Interactive optimization for supporting multicriteria decisions in urban and energy system planning

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To Georgios Kazas

In the center of Fedora, that gray stone metropolis, stands a metal building with a crystal globe in every room. Looking into each globe, you see a blue city, the model of a different Fedora. These are the forms the city could have taken if, for one reason or another, it had not become what we see today. In every age someone, looking at Fedora as it was, imagined a way of making it the ideal city, but while he constructed his miniature model, Fedora was already no longer the same as before, and what had been until yesterday a possible future became only a toy in a glass globe.

The building with the globes is now Fedora's museum: every inhabitant visits it, chooses the city that corresponds to his desires, contemplates it, imagining his reflection in the medusa pond that would have collected the waters of the canal (if it had not been dried up), the view from the high canopied box along the avenue reserved for elephants (now banished from the city), the fun of sliding down the spiral, twisting minaret (which never found a pedestal from which to rise).

On the map of your empire, Ô Great Khan, there must be room both for the big, stone Fedora and the little Fedoras in glass globes. Not because they are all equally real, but because all are only assumptions.

— Italo Calvino (1974), Invisible Cities

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Abstract

Climate change and growing urban populations are increasingly putting pressure on cities to reduce their carbon emissions and transition towards efficient and renewable energy systems. This challenges in particular urban planners, who are expected to integrate technical energy aspects and balance them with the conflicting and often elusive needs of other urban actors. This thesis explores how multicriteria decision analysis, and in particular multiobjective optimization techniques, can support this task. While multiobjective optimization is particularly suited for generating efficient and original alternatives, it presents two shortcomings when targeted at large, intractable problems. First, the problem size prevents a complete identification of all solutions. Second, the preferences required to narrow the problem size are difficult to know and formulate precisely before seeing the possible alternatives. Interactive optimization addresses both of these gaps by involving the human decision-maker in the calculation process, incorporating their preferences at the same time as the generated alternatives enrich their understanding of acceptable tradeoffs and important criteria. For interactive optimization methods to be adopted in practice, computational frameworks are required, which can handle and visualize many objectives simultaneously, provide optimal solutions quickly and representatively, all while remaining simple and intuitive to use and understand by practitioners. Accordingly, the main objective of this thesis is:

> *To develop a decision support methodology which enables the integration of energy issues in the early stages of urban planning.*

The proposed response and main contribution is SAGESSE (Systematic Analysis, Generation, Exploration, Steering and Synthesis Experience), an interactive multiobjective optimization decision support methodology, which addresses the practical and technical shortcomings above. Its innovative aspect resides in the combination of (i) parallel coordinates as a means to simultaneously explore and steer the alternative-generation process, (ii) a quasi-random sampling technique to efficiently explore the solution space in areas specified by the decision maker, and (iii) the integration of multiattribute decision analysis, cluster analysis and linked data visualization techniques to facilitate the interpretation of the Pareto front in real-time.

Developed in collaboration with urban and energy planning practitioners, the methodology was applied to two Swiss urban planning case-studies: one greenfield project, in which all buildings and energy technologies are conceived *ex nihilo*, and one brownfield project, in which an existing urban neighborhood is redeveloped. These applications led to the progressive development of computational methods based on mathematical programming and data modeling (in the context of another thesis) which, applied with SAGESSE, form the planning support system URB^{io}. Results indicate that the methodology is effective in exploring hundreds of plans and revealing tradeoffs and synergies between multiple objectives. The concrete outcomes of the calculations provide inputs for specifying political targets and deriving urban master plans.

Keywords. urban energy system; urban planning; multicriteria decision analysis; decision support; multi-objective optimization; interactive optimization; parallel coordinates.

Résumé

Le changement climatique et l'augmentation de la population urbaine contraignent de plus en plus les villes à réduire leurs émissions de gaz à effets de serre et à basculer vers des systèmes énergétiques efficients et renouvelables. Cela pose particulièrement un défi aux urbanistes, qui sont censés intégrer les aspects techniques de l'énergie et les équilibrer avec les enjeux conflictuels et parfois insaisissables des autres acteurs urbains. Cette thèse explore comment l'analyse décisionnelle multicritères, et en particulier les techniques d'optimisation multiobjectifs, peut faciliter cette tâche. L'optimisation multiobjectifs est particulièrement reconnue pour sa capacité de générer des alternatives originales et efficientes. Elle présente cependant deux inconvénients lorsqu'appliquée à des problèmes de grande échelle et difficile à formuler en termes exacts. Premièrement, la taille du problème empêche une identification complète de toutes les solutions. Deuxièmement, il est difficile pour les décideurs de formuler les problèmes ainsi que leurs préférences avant de voir les alternatives possibles. L'optimisation interactive permet de combler ces deux lacunes en impliquant le décideur humain dans le processus de calcul, et en incorporant ses préférences en même temps que les alternatives générées enrichissent sa compréhension du problème et des critères importants. Pour que les méthodes d'optimisation interactives soient utilisables dans la pratique, des solutions logicielles pouvant gérer et visualiser simultanément de nombreux objectifs, fournir des solutions optimales rapidement et de manière représentative, tout en restant simples et intuitives sont nécessaires. En conséquence, l'objectif principal de cette thèse est de:

> *Développer une méthodologie d'aide à la décision permettant l'intégration des questions énergétiques dans les étapes amont de la planification urbaine.*

La principale contribution de ce travail est SAGESSE (Systematic Analysis, Generation, Exploration, Steering and Synthesis Experience), une méthodologie interactive d'aide à la décision d'optimisation multiobjectifs, qui aborde les lacunes pratiques et techniques ci-dessus. Son aspect novateur réside dans la combinaison de (i) coordonnées parallèles comme moyen de simultanément explorer et piloter le processus de générations d'alternatives, (ii) une technique d'échantillonnage quasi-aléatoire pour explorer efficacement l'espace de solution dans les domaines spécifiés par le décideur, et (iii) l'intégration de méthodes d'analyse multiattributs, de méthodes de partitionnement de données (*clustering*), ainsi que de techniques de visualisation de données interactives pour faciliter l'interprétation du front de Pareto résultant de l'optimisation.

Développée en collaboration avec des praticiens en planification urbaine et énergétique, la méthodologie a été appliquée à deux cas d'étude suisses: un projet de développement urbain, dans lequel tous les bâtiments et technologies énergétiques sont déterminés *ex nihilo*, et un projet de redéveloppement urbain, dans lequel un quartier urbain existant est réaménagé. Ces applications ont conduit au développement progressif de méthodes computationnelles basées sur la programmation mathématique et la modélisation de données (dans le cadre d'une autre thèse) qui, appliquées avec SAGESSE, constituent le système d'aide à la planification URB^{io}. Les résultats indiquent que la méthodologie est efficace pour explorer des centaines de plans et révéler les compromis et les synergies entre des objectifs multiples. Les résultats obtenus par cette approche permettent notamment de préciser les objectifs politiques et d'élaborer des plans directeurs d'urbanisme.

Mots-clés. système énergétique urbain; planification urbaine; méthodes d'analyse multicritères; aide à la décision; optimisation multi-objectifs; optimisation interactive; coordonnées parallèles.

Zusammenfassung

Klimawandel und wachsende Stadtevölkerungen üben zunehmend Druck auf Städte aus, ihre CO2-Emissionen zu reduzieren und den Übergang zu effizienten und erneuerbaren Energiesystemen zu vollziehen. Dies stellt insbesondere Stadtplaner vor Herausforderungen, von denen erwartet wird, dass sie energietechnische Aspekte integrieren und mit den widersprüchlichen und oft schwer fassbaren Bedürfnissen anderer städtischer Akteure in Einklang bringen. Diese Arbeit untersucht, wie multikriterielle Entscheidungsanalyse, und insbesondere multikriterielle Optimierungstechniken, diese Aufgabe unterstützen können. Während multikriterielle Optimierung besonders geeignet ist, um effiziente und originelle Alternativen zu generieren, weist sie zwei Mängel auf, wenn sie auf große, schwer lösbare Probleme angewendet wird. Zum einen verhindert die Problemgröße eine Identifikation aller Lösungen. Zum anderen sind die Präferenzen, die zur Beschränkung der Problemgröße erforderlich sind, ohne Kenntnis möglicher Alternativen schwerlich abzuwägen und auszuformulieren. Interaktive Optimierung addressiert diese beiden Lücken, indem sie den menschlichen Entscheidungsträger in den Berechnungsprozess einbezieht, indem sie gleichzeitig dessen Präferenzen berücksichtigt, während die generierten Alternativen das Verständnis für akzeptable Kompromisse und wichtige Kriterien fördern. Damit interaktive Optimierungsmethoden in der Praxis eingesetzt werden können, sind Computersysteme erforderlich, die viele Zielfunktionen gleichzeitig handhaben und visualisieren können, schnell und repräsentativ optimale Lösungen liefern, dabei aber einfach und intuitiv zu bedienen und für Anwender verständlichsind. Dementsprechend ist das Hauptziel dieser Arbeit:

> *Die Entwicklung einer Methodik zur Entscheidungsunterstützung, die die Integration von Energiefragen in frühen Phasen der Stadtplanung ermöglicht.*

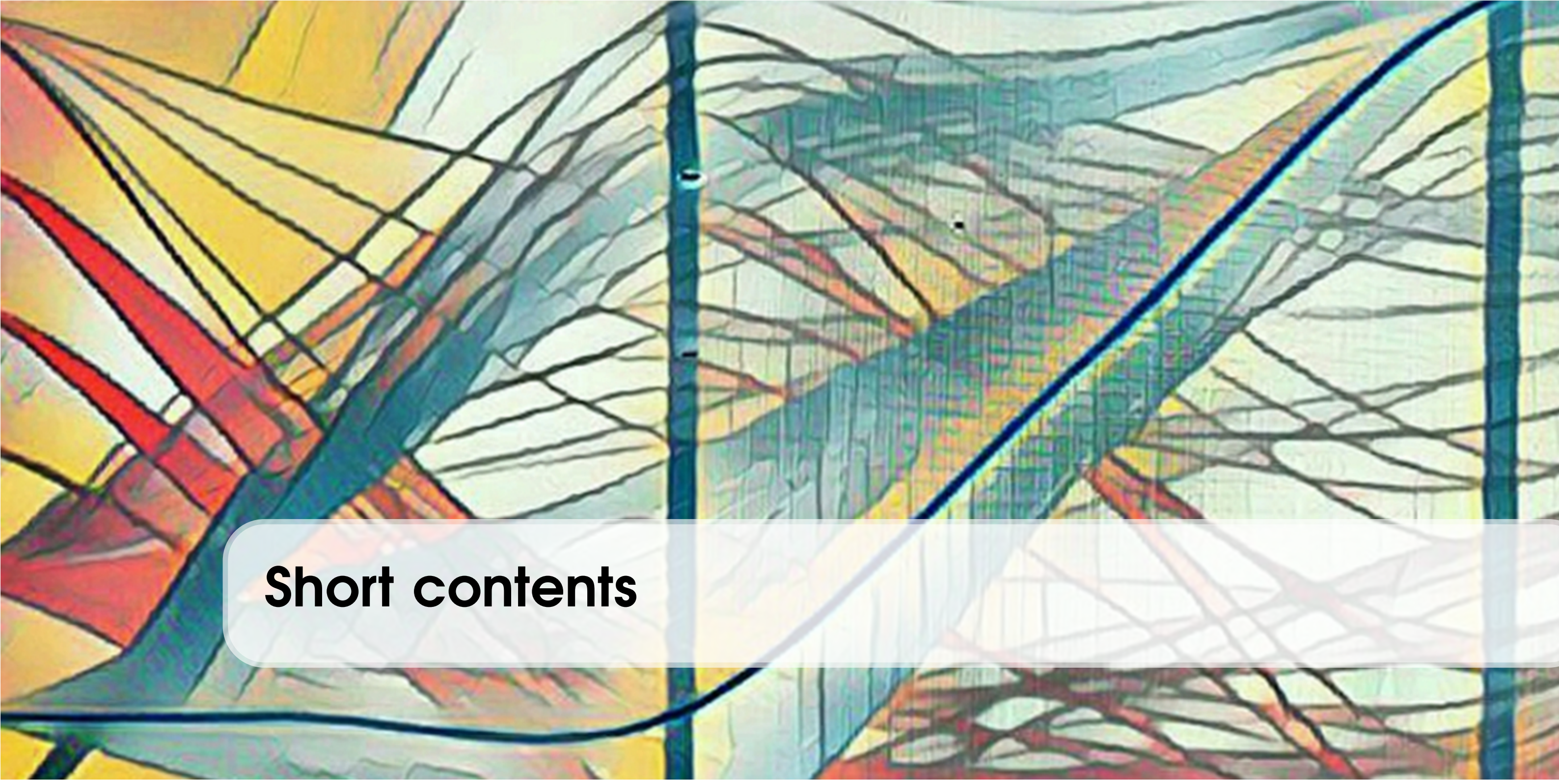
Der vorgeschlagenen Ansatz und der Hauptbeitrag ist SAGESSE (Systematic Analysis, Generation, Exploration, Steering and Synthesis Experience), eine interaktive, multikriterielle Optimierungsmethode zur Entscheidungsunterstützung, die die oben genannten praktischen und technischen Defizite addressiert. Der innovative Aspekt dieser Methode liegt in der Kombination von (i) parallelen Koordinaten als Mittel zur gleichzeitigen Erforschung und Steuerung des Prozesses zur Generierung von Alternativen, (ii) eine quasi-random Samplingmethode, um den

Lösungsraum in den vom Entscheidungsträger spezifizierten Bereichen effizient zu erforschen, und (iii) die Integration von multiattributiver Entscheidungsanalyse, Clusteranalyse und vernetzten Datenvisualisierungstechniken, um die Interpretation der Pareto-Front in Echtzeit zu erleichtern.

Die in Zusammenarbeit mit Stadt- und Energieplanern entwickelte Methodik wurde auf zwei Schweizer Städtebaufallstudien angewendet: ein Projekt zur Entwicklung eines neuen Stadtteils, in dem alle Gebäude und Energietechnologien *ex nihilo* ermