distances between each consecutive pair of Pareto-points. Consequently, Paref searches for an optimal solution between the two Pareto-points with the most significant normalized distance. If no new Pareto-point is identified, the algorithm attempts to find a point at the same location again, which can lead to accumulation in some areas. Nevertheless, the identified points contribute to improved PF representation in these regions. After each search step, the user may decide to terminate the optimization or change the search strategy by using another algorithm or manually restricting the search space.

Due to the Python 3 based optimization algorithms in Paref, direct integration into the parametric model is not feasible as Grasshopper currently only supports IronPython 2 (version 2.7). Therefore, the data exchange is facilitated via comma-separated values (csv) and checkpoint files, with the contents of a network drive being continuously monitored by both the simulation and the optimization environment. Upon completion of a simulation or optimization iteration, the respective environment generates a csv file with inputs for the simulation (in the case of the optimization environment) or results of the simulation run (in the case of the simulation environment). Subsequently, the corresponding checkpoint file is created. The coupled environment recognizes these files and initiates reading the inputs or outputs, thereby starting the simulation or optimization. After the process is finished, the previous checkpoint file is deleted, and the new csv and checkpoint files are written, which toggles the next iteration loop. This coupling approach has multiple benefits compared to direct integration into Grasshopper. For instance, performing simulation and optimization on different computers is possible. This enables the allocation of resources to tasks according to their requirements (e.g., high CPU performance for the optimization on one computer, high GPU performance for simulation on another computer). Additionally, it enhances the robustness of simulations by allowing manual pausing or restarting of individual iterations.

4.2.4. Decision support

After obtaining a discrete representation of the PF, we construct a surrogate model from the optimization results for further analysis (8). GPR is utilized as it is a suitable method for creating surrogate models with few training points while also capturing uncertainties. The GPR receives the Pareto-points obtained from the optimization process as initial training points. Since our approach identifies many points very close to the actual PF, we select 75 % of all available points closest to the optimized PF as full training set. These points increase the prediction accuracy of the model in areas where an actual Pareto-point could not be identified. Additionally, points far away from the PF are excluded by this procedure. These dominated points stem from the initial LHS and are scattered over a large area. They would introduce high uncertainty for predictions far away from the PF.

After creating the surrogate models and verifying its prediction quality, we determine sensitivities (9). This gives a sense of the inputs

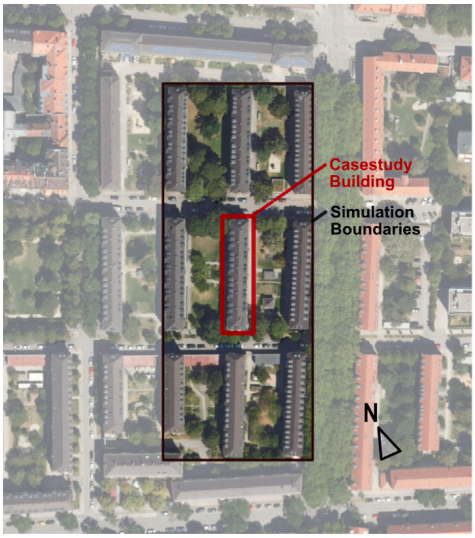

Fig. 6. Case study area in Munich.
Source: Adapted from [78].

to focus on for subsequent evaluation. In the last step, we use linear interpolation to derive dense and equally distributed Pareto-solutions (10). This is necessary as we want to show the spread of inputs for certain PF areas to give urban planners an impression of the related Design Space. Non-equal distribution would cause misleading conclusions due to accumulation in certain areas. A differential evolution algorithm determines the corresponding input (i.e. Design Space) values for each of the equally distributed points using the GPR surrogates. Due to the probabilistic nature of GPR, model uncertainties in the form of standard deviations can be investigated at each point. This allows identifying outliers and excluding them from further analysis. The result is a PF where each Pareto-solution is mapped into the Design Space and planners can investigate the distribution of input parameters in certain areas of the PF. This allows them to decide on the necessary boundary conditions to achieve a certain trade-off balance. Additionally, they can identify inputs with more open boundaries. These are necessary to open up design options and thus ensure productive planning competitions.

4.3. Case study area

The case study aims to quantify the trade-offs and conflicts arising from the simultaneous consideration of climate change adaptation and climate change mitigation in urban planning. We use the coupled indoor – outdoor simulation model combined with multi-objective optimization to visualize trade-offs and derive recommendations for steering design into specific trade-off areas. The proposed process is implemented via the described tool-chain and applied to a case study neighborhood in Munich, Germany.

The case study area is a typical massive row house development from the 1930s, which is representative for this type of settlement [79]. Fig. 6 shows an aerial photo of the area's boundaries with the central building highlighted. Table 3 summarizes the information on the central building used for energy simulation. These properties remain unchanged in the optimization process.

For the LCA we use component data sets generated based on the German Ökobaudat database [80], version 2020-II. The life cycle phases of construction (A1 – A3), building operation (B4, B6), and end-of-life (C3 – C4) are considered for products that are newly installed to the building, such as additional insulation. For existing products, exchange according to the components' service life (B4) and end-of-life (C3 – C4) after the 50-year study period are considered. Components' service life is set according to [81] for new and existing parts. The considered building parts are: roof, ceilings, exterior walls, interior walls, windows, and base slab.

Table 3
Characteristics of the central case study building used for energy simulation and LCA.

Characteristic	Value
Building length	62 m
Building width	10.5 m
Building height	15 m
Number of floors	4 full, 1 attic
Distance to neighbors east – west	20 m
Distance to neighbors north – south	12 m
Year of construction	1930
North orientation	10°

The hourly matching of electricity demand and PV generation allows detailed consideration of consumed and exported energy. The GWP credit for exported electricity is linearly reduced to zero by the assessment year 25. This means that from year 25 to year 50 of the assessment, no credit is given for exported electricity, as by then, a primarily regenerative energy supply is assumed in the German electricity mix [82]. PV is modeled with an efficiency of 22 %, corresponding to Crystalline Si Cells or Thin-film technologies [71].

Two refurbishment scenarios are examined for the area. The legal standard (GEG, [67]) represents the base level of refurbishment, and the Passive House (PH, [68]) an improved standard. A heat pump (Coefficient of Performance = 3.0) is assumed as the primary heat supply for both scenarios. Energy requirements for heating, lighting, and hot water are included. Active cooling is not available in most of the German building stock and is therefore not considered in this study [83].

5. Results of case study application

We present our results first regarding the properties of the Pareto-solutions. Second, we compare three different approaches for the MOO in terms of PF representation. Third, the surrogate models are evaluated for their prediction quality and the necessary number of black-box function evaluations. Finally, steering options for the trade-off are presented.

5.1. Properties of pareto-solutions

The results obtained from the optimization process allow for an initial evaluation of the outcomes and plausibility checks. Fig. 7 illustrates the PF, taking into account the attributes of *Tree-%* and *Roof-PV-%*. Direct causal relationships can be inferred from this representation. It is evident that *Tree-%* is a significant control lever for positioning on the PF. As *Tree-%* increases, the outdoor thermal comfort indicator improves, i.e. UTCI lowers. In contrast, lifecycle-based GWP rises with a higher proportion of trees as heating and lighting energy demands increase, and positively contributing PV surfaces may become shaded. For the design parameter of *Roof-PV*, mostly values above 50 % are situated on or close to the PF, with more significant PV percentages being required for very low GWP outcomes.

