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Interactive optimization for the planning of urban systems

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Abstract

This paper introduces URB^{io}, an interactive optimization framework for the planning of urban systems. Addressing the elusive nature of urban planning and its need to cope with more technical sectors, the framework allows urban planners to generate and evaluate many alternative urban configurations, while focusing their attention on the most promising ones. First, addressing the need for integrated urban modeling approaches, a Mixed Integer Linear Programing (MILP) optimization model representing both urban and energy system components was developed. Second, an interface based on parallel coordinates and georeferenced maps is proposed to effectively communicate the optimization results to decision makers, revealing tradeoffs and synergies between competing objectives. Interaction with the parallel coordinates charts further allows planners to steer consecutive optimization runs based on their preferences and experience. The framework is applied to an urban development project in Switzerland to demonstrate its usability and relevance.

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Keywords: urban planning; energy planning; urban energy system; optimization; parallel coordinates.

1. Introduction

In the last decades, urban planning has progressively shifted from the rather spatial-oriented task of accommodating social growth and economic development, to a more strategic and integrative process [1,2]. No longer confined to the role of technical experts who design cities based on assumed universal principles, urban planners must today involve and arbitrate the interests of various stakeholders [3]. Additionally, their strategic plans must bring together and coordinate different sectors, consider effects on multiple scales and cover long-term horizons. Given global concerns for the climate and the environment, the energy sector is in particular receiving attention as to how it might be better integrated in urban planning processes. By considering energy efficiency and renewable energy integration beyond the individual building scale, urban planning can effectively help reach energy and climate targets [4,5]. Such strategic tasks imply taking high-stake decisions in the earlier phases of a project, where precise information may be lacking, and feasible alternatives to choose from are plentiful. This holds true for both general planning approaches, although

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to different extents: brownfield planning requires precise knowledge of the local existing infrastructure and actors, whereas greenfield masterplanning presents a very large solution space in which good, energy efficient solutions could easily be overlooked [6,7]. In either case, whether the planning is a government-led or more competitive and developer-led process, planners require both accountability and speed in the generation and evaluation of plans [7,8].

Many tools have been developed to support planners in these regards, ranging from GIS tools to detailed simulation models of the urban system [7]. Among these, optimization approaches are gaining momentum in the research community. They are believed to improve on traditional planning practices, by avoiding alternative-driven decisions, as opposed to decisions guided by the values at stake [9,10]. Some notable examples of optimization applications in urban planning contexts include the optimization of dwelling locations to minimize transport costs or flood event risks [11], or the search for land-use plans minimizing traffic congestion, costs and required change from status quo [9].

However, modelers striving to harness the benefits of optimization for urban planning face two key challenges. First, their models must overcome the inherent elusive and undefinable nature of urban planning, and avoid falling into a too narrow representation of the different sectors [7]. Second, they must ensure that the experience and knowledge of the planners are well integrated in the model, and not replaced by it. As Raphael[12] notes, very often designers are able to criticize specific designs, without being able to precisely state the underlying reasons. It is because of this difficulty to express such reasons that human-computer interaction is expected to play a central role in overcoming the divide between optimization techniques and urban planners, which has been lasting for decades [2,13,14].

An early example of an interactive tool for exploring optimization-based efficient plans is found in [15]. This however is not per say interactive optimization, which is defined as applications in which the decision maker's preferences are included *during* the optimization process [16].

Interactive methods are particularly relevant to address the difficulty in design problems to know preferences before understanding their interdependencies, and the high computational costs related to the optimization of large problems, such as when dealing with an entire neighborhood (>100 buildings) [12,17]. In that sense, interactive methods can be considered superior to *a posteriori* methods, which require the generation of the solution space before evaluating it, and to *a priori methods*, which require a clear understanding of the priorities and relationships between objectives beforehand. Various examples of interactive methods can be found in [16]. In particular, two studies have pointed out the advantages of relying on parallel coordinates (which will be introduced below) for inputting user preferences in multi-objective optimization [18,19].

A previous article documented the initial development and a first application of an integrated Mixed Integer Linear Programing (MILP) model for urban and energy planning [20]. Building on this, the current article's purpose is to describe how this optimization model is employed within an interactive framework based on parallel coordinates to support early-stage urban planning.

The remainder of this article is structured as follows: Section 2 describes the methodological aspects adopted in the study. After briefly introducing the basic notions of the optimization model and the parallel coordinates interface, their combination to form an interactive optimization framework, and its corresponding workflow, are presented. Section 3 demonstrates how the decision support tool can be used in practice and illustrates actual results obtained by application of the method to an urban development project in Switzerland. Finally, the article is concluded with a discussion on the significance of the framework to improve energy-oriented urban planning (Section 4).

2. Methodology

In this section, the main components of the interactive optimization framework URB^{io} are described (Figure 1). Its main aim is to support the early-stage planning of urban areas, by generating a large variety of urban and energy system configurations and revealing synergies and tradeoffs between decisions. The decision support framework consists of two main, iterative phases (Figure 1). The first phase is user-driven: the decision maker explores optimized results in parallel coordinates and geo-referenced maps, and requests additional solutions based on their preferences and acquired insights. The second phase is computer-driven: optimal urban configurations are calculated according to user-specified objectives and constraints in an MILP model, and the results are stored in a database.

URB^{io}'s first innovation compared to existing optimization-based approaches is an extensive integration of energy aspects with other more traditional urban planning concerns in a single MILP model. In addition, the decision maker is directly involved in the optimization process, allowing them to explore and learn from the intermediate so-

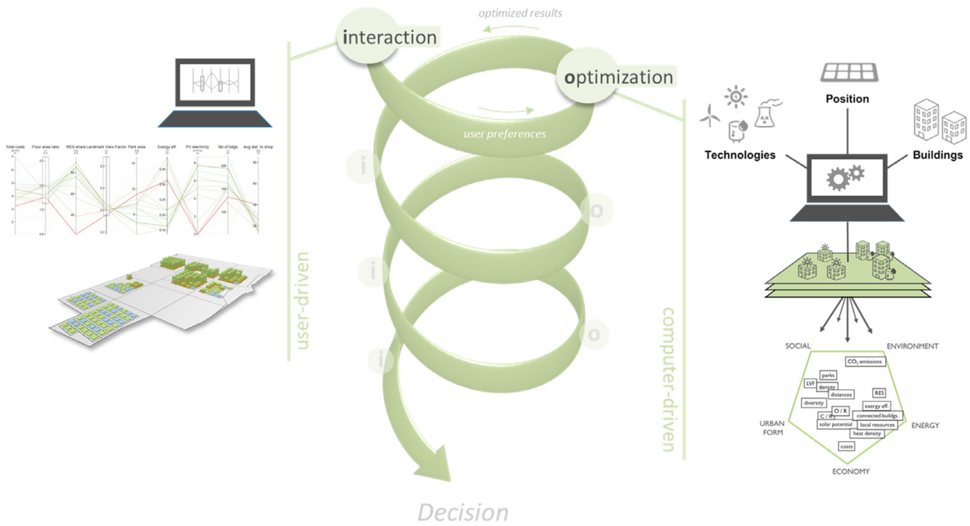

Fig. 1. URB^{io}: an interactive optimization framework supporting urban planning. The workflow is an iteration between a user-driven phase, where results are explored and preferences input, and a computer-driven phase, where an optimization model generates urban configurations.

lutions through parallel coordinate charts. By interacting with the parallel coordinates, they can furthermore steer the optimization according to their expertise and preferences, in order to iteratively populate the chart with new solutions.

2.1. Mixed Integer Linear Programing

Mixed Integer Linear Programing is an optimization technique which allows to incorporate decisions in both continuous and discrete solution spaces. At the price of being restricted to linear formulations it is known for rapidly converging to globally optimal solutions for a large range of problem instances in terms of varying input parameters. The formulation of an optimization problem comprises an objective function which shall be maximized or minimized by changing the values of decision variables, while respecting constraints on the latter. One way of exploring the interdependencies of conflicting objectives is the ϵ-constraint method, where all but one objectives are converted into constraints whose parameters are successively changed.

Key decision variables of the optimization model underlying URB^{io} are building type and number and occupancy type of floors per parcel, as urban variables, and the geo-referenced choice of technologies and their employment per time step as energy-related variables. Both aspects are coupled via energy balances, whose closure determines how the energy demand of buildings is met by supply technologies in e.g. a cost-effective or low-emission manner. Further examples for objectives and constraints will be given in section 3. For a detailed description of the model, refer to [20].

2.2. Parallel coordinates

In URB^{io} (Figure 1), parallel coordinates serve two main functions: data exploration and inputting preferences. Regarding the first function, parallel coordinates offer an efficient and intuitive way to display multivariate data, revealing correlations between various attributes in a two dimensional plane [13]. They consist of a set of vertical axes (which contain quantitative or semantic information pertaining to the attributes), and horizontally flowing lines, each of which represents a given alternative to be assessed. The user can visually grasp how various criteria interact with each other, and easily evaluate tradeoffs (denoted by a crossing of lines between two axes) or synergies (denoted by relatively parallel lines) [21]. Parallel coordinates present certain limitations, such as the difficulty to interpret useful patterns when excessive lines are displayed, or the order of the axes which implicitly determines which correlations are directly observable [22]. However, these limitations are partly diminished by the possibility to dynamically rearrange the axes positions, and to filter the display of lines by brushing (i.e. selecting) the desired range on an axis. The parallel coordinates interface developed in URB^{io} is based on the Data Driven Documents (`d3js.org`) library, and expands on an existing implementation for parallel coordinates (`syntagmatic.github.io/parallel-coordinates`).

The next section will present the typology and workflow associated with the second function of the parallel coordinates interface, namely how the user can input their preferences to control the optimization.

2.3. Interactive optimization workflow

As the process is iterative, all solutions are not immediately available in the parallel coordinates. The user can therefore specify where the next solutions should be generated, reflecting their preferences and expectations. This *steering* of the optimization can be done through several actions described hereafter. Each of these actions is performed directly within the parallel coordinates interface, by brushing the desired axes' ranges with the pointer on screen.

Objectives are what the solver aims to maximize or minimize. Therefore, a preferred direction is defined for each criterion, e.g. costs are to be minimized, while the share of RES should be maximized. When a criterion is marked as *ϵ-constraint*, it is associated with 3 user-specified values. A minimum and maximum value, defining the range in which the alternatives should be calculated, and the number of constraints, i.e. the number of expected solutions, which should be set. The constraints are automatically and regularly distributed in between the minimum and maximum values. By combining multiple ϵ-constraints on various criteria, it becomes possible to quickly generate a large amount of solutions. A criterion can *constrain* the solution space with upper or lower bounds. These are defined by the user by brushing an axis below or above the desired threshold. *Attributes* refer to the criteria which do not play an active role in the optimization process. As such, these are values which are calculated after the optimization finished, based on the resulting values of the decision variables.

3. Application

This section describes an application of URB^{io} to a Swiss case-study, providing an example of the actions and thought process when iterating through the spiral in Figure 1. Les Cherpines is one of the large ongoing urban development projects in Geneva, aiming to accomodate 3000 dwellings and 2500 jobs in a mixed-use eco-district. Stemming from political goals specified in the cantonal and neighborhood master plans, several criteria were implemented, nine of which are depicted in the axes on Figures 2-4. The first four axes were described in a previous work [20]. The fifth indicates the share of connected buildings to a heating network, the sixth reflects the amount of natural gas required normalized by gross floor area (GFA) , the seventh represents how much of the area is covered by parks, the eighth indicates the average walking distance from residential buildings to the nearest tram stop, and the ninth indicates the landmark view factor (LVF), or the share of dwellings with direct view on predefined landmarks.

The process begins with the visualization of 25 pre-calculated solutions, chosen loosely to cover a wide sample of the solution space. They were established by setting two 5-fold epsilon-constraints on respectively the floor area ratio (between 0.5-2.5) and RES share (between 10-100%), while minimizing total costs for each configuration of geo-referenced energy technologies and building types.

In the first iteration, the user might begin the exploration of these results by considering the FAR axis, density being a central urban planning parameter (Figure 2). First, a negative correlation between costs per built square meter and FAR is noticeable by the crossing lines. For this reason, and possibly guided by other political or contextual reasons, they can limit the search to solutions with densities of at least 1.2. To force the generation of multiple additional solutions also for higher densities, a 10-fold ϵ-constraint is set between 1.2-2.5. Aiming to improve further criteria, the user might realize that parks are still underrepresented in the neighborhood. They can request additional parks in the next solutions by setting the park area share as the new objective to maximize.

In the second iteration, new solutions maximizing the possible park area are provided (Figure 3). However, these configurations also present lower shares of renewable energy. This can partly be explained by the fact that less roof tops are available for PV panels, which contribution must be replaced by e.g. gas boilers or imports from the partly fossil-based electricity grid. Solutions which improve on RES shares can be requested by setting a 10-fold ϵ-constraint on RES share, while keeping the previous objective on park area (Figure 4).

In a third iteration, the new ϵ-constraint allowed to identify solutions which improve both urban and energy goals (Figure 4). Although this may come at the expense of other important criteria (such as density or costs) which

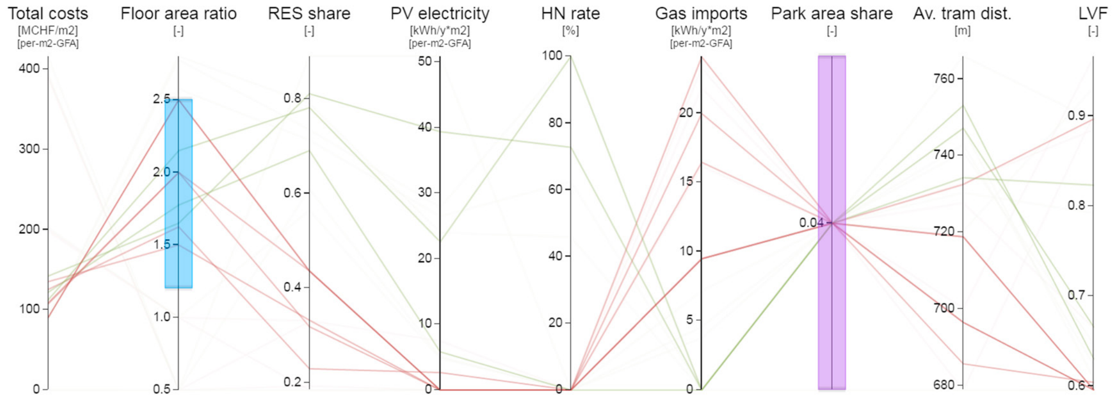

Fig. 2. In a first iteration, an objective (purple) and an ϵ-constraint (blue) are set to generate 10 solutions. Green lines indicate high-RES shares, red lines low-RES. GSF: Gross Floor Area, RES: Renewable Energy Source, PV: Photovoltaic, HN: Heating Network, LVF: Landmark View Factor.

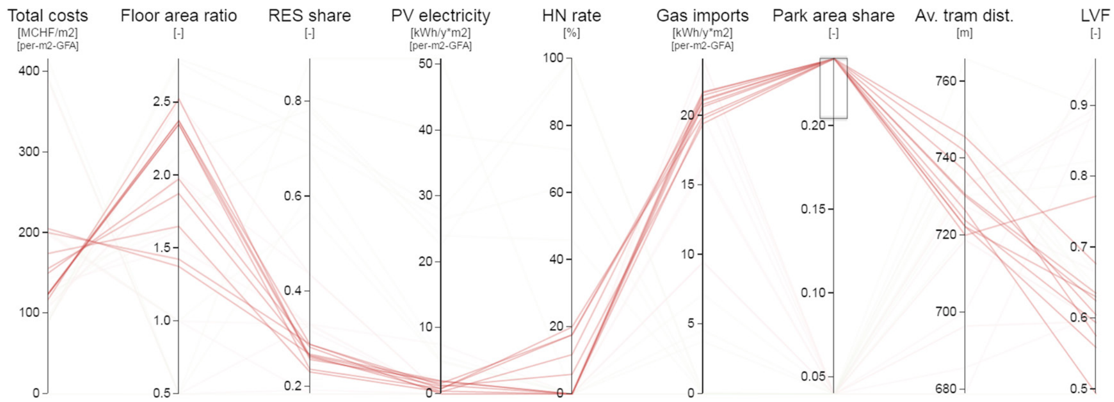

Fig. 3. In the second iteration, new urban configurations have been calculated, which now include a maximum of park areas with respect to other constraints. However, they do not yet contain high shares of RES, as denoted by the red-colored lines.

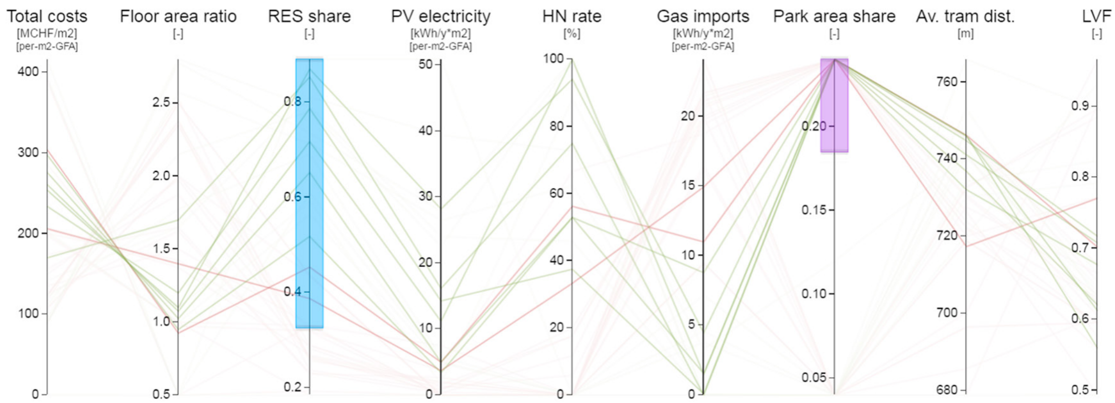

Fig. 4. In a third iteration, a 10-fold ϵ-constraint is included on RES (in blue) to search for improved solutions in this criteria. These are found at the expense of other criteria (e.g. FAR or costs). Note: the colored boxes were added again after calculation of solutions for illustration purpose.

should be further investigated, some tradeoffs have been made clear and quantified. The iterations continue until the user identifies a satisfying and efficient solution in regard to the criteria of interest. Due to space constraints, the visualization of the results in geo-referenced maps was not included, although they are an inherent part of the framework and essential to communicate the spatial information lacking from the parallel coordinates.

4. Discussion and conclusion

The purpose of this paper was to introduce an interactive optimization framework and its underlying workflow. Through an application based on an urban development project, a sample of the many possible outcomes and interpretations of the optimization results was presented. In particular, the importance of the planner, and their central role throughout the workflow was highlighted. From exploration and interpretation of the results, to incorporation of knowledge and preferences, they are key in exploiting the possible benefits of the optimization model. While the framework is able to generate a variety of good solutions more systematically and rapidly than a human, the decision making ultimately remains on the planners' side. However, the systematic generation of solutions and quantification of tradeoffs provides a gain of time, an overall improvement of the various objectives, and an increased accountability and rationality of the final decision.

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