However, the points are unevenly distributed throughout the PF, potentially leading to bias when mapping them back into the Design Space. As described in the methodology section, especially applying Paref's fill-gaps search algorithm may lead to a concentration of points in certain areas. This is the case in the steeply increasing section of the PF around an UTCI of 29 °C (see Fig. 7).

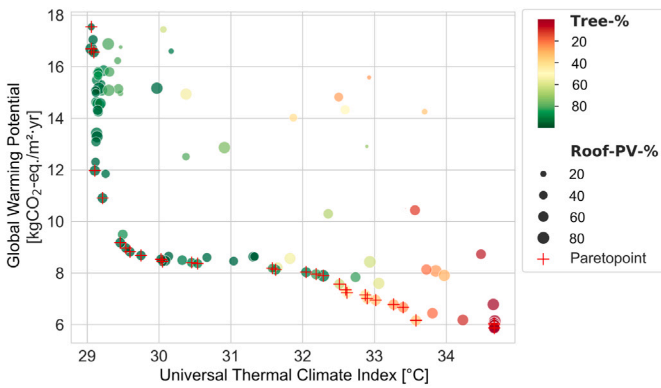

Fig. 7. Pareto Front obtained from multi-objective optimization of the GEG scenario with Design Space properties. Included lifecycle phases: A1 – A3, B4, B6, C3 – C4.

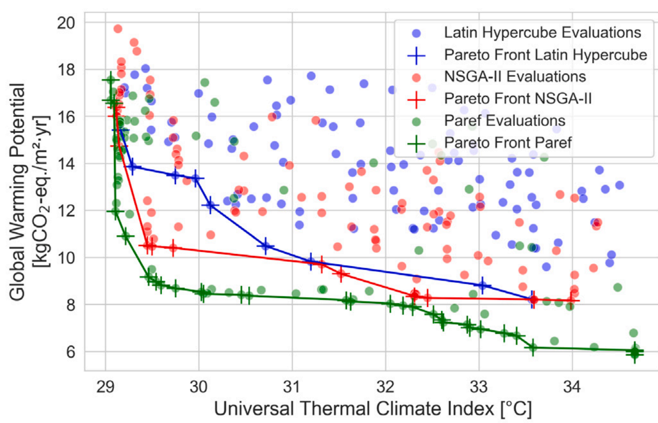

Fig. 8. Pareto Front obtained from Paref, NSGA-II, and Latin Hypercube Sampling.

5.2. Representation of the pareto front

To check the quality and coverage of the PF obtained from the optimization, we simulated 100 samples generated by LHS for the GEG scenario. MOO was performed using the NSGA-II algorithm with a population size of 25. As described in the case study, the Paref package with 15 initial LHS samples and a combination of the evenly-scanned and the fill-gaps algorithms was applied. Overall, each of the three approaches got 100 model evaluations to identify Pareto-points.

Fig. 8 shows the Target Space results, where both KPIs should be minimized. The LHS run resulted in a majority of model evaluations with a high distance to the Pareto-property. It covers a smaller Hypervolume compared to the optimization approaches (37.17 (LHS) compared to 44.26 (NSGA-II) and 53.92 (Paref)). This corresponds to a 16.02 % (NSGA-II) and 31.06 % (Paref) improvement by applying MOO algorithms. Additionally, Paref identifies many points close to Pareto-solutions, which is valuable information for the training of surrogate models in the next steps of our methodology. Overall, the Pareto-solutions obtained with Paref dominate the NSGA-II solutions and fulfill our requirement for even distribution.

5.3. Necessary number of model evaluations

In the following, we evaluate the quality of the final surrogate models with an increasing number of training points. This knowledge is especially relevant for applying the tool-chain in other contexts where computational resources are limited, and only a minimum number of model evaluations should be performed. In the context of prediction quality, Root Mean Squared Error (RMSE) is a measure of the differences between predicted and observed values commonly used to evaluate the accuracy of a surrogate model. R^2 is a statistical measure representing the proportion of variance for a dependent variable explained by variables in a regression model. The negative log predictive density (NLPD) measures how well the model's predictions match the actual data, with lower values indicating better predictions. NLPD is mainly used in probability modeling as performed with the GPR. Fig. 9 shows these metrics' dependence on the size of the training dataset. We split 20 % of the data points as a test dataset and tested ten variations of the training data to determine the confidence intervals. With a minimum of 40 training points, the metrics achieved convergence. This finding is beneficial for determining the necessary model evaluations in optimization to make the optimization process more efficient and avoid unnecessary runs.

5.4. Deriving multi-criteria decision support

After checking their quality, the surrogate models are finally trained for the two refurbishment scenarios (GEG, PH). Initial predictions of the Target Space with 100,000 samples per model were generated using LHS. Fig. 10 shows the resulting data points with the PF marked. The results extend beyond the initially determined PF, particularly in the edge areas. This is due to the higher uncertainties of the GPR model in these areas. The results generally show a better performance for the PH scenario, although overlapping areas can be achieved in both refurbishment scenarios. This highlights the decision making options in cases where the same results are possible in several scenarios. Nevertheless, regarding the Pareto-solutions, the PH scenario performs better than the GEG scenario in all cases.

A Sobol sensitivity study was performed with the PH surrogate model to select the most influential input parameters for further analysis. This variance-based sensitivity analysis allows to investigate how the output variance depends on the input uncertainty. The methodology builds a total effect, which is composed of direct and interactive effects. As we emphasized in the state of research, urban design is most often nonlinear and, therefore, requires such an approach. The resulting Total Sobol Indices give an indication of which inputs can be fixed without affecting the output and, accordingly, which inputs are useful levers [84]. The results show that, in particular, tree percentage, tree crown diameter, and PV percentage of the east – west façades can be used as control parameters (see Fig. 11). For clarity in the presentation of the results, we focus on these three parameters in the following sections. Furthermore, there are several inputs that mainly influence one of the two targets, such as PV-Roof-%. However, this may still indicate a relevant role for the combined trade-off investigation, as changes in one target can lead to losing the Pareto property of single solutions. It is important to mention that the sensitivity analysis is conducted over the whole space of possible model outcomes and is not limited to Pareto-optimal solutions. Therefore, there should not be hasty decisions to exclude seemingly less sensitive parameters. Our application of sampling over the entire Design Space in Section 5.4 (Fig. 10) showed that the surrogate models do not necessarily cover the complete PF when only sampling is applied.

We select the PH scenario for further investigation as it outperforms the GEG scenario. The gaps in the PF obtained from the optimization are filled at regular intervals using linear interpolation. Consequently, the corresponding input combinations for each point in the Design Space are identified using the surrogate models for the two KPIs and the differential evolution minimizer from the Sci-kit Learn package [85]. To better communicate the trade-offs on the PF, k-means clustering is applied. Gap statistic indicated seven as an appropriate number of clusters. Fig. 12(a) shows the clusters in the Target Space. They are characterized as regions with very low heat stress but higher GWP (e.g., clusters 1 and 5) and regions with higher heat stress but better

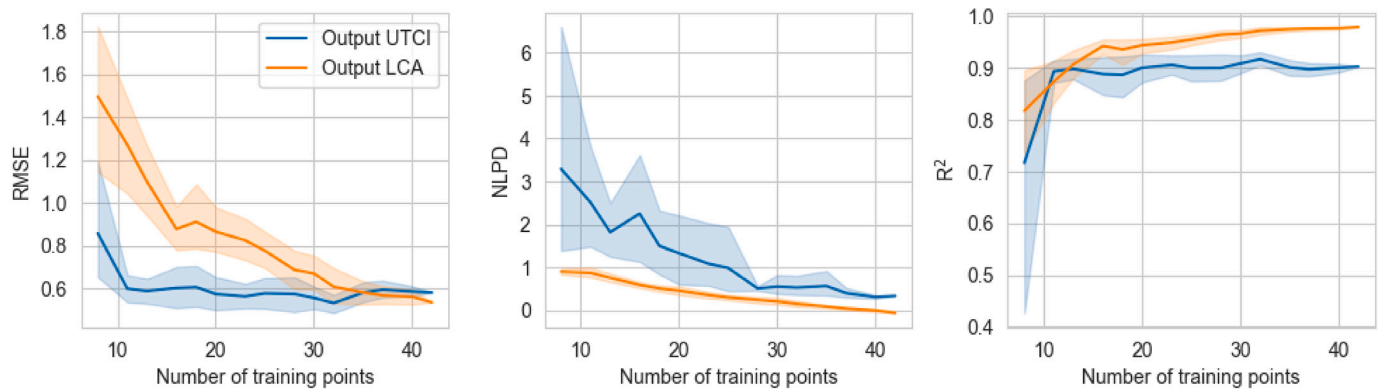

Fig. 9. Development of quality indicators for the GPR surrogate models (GEG scenario) with confidence intervals from 10 runs: (a) Root Mean Squared Error (RMSE); (b) Negative Log Predictive Density (NLPD); (c) Coefficient of Determination (R^2).

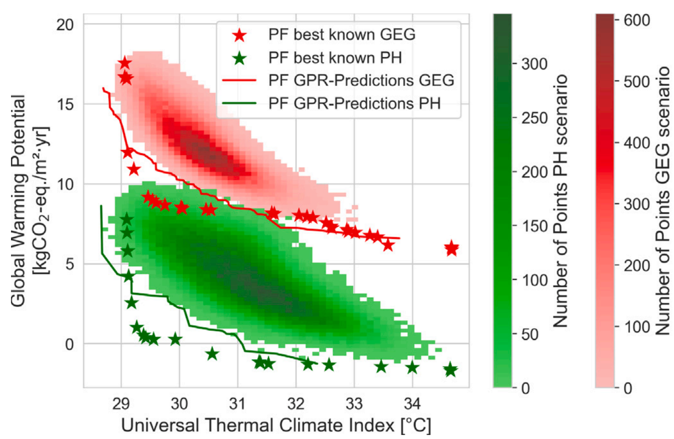

Fig. 10. Predictions of the two scenarios in the whole Design Space with 100,000 Latin Hypercube Samples each.

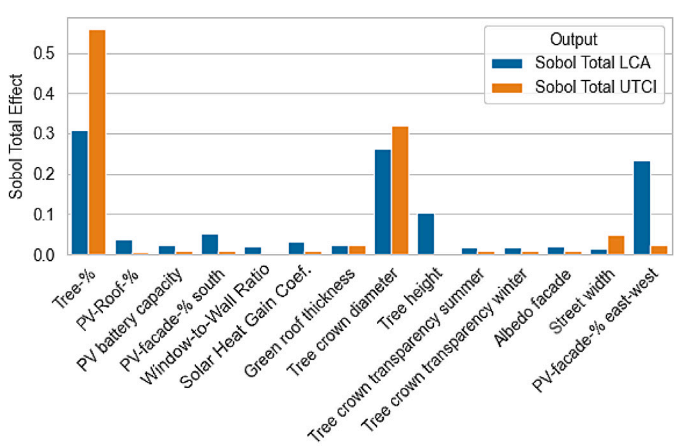

Fig. 11. Total Sobol Effect for the two Target Space variables lifecycle-based global warming potential (LCA) and Universal Thermal Climate Index (UTCI).

performance in terms of GWP (e.g., clusters 2 and 4). This representation allows an initial interpretation of the trade-off. The points are transferred to the Design Space to guide realization of a specific cluster. Fig. 12(b) illustrates this for the sensitive parameters *Tree-%* and *PV-façade east−west-%*. On the one hand, the balance between these two parameters is particularly relevant when targeting an area with very low GWP (clusters 0, 2, 4). On the other hand, the points in other clusters (1, 3, 5, 6) concentrate in the area of *Tree-%* between 80 % and 100 %. This suggests that other parameters are relevant for their further adjustment. Fig. 12(c) demonstrates this idea by taking the WWR into consideration. This additional design parameter can improve control on cluster 1 and 5.

Beyond coordinating selected parameters, the methodology allows to present a complete picture of Design Space ranges for specific clusters. Fig. 13 shows the range of all inputs for Pareto-optimal solutions classified in cluster 6 and the corresponding medians. Normalizing the inputs allows to represent them on a qualitative scale from low to high. This enables urban planners to set boundary conditions for further design based on these qualitative aspects. Thereby, Fig. 13 visualizes that planners can achieve the best possible trade-off balance represented by cluster 6 with a high number of trees and low to medium crown diameters. PV on façades should reach a high level and can be combined with a local battery to increase self consumption. Additionally, this kind of representation allows to identify inputs that should be more restricted than others for the case study area. One of these loose parameters are the tree properties (tree height, crown diameter, crown transparency) which show wider ranges than, e.g., the *Tree-%*. This means for the trade-off represented by cluster 6, having a high number of trees is more important than having a specific species.

6. Discussion

In the following, we interpret the outcomes of our case study and compare them to existing research while showing limitations. Subsequently, we discuss the process for MOO in urban simulation. Finally, possibilities for utilizing the outcomes for decision support in early design phases are explained.

6.1. Case study application

The simulation results indicate that the PH refurbishment scenario performs significantly better than the GEG scenario regarding the trade-off between GWP and outdoor thermal comfort. However, there are areas where the results overlap, indicating solutions that could be achieved with both scenarios. Regarding Pareto-solutions for GWP and outdoor thermal comfort, the PH scenario always represents the best possible option and should therefore be preferred. In this context, lifecycle-based calculation is an important requirement. High energy standards lead to increased GWP from insulation material that may offset the operational savings [46]. As general benchmarks for lifecycle-based GWP in building refurbishment are to be developed, a general comparison of absolute results is hardly feasible [86]. Due to the credited electricity production from PV during the period of electric grid decarbonization, the PH scenario achieves negative GWP results in some constellations. However, other studies show that even with PV, a zero-energy building could not be realized hourly, but this strongly

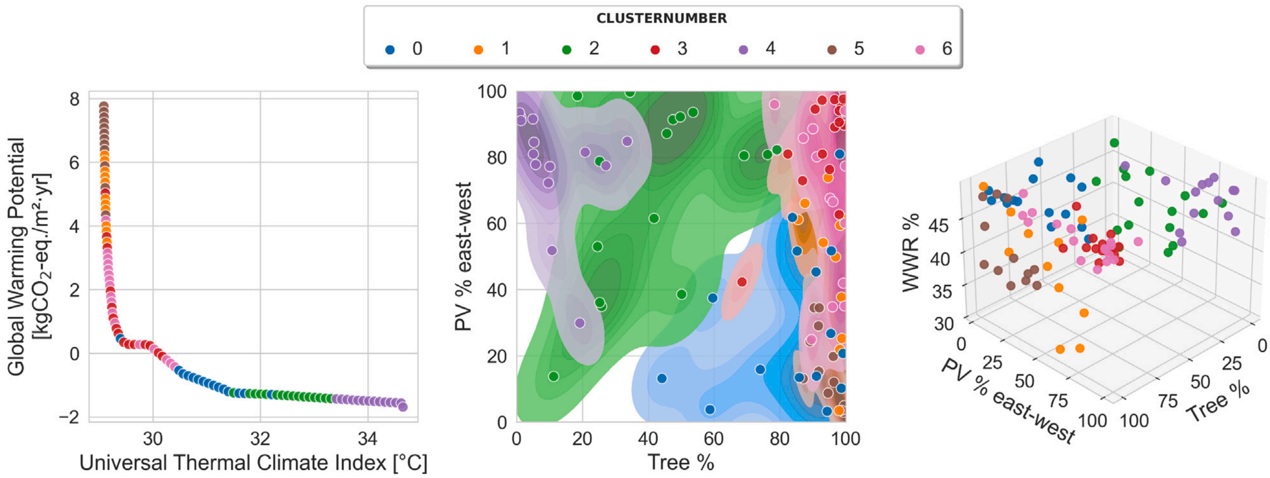

Fig. 12. Results of the Passive House scenario: (a) Target Space clusters. (b) Design Space clusters and densities for two inputs. (c) Design Space clusters for three inputs.

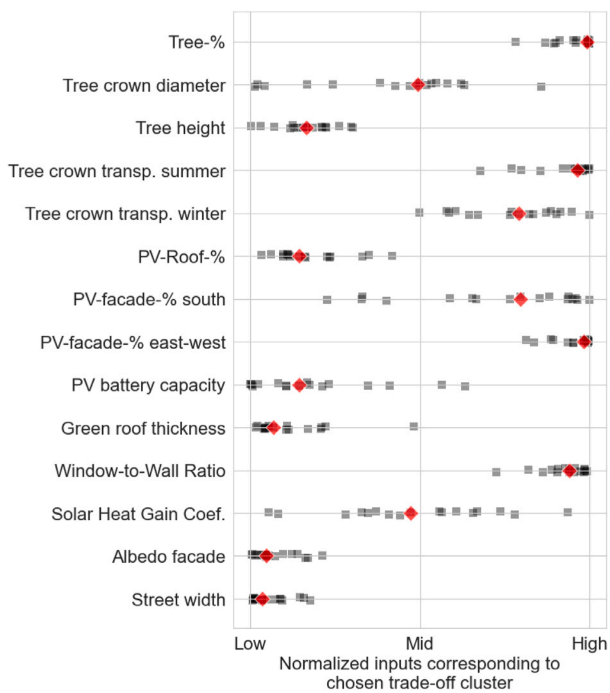

Fig. 13. Normalized Design Space of the Pareto-optimal solutions in cluster 6 with medians in red.

depends on the assumptions made in the investigation [87]. In our study, PV integration on roof and façades proofs as a valuable option for today's refurbishment interventions in terms of GWP reduction. Solutions with high PV percentages are present in the Pareto-optimal set (Figs. 7 and 12(b)), although shading by trees may affect their efficiency. Heat pumps strongly support the share of consumed PV electricity. Therefore, other heating systems may behave differently regarding GWP.

In our case study, the trade-off between lifecycle-based GWP and outdoor thermal comfort could already be shown in early planning phases. Tree percentage, crown diameter, and façade-PV shares are particularly sensitive control parameters for this trade-off. However, the clustering of the PF and the inverse transformation into the Design Space show that other input values (e.g., WWR, see Fig. 12) are also relevant for balancing the trade-off when targeting for specific clusters.

In this study, we chose the KPIs for an existing neighborhood and made several assumptions. These include averaging UTCI values over a grid around the central building. Although, this has been proposed in other studies [88] it might not be an appropriate approach for new developments or other neighborhood typologies. Accordingly, other cases or scales need context-specific evaluation criteria [89].

6.2. Process and tool-chain for trade-off investigation

The presented process can serve as a guideline for setting up coupled urban simulation models and exploring trade-offs. The exemplary tool-chain allows a fast and effective determination of the PF in the context of computationally expensive urban simulation models. This contributes to making informed decisions on the prevailing trade-offs and their control options with few simulations. The GPR-based Paref algorithms require significantly fewer model evaluations than evolutionary algorithms such as NSGA-II, to obtain an initial representation of the PF. This finding is consistent with studies that have applied Paref to mathematical problems [76]. With our case study, we demonstrate its usability in the context of practical urban design.

The coupling of regular search and fill-gaps algorithms from the Paref library leads to a well-covered PF. In this context, points that are not identified as Pareto-solutions but are very close to this property also contribute to a better surrogate model quality. The treatment of these points close to the PF is discussed in research regarding the robustness of the obtained results. It may be preferable for urban planners to have solutions that are very close to optimal, but more robust to uncertainties in the urban system. [90].

Surrogate model validation shows that the necessary number of training points required for good prediction quality can vary significantly depending on the target value. For instance, the LCA-GWP surrogate model performs well with few training points. In contrast, the UTCI model shows lower uncertainties and convergence only with a significantly higher number of input values (see Fig. 9).

Utilizing the presented tool-chain allows to perform optimization and simulation mostly independently via exchange files. This allows for the future integration of additional simulation components and aspects on the urban scale. However, users need to be aware of the difficulties that arise from such sophisticated simulation models. The more components and relationships are integrated, the more difficult it becomes to comprehend the underlying mechanisms and to verify the model.

6.3. Multi criteria decision support in early design phases

The evaluation of the Pareto-points identified in the optimization process offers the possibility to present the scope of action and gives an overview of feasible trade-off balances. The exploration with surrogate models also reveals intervention options that allow to steer the design into a specific trade-off area. Relevant control variables (Design Space) for the considered aspects (Target Space) can be narrowed down and further analysis can be built upon through sensitivity analyses. This is especially important due to the nonlinear nature of building simulations [91]. Sobol Sensitivity Analysis provides a way to obtain the influence of input uncertainty on output variance in such nonlinear systems [92]. However, the analysis has been applied to surrogate models, which may cause inferences if these models are not fitted sufficiently to the data.

The presentation of Design Space variables in two- and three-dimensional spaces provides easily interpretable support for neighborhood planning in early phases (Fig. 12), where significant influence on lifecycle-based GWP of neighborhoods can be exerted [93,94]. The early knowledge of design options and their influence on the resulting trade-off balance can improve designers' understanding of the tasks and set the base for better designs in later phases [95]. In order to allow urban planners to benefit from the developed process, urban planning departments need to widen their view and allow a broad perspective on given tasks. This fosters an early understanding of the necessary boundary conditions for designing or transforming urban neighborhoods where practicable advice is currently missing [3,4].

6.4. Case study limitations

Besides the evaluated KPIs, various qualitative aspects of the urban environment need to be considered in decision making [96]. The simulation model in this study is limited in many respects to essential aspects of outdoor and indoor simulation. Therefore, a comprehensive representation of reality is hardly possible, particularly in early project phases where little information is available on construction and outdoor space. The model used in this context represents a compromise between accuracy and computational costs. The results of wind considerations could be improved by applying a more expensive Computational-Fluid-Dynamics method. Additionally, the selected parameters should be validated against measured data to adjust the model more accurately for the site under consideration. Another disadvantage of the simulation model is its complexity, which requires expertise, simplifications, and the specification of numerous boundary conditions. These include usage profiles, existing materials properties, PV efficiencies, or future prospects on LCA data, such as the decarbonization rate of the electricity grid.

Regarding MOO, only two aspects (GWP and outdoor thermal comfort) have been evaluated in this study. Due to the necessary fixation of research interest at the beginning of the workflow, there is a risk of not recognizing further trade-offs resulting from the identified solutions.

The results of the case study were generated in the context of Germany. This brings boundary conditions to climate and LCA data sets. Accordingly, they cannot be transferred to other countries without restrictions.

7. Conclusion

This paper describes the generic process of Urban Systems Exploration. This process integrates multi-objective optimization (MOO) into urban planning to support multi-criteria decision making and demonstrates its application in a case study. The developed simulation model of the urban environment captures various interactions between buildings and the outdoor space, but the model evaluation is computationally expensive. By developing a tool-chain based on the generic process and applying it to a case study neighborhood, it was possible to identify the Pareto Front (PF) between lifecycle-based global warming potential (GWP) and outdoor thermal comfort with 100 evaluations of the simulation model. We showed how the results of the process can be used to demonstrate the scope for action in early design phases. In addition, the most relevant aspects for controlling the prevailing trade-off were identified.

While many MOO applications focus on optimizing individual buildings or improving already existing design ideas, this study shows how general guidelines for multi-criteria decision making can be derived on a neighborhood scale. This perspective is becoming increasingly important as city administrators need to set the boundaries for sustainable urban development, especially in the existing building stock. Thereby, urban planners get the opportunity to derive general conditions for neighborhood development plans or for initializing a planning competition. Our work shows that MOO can support urban planning and decision making with this information but it needs a structured process for its implementation in current urban design practice. The results from this process support urban planners and decision makers in discussions with different departments, by emphasizing that not only one, but a variety of optimal solutions are feasible. Urban Systems Exploration can serve as an eye-opener in discussions where positions are deadlocked and each party is predominantly fixated on their own aspects.

The intensive development of sophisticated simulation models for individual aspects has led to the need for processes and methods that allow for the coupling and efficient analysis of these models, as advances in computing power are struggling to keep pace. The approach presented here offers such advantages by going beyond the identification of single optimal solutions and focusing on obtaining a complete picture of the prevailing trade-offs and possible interventions. Deriving actionable recommendations from the results is critical because only a small group of users can operate these complex models. Thus, the presented methodology contributes to a better integration of a systemic perspective into urban planning practice.

The application in our case study shows a clear trade-off between the considered aspects. The better the outdoor thermal comfort in summer, the worse the GWP, and vice versa. The observed trade-off is particularly relevant in the context of advancing climate change and the necessary transformation of the urban environment. While this finding cannot be generalized because it depends on modeling assumptions, it highlights the importance of investigating such relationships. The integration of trees and PV is an essential lever to balance this trade-off. The results also show that the first intention of the contradiction between shading trees and sun-exposed PV may be misleading, as we also identify Pareto-solutions with high shares of trees and PV. Thus, both should be considered when designing interventions to support the ongoing urban transformation process.

There is scope for further development, particularly in scaling up the approach to the city level. Urban typologies offer a promising way to identify general recommendations. In addition, further interventions should be included in the study, such as densification, conversion, and a variety of deep refurbishment packages for existing buildings. Extending the MOO algorithm to more than two-dimensional problems is also challenging due to the increasing number of simulation runs required. The development of a practical Grasshopper plugin that allows better integration of the Paref algorithm in the simulation framework could foster this. In addition, no categorical inputs have been incorporated into the optimization approach. This advancement can also contribute to integrating more qualitative aspects in the optimization, such as individual perception of the environment or social interaction. The probabilistic nature of the GPR surrogate models offers the possibility of an in-depth evaluation of prediction uncertainties to support decision making. Hence, further evaluation and presentation of the results should be developed in cooperation with urban planners in order to make the results accessible to practitioners in the most helpful form. The generic Urban Systems Exploration process has been shown to be a suitable methodological framework for this purpose, in which the integration of other search and evaluation methods is possible.

Abbreviations

CPU: Central Processing Unit
GEG: Gebäudeenergiegesetz
GPR: Gaussian Process Regression
GPU: Graphics Processing Unit
GWP: Global Warming Potential
HSE: Hyper Space Exploration
KPI: Key Performance Indicator
LCA: Life Cycle Assessment
LHS: Latin Hypercube Sampling
MOO: Multi-Objective Optimization
NLPD: Negative Log Predictive Density
NSGA-II: Non-dominated Sorting Genetic Algorithm, version II
PF: Pareto Front
PH: Passive House
PV: Photovoltaic
RMSE: Root Mean Squared Error
UTCI: Universal Thermal Climate Index
WWR: Window-to-Wall Ratio

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CRediT authorship contribution statement

Roland Reitberger: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Nicolai Palm:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation. **Herbert Palm:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Werner Lang:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

[1] G. Mboup, Urbanization and Migration – Two Global Mega Trends: Diversity, Opportunities and Challenges, in: 51st Session on Sustainable Cities, Human Mobility and International Migration. United Nations, 2018.
[2] United Nations - Department of Economic and Social Affairs, World Urbanization Prospects: The 2018 Revision, New York, 2018.
[3] L. Xu, X. Wang, J. Liu, Y. He, J. Tang, M. Nguyen, S. Cui, Identifying the trade-offs between climate change mitigation and adaptation in urban land use planning: An empirical study in a coastal city, Environ. Int. 133 (Pt B) (2019) 105162, http://dx.doi.org/10.1016/j.envint.2019.105162.
[4] E.M. Hamin, N. Gurran, Urban form and climate change: Balancing adaptation and mitigation in the U.S. and Australia, Habitat Int. 33 (3) (2009) 238–245, http://dx.doi.org/10.1016/j.habitatint.2008.10.005.
[5] M. Landauer, S. Juhola, M. Söderholm, Inter-relationships between adaptation and mitigation: a systematic literature review, Clim. Change 131 (4) (2015) 505–517, http://dx.doi.org/10.1007/s10584-015-1395-1.
[6] A.S. Abd Elrahman, M. Asaad, Urban design & urban planning: A critical analysis to the theoretical relationship gap, Ain Shams Eng. J. 12 (1) (2021) 1163–1173, http://dx.doi.org/10.1016/j.asej.2020.04.020.
[7] T.M. Baynes, T. Wiedmann, General approaches for assessing urban environmental sustainability, Curr. Opin. Environ. Sustain. 4 (4) (2012) 458–464, http://dx.doi.org/10.1016/j.cosust.2012.09.003.
[8] W. Jiang-Ping, T. Qun, Urban planning decision using multi-objective optimization algorithm, in: 2009 ISECS International Colloquium on Computing, Communication, Control, and Management, IEEE, New York, 2009, pp. 392–394, http://dx.doi.org/10.1109/CCCM.2009.5267600.
[9] R. Webb, X. Bai, M.S. Smith, R. Costanza, D. Griggs, M. Moglia, M. Neuman, P. Newman, P. Newton, B. Norman, C. Ryan, H. Schandl, W. Steffen, N. Tapper, G. Thomson, Sustainable urban systems: Co-design and framing for transformation, Ambio 47 (1) (2018) 57–77, http://dx.doi.org/10.1007/s13280-017-0934-6.
[10] C. Ju, Y. Ning, W. Pan, A review of interdependence of sustainable building, Environ. Impact Assess. Rev. 56 (2016) 120–127, http://dx.doi.org/10.1016/j.eiar.2015.09.006.
[11] N. Schüler, S. Cajot, M. Peter, J. Page, F. Maréchal, The optimum is not the goal: Capturing the decision space for the planning of new neighborhoods, Front. Built Environ. 3 (2018) http://dx.doi.org/10.3389/fbuil.2017.00076.
[12] H. Palm, J. Holzmann, Hyper space exploration a multicriterial quantitative trade-off analysis for system design in complex environment, in: International Systems Engineering Symposium, ISSE, 2018, pp. 1–6, http://dx.doi.org/10.1109/SysEng.2018.8544435.
[13] J. Holzmann, Hyper Space Exploration: Methodik zur Multi-Kriteriellen Trade-Off-Analyse Von Systemen Im Disruptiven Kontext Am Beispiel Elektromobilität (Ph.D. thesis), Universität der Bundeswehr München, 2017.
[14] M. Mühlbauer, F. Rang, H. Palm, O. Bohlen, M.A. Danzer, Pareto-optimal power flow control in heterogeneous battery energy storage systems, J. Energy Storage 48 (2022) 103803, http://dx.doi.org/10.1016/j.est.2021.103803.
[15] A. Stadler, D. Mutzhas, J. Vollmar, H. Palm, Prozess und Werkzeugkette zur multikriteriell optimierten Auslegung kommunaler Energiesysteme, in: 17. Symposium Energieinnovation Graz, 2022, pp. 1–10, http://dx.doi.org/10.13140/RG.2.2.24208.69122.
[16] V. Oliveira, P. Pinho, Evaluation in urban planning: Advances and prospects, J. Plan. Literat. 24 (4) (2010) 343–361, http://dx.doi.org/10.1177/0885412210364589.
[17] W. Schoenwandt, Planning in Crisis? Theoretical Orientations for Architecture and Planning, first ed., Taylor and Francis, London, 2008, http://dx.doi.org/10.4324/9781315600765.
[18] T. Yigitcanlar, S. Teriman, Rethinking sustainable urban development: towards an integrated planning and development process, Int. J. Environ. Sci. Technol. 12 (1) (2015) 341–352, http://dx.doi.org/10.1007/s13762-013-0491-x.
[19] J.T. Lang, Urban Design: a Typology of Procedures and Products, Routledge, London, 2017.
[20] T. Heath, Public Places - Urban Spaces: The Dimensions of Urban Design, second ed., Taylor and Francis, Hoboken, 2011.
[21] G. Abou Jaoude, O. Mumm, V.M. Carlow, An overview of scenario approaches: A guide for urban design and planning, J. Plan. Literat. 37 (2022) 467–487.
[22] D.R. Lumpkin, W.T. Horton, J.V. Sinfield, Holistic synergy analysis for building subsystem performance and innovation opportunities, Build. Environ. 178 (106908) (2020) http://dx.doi.org/10.1016/j.buildenv.2020.106908.
[23] S. Lehmann, Sustainable urbanism: towards a framework for quality and optimal density? Future Cities Environ. 2 (8) (2017) http://dx.doi.org/10.1186/s40984-016-0021-3.
[24] J. Natanian, T. Auer, Beyond nearly zero energy urban design: A holistic microclimatic energy and environmental quality evaluation workflow, Sustainable Cities Soc. 56 (2020) 102094, http://dx.doi.org/10.1016/j.scs.2020.102094.
[25] H. Liu, Y. Pan, Y. Yang, Z. Huang, Evaluating the impact of shading from surrounding buildings on heating/ cooling energy demands of different community forms, Build. Environ. 206 (2021) 108322, http://dx.doi.org/10.1016/j.buildenv.2021.108322.
[26] R. Loeffler, D. Österreicher, G. Stoeglehner, The energy implications of urban morphology from an urban planning perspective – A case study for a new urban development area in the city of Vienna, Energy Build. 252 (2021) 111453, http://dx.doi.org/10.1016/j.enbuild.2021.111453.
[27] E. Naboni, J. Natanian, G. Brizzi, P. Florio, A. Chokhachian, T. Galanos, P. Rastogi, A digital workflow to quantify regenerative urban design in the context of a changing climate, Renew. Sustain. Energy Rev. 113 (2019) 109255, http://dx.doi.org/10.1016/j.rser.2019.109255.
[28] X. Zheng, L. Chen, J. Yang, Simulation framework for early design guidance of urban streets to improve outdoor thermal comfort and building energy efficiency in summer, Build. Environ. 228 (2023) 109815, http://dx.doi.org/10.1016/j.buildenv.2022.109815.
[29] W. Loibl, G. Etminan, D. Österreicher, M. Ratheiser, R. Stollnberger, S. Tschannett, T. Tötzer, M. Vuckovic, K. Walal, Urban densification and urban climate change – assessing interaction through densification scenarios and climate simulations, REAL Corp. 2019 (2019) 809–817.
[30] Y. Hu, Y. Peng, Z. Gao, F. Xu, Application of CFD plug-ins integrated into urban and building design platforms for performance simulations: A literature review, Front. Archit. Res. (2022) http://dx.doi.org/10.1016/j.foar.2022.06.005.
[31] F. Johari, J. Munkhammar, F. Shadram, J. Widén, Evaluation of simplified building energy models for urban-scale energy analysis of buildings, Build. Environ. 211 (2022) 108684, http://dx.doi.org/10.1016/j.buildenv.2021.108684.

[32] M. Manni, A. Nicolini, Multi-objective optimization models to design a responsive built environment: A synthetic review, Energies 15 (2) (2022) 486, http://dx.doi.org/10.3390/en15020486.

[33] V. Pareto, Manuel d'Economie politique, Bull. Amer. Math. Soc. 18 (1912).

[34] T. Wortmann, J. Natanian, Multi-objective optimization for zero-energy urban design in China: A benchmark, in: SimAUD, 2020, pp. 203–210.

[35] K.-H. Chang, Multiobjective optimization and advanced topics, in: E-Design, Elsevier, 2015, pp. 1105–1173, http://dx.doi.org/10.1016/B978-0-12-382038-9.00019-3.

[36] L. Magnier, F. Haghighat, Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network, Build. Environ. 45 (3) (2010) 739–746, http://dx.doi.org/10.1016/j.buildenv.2009.08.016.

[37] T. Wortmann, G. Nannicini, Introduction to architectural design optimization, in: City Networks, Springer, Cham, 2018, pp. 259–278, http://dx.doi.org/10.1007/978-3-319-65338-9.

[38] T. Wortmann, J. Cichocka, C. Waibel, Simulation-based optimization in architecture and building engineering – Results from an international user survey in practice and research, Energy Build. 259 (2022) 111863, http://dx.doi.org/10.1016/j.enbuild.2022.111863.

[39] T. Wortmann, Model-based optimization for architectural design: Optimizing daylight and glare in grasshopper, Technol.|Architecture + Des. 1 (2) (2017) 176–185, http://dx.doi.org/10.1080/24751448.2017.1354615.

[40] R. Zhang, X. Xu, P. Zhai, K. Liu, L. Kong, W. Wang, Agile and integrated workflow proposal for optimising energy use, solar and wind energy potential, and structural stability of high-rise buildings in early design decisions, Energy Build. 300 (2023) 113692, http://dx.doi.org/10.1016/j.enbuild.2023.113692.

[41] G. Guariso, M. Sangiorgio, Improving the performance of multiobjective genetic algorithms: An elitism-based approach, Information 11 (12) (2020) 587, http://dx.doi.org/10.3390/info11120587.

[42] L. Zhao, W. Zhang, W. Wang, BIM-based multi-objective optimization of low-carbon and energy-saving buildings, Sustainability 14 (20) (2022) http://dx.doi.org/10.3390/su142013064.

[43] J. Bader, E. Zitzler, HypE: An algorithm for fast hypervolume-based many-objective optimization, Evolut. Comput. 19 (1) (2011) 45–76.

[44] B. Kiss, Z. Szalay, Modular approach to multi-objective environmental optimization of buildings, Autom. Constr. 111 (2020) 103044, http://dx.doi.org/10.1016/j.autcon.2019.103044.

[45] N. Abdollahzadeh, N. Biloria, Urban microclimate and energy consumption: A multi-objective parametric urban design approach for dense subtropical cities, Front. Archit. Res. 11 (3) (2022) 453–465, http://dx.doi.org/10.1016/j.foar.2022.02.001.

[46] J. Mukkavaara, F. Shadram, An integrated optimization and sensitivity analysis approach to support the life cycle energy trade-off in building design, Energy Build. 253 (2021) 111529, http://dx.doi.org/10.1016/j.enbuild.2021.111529.

[47] P. Li, T. Xu, S. Wei, Z.-H. Wang, Multi-objective optimization of urban environmental system design using machine learning, Comput. Environ. Urban Syst. 94 (2022) 101796, http://dx.doi.org/10.1016/j.compenvurbsys.2022.101796.

[48] Robert McNeel & Associates, Rhinoceros 3D, Version 7.26, Robert McNeel & Associates, Seattle, WA, 2023, URL https://www.rhino3d.com/.

[49] C.E. Rasmussen, C.K. Williams, et al., Gaussian Processes for Machine Learning, Vol. 1, Springer, 2006.

[50] T. Rötzer, A. Moser-Reischl, M.A. Rahman, R. Grote, S. Pauleit, H. Pretzsch, Modelling urban tree growth and ecosystem services: Review and perspectives, in: F.M. Cánovas, U. Lüttge, M.-C. Risueño, H. Pretzsch (Eds.), Progress in Botany, Vol. 82, Springer International Publishing, Cham, 2021, pp. 405–464, http://dx.doi.org/10.1007/124_2020_46.

[51] L. O'Brien, R. De Vreese, M. Kern, T. Sievänen, B. Stojanova, E. Atmiş, Cultural ecosystem benefits of urban and peri-urban green infrastructure across different European countries, Urban Forestry Urban Green. 24 (2017) 236–248, http://dx.doi.org/10.1016/j.ufug.2017.03.002.

[52] A. Sharifi, Trade-offs and conflicts between urban climate change mitigation and adaptation measures: A literature review, J. Clean. Prod. 276 (2020) 122813, http://dx.doi.org/10.1016/j.jclepro.2020.122813.

[53] A. Darvish, G. Eghbali, S.R. Eghbali, Tree-configuration and species effects on the indoor and outdoor thermal condition and energy performance of courtyard buildings, Urban Clim. 37 (2021) 100861, http://dx.doi.org/10.1016/j.uclim.2021.100861.

[54] Z. Tan, A. Wang, T.E. Morakinyo, Yung, Esther, Chan, Edwin, Assessing the mitigation perfromance of building setback from street and the combination with roadside tree planting, Build. Environ. 212 (2022) http://dx.doi.org/10.1016/j.buildenv.2022.108814.

[55] M.S. Roudsari, M. Pak, Ladybug: a parametric environmental plugin for grasshopper to help designers create an environmentally-conscious design, in: Proceedings of the 13th International IBPSA Conference Held in Lyon, France, 2013, pp. 3128–3135.

[56] C. Waibel, L. Bystricka, A. Kubilay, R. Evins, J. Carmeliet, L. Bystricky, A. Kubilay, Validation of grasshopper-based fast fluid dynamics for air flow around buildings in early design stage, in: Proceedings of the 15th IBPSA Conference (San Francisco), 2017, http://dx.doi.org/10.26868/25222708.2017.582.

[57] U.S. Department of Energy, EnergyPlus documentation: Input output reference, 2021.

[58] DIN Deutsches Institut für Normung e.V., DIN EN 15978 Nachhaltigkeit von Bauwerken - Bewertung der umweltbezogenen Qualität von Gebäuden - Berechnungsmethode; Deutsche Fassung EN 15978:2011, Beuth Verlag, Berlin, 2012, http://dx.doi.org/10.31030/1917049.

[59] Solemma, ClimateStudio, 2023, URL https://www.solemma.com/climatestudio.

[60] F. Banihashemi, R. Reitberger, W. Lang, Investigating urban heat island and vegetation effects under the influence of climate change in early design stages: For performance-based early urban design decisions, in: Proceedings of the 27th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2022, Vol. 2, 2022, pp. 679–688, http://dx.doi.org/10.52842/conf.caadria.2022.2.679.

[61] R. Reitberger, K. Theilig, M. Vollmer, I. Takser, W. Lang, Connecting building density and vegetation to investigate synergies and trade-offs between thermal comfort and energy demand – a parametric study in the temperate climate of Germany, IOP Conf. Ser.: Earth Environ. Sci. 1196 (2023) http://dx.doi.org/10.1088/1755-1315/1196/1/012034.

[62] B. Bueno, L. Norford, J. Hidalgo, G. Pigeon, The urban weather generator, J. Build. Perform. Simul. 6 (4) (2013) 269–281, http://dx.doi.org/10.1080/19401493.2012.718797.

[63] U.S. Department of Energy, Energy Plus V9.5.0, Washington, 2021, URL https://energyplus.net/.

[64] A. Mastrucci, A. Marvuglia, E. Benetto, U. Leopold, A spatio-temporal life cycle assessment framework for building renovation scenarios at the urban scale, Renew. Sustain. Energy Rev. 126 (2020) 109834, http://dx.doi.org/10.1016/j.rser.2020.109834.

[65] K. Błażejczyk, G. Jendritzky, P. Bröde, D. Fiala, G. Havenith, Y. Epstein, A. Psikuta, B. Kampmann, An introduction to the Universal Thermal Climate Index (UTCI), Geographia Polonica 86 (1) (2013) 5–10, http://dx.doi.org/10.7163/GPol.2013.1.

[66] T. Loga, B. Stein, N. Diefenbach, R. Born, Typology Approach for Building Stock Energy Assessment, EPISCOPE - Energy Performance Indicator Tracking Schemes for the Continous Optimisation of Refurbishment Processes in European Housing Stocks, IWU, Darmstadt, 2015, 2., erw. Aufl..

[67] Bundesministerium für Wohnen Stadtentwicklung und Bauwesen, Gebäudeenergiegesetz: GEG, in: Bundesgesetzblatt, (Teil I Nr. 37) 2020.

[68] Passivhaus Institut, Kriterien für den Passivhaus-, EnerPHit- und PHI-Energiesparhaus-Standard: Version 10b, Darmstadt, 2022.

[69] Meteotest AG, Meteonorm, Bern, Schweiz, 2023, URL https://meteonorm.com/.

[70] DIN Deutsches Institut für Normung e.V., Energetische Bewertung von Gebäuden – Berechnung des Nutz-, End- und Primärenergiebedarfs für Heizung, Kühlung, Lüftung, Trinkwarmwasser und Beleuchtung – Teil 10: Nutzungsrandbedingungen, Klimadaten, DIN V 18599-10, Beuth Verlag, Berlin, 2018, http://dx.doi.org/10.31030/2874436.

[71] National Renewable Energy Laboratory, Best research-cell efficiency chart, 2023, URL https://www.nrel.gov/pv/cell-efficiency.html.

[72] F. Banihashemi, S. Erlwein, J. Fellner, J. Meister, R. Reitberger, C. Schade, W. Lang, S. Pauleit, F. Petzold, Nachverdichtung im Kontext des Klimawandels - Schlussbericht, Tech. rep., Bayerisches Staatsministerium für Umwelt und Verbraucherschutz (StMUV), München, 2022, http://dx.doi.org/10.14459/2023md1703685.

[73] P.J. Littlefair, Site Layout Planning for Daylight and Sunlight: a Guide to Good Practice, BRE, Bracknell, 2011.

[74] D.J. Sailor, M. Georgescu, J.M. Milne, M.A. Hart, Development of a national anthropogenic heating database with an extrapolation for international cities, Atmos. Environ. 118 (2015) 7–18, http://dx.doi.org/10.1016/j.atmosenv.2015.07.016.

[75] N. Palm, M. Landerer, H. Palm, Gaussian process regression based multi-objective Bayesian optimization for power system design, Sustainability 14 (19) (2022) 12777, http://dx.doi.org/10.3390/su141912777.

[76] N. Palm, paref, 2023, URL https://pypi.org/project/paref/.

[77] N. Palm, H. Palm, Multi-objective optimization algorithm classification by composing black box with Pareto-reflecting functions, 2023, http://dx.doi.org/10.2139/ssrn.4668407, SSRN Preprint.

[78] Bavarian State Ministry of Finance and Regional Identity, Bayern atlas, 2023, URL https://geoportal.bayern.de/bayernatlas/.

[79] Zentrum für Stadtnatur und Klimaanpassung, Klimaschutz und grüne Infrastruktur in der Stadt: Abschlussbericht, Technische Universität München, 2017.

[80] Bundesministerium für Wohnen, Stadtentwicklung und Bauwesen, Ökobaudat: Informationsportal Nachhaltiges Bauen, 2023, URL https://www.oekobaudat.de/.

[81] Bundesministerium für Wohnen, Stadtentwicklung und Bauwesen, Nutzungsdauern von Bauteilen für Lebenszyklusanalysen nach Bewertungssystem Nachhaltiges Bauen (BNB), Bundesinstitut für Bau-, Stadt- und Raumforschung, 2017.

[82] Bundesnetzagentur, Genehmigung des Szenariorahmens 2023–2037/2045, Bonn, 2022.

[83] dena, Dena Gebäudereport 2022: Zahlen, Daten, Fakten, Deutsche Energie-Agentur, Berlin, 2021.

[84] A. Saltelli, M. Ratto, T. Andres, F. Camplongo, J. Cariboni, D. Gatelli, M. Saisana, S. Tarantola, Global Sensitivity Analysis: the Primer, John Wiley, Wiley InterScience, Chichester, England and Hoboken, NJ, 2008, http://dx.doi.org/10.1002/9780470725184.

[85] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, E. Duchesnay, Scikit-learn: Machine learning in Python, J. Mach. Learn. Res. 12 (2011) 2825–2830.

[86] F.N. Rasmussen, D. Trigaux, E. Alsema, M. Balouktsi, H. Birgisdóttir, R. Bohne, M. Dixit, D. Dowdell, N. Francart, R. Frischknecht, G. Foliente, A. Lupisek, T. Lützkendorf, T. Malmqvist, A. Garcia Martinez, C. Ouellet-Plamondon, A. Passer, B. Peuportier, L. Ramseier, D. Satola, S. Seo, Z. Szalay, M. Wiik, Existing benchmark systems for assessing global warming potential of buildings – Analysis of IEA EBC Annex 72 cases, IOP Conf. Ser.: Earth Environ. Sci. 1078 (1) (2022) 012054, http://dx.doi.org/10.1088/1755-1315/1078/1/012054.

[87] D. D'Agostino, F. Minelli, F. Minichiello, New genetic algorithm-based workflow for multi-objective optimization of net zero energy buildings integrating robustness assessment, Energy Build. 284 (2023) 112841, http://dx.doi.org/10.1016/j.enbuild.2023.112841.

[88] J. Geletič, M. Lehnert, J. Resler, P. Krč, A. Middel, E.S. Krayenhoff, E. Krüger, High-fidelity simulation of the effects of street trees, green roofs and green walls on the distribution of thermal exposure in prague-dejvice, Build. Environ. 223 (2022) 109484, http://dx.doi.org/10.1016/j.buildenv.2022.109484.

[89] M. Balouktsi, Principles and Tools for Designing Strategies for Sustainable Urban Development: A "Process-based" and "Action-oriented" Approach at Neighbourhood Level (Ph.D. thesis), Karlsruhe Institute Of Technology, 2018.

[90] R. Calandra, J. Peters, M.P. Deisenroth, Pareto front modeling for sensitivity analysis in multi-objective Bayesian optimization, Comput. Sci. (2014) 1–5.

[91] A.-T. Nguyen, S. Reiter, A performance comparison of sensitivity analysis methods for building energy models, Build. Simul. 8 (6) (2015) 651–664, http://dx.doi.org/10.1007/s12273-015-0245-4.

[92] A. Saltelli, K. Aleksankina, W. Becker, P. Fennell, F. Ferretti, N. Holst, S. Li, Q. Wu, Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices, Environ. Model. Softw. 114 (2019) 29–39, http://dx.doi.org/10.1016/j.envsoft.2019.01.012.

[93] J. Basbagill, F. Flager, M. Lepech, M. Fischer, Application of life-cycle assessment to early stage building design for reduced embodied environmental impacts, Build. Environ. 60 (2013) 81–92, http://dx.doi.org/10.1016/j.buildenv.2012.11.009.

[94] E. Meex, A. Hollberg, E. Knapen, L. Hildebrand, G. Verbeeck, Requirements for applying LCA-based environmental impact assessment tools in the early stages of building design, Build. Environ. 133 (2018) 228–236, http://dx.doi.org/10.1016/j.buildenv.2018.02.016.

[95] S. Shahi, P. Wozniczka, C. Rausch, I. Trudeau, C. Haas, A computational methodology for generating modular design options for building extensions, Autom. Constr. 127 (2021) 103700, http://dx.doi.org/10.1016/j.autcon.2021.103700.

[96] S. Anders, Stadt als System: Methode zur ganzheitlichen Analyse von Planungskonzepten (Ph.D. thesis), Städtebau-Institut, Universität Stuttgart, 2016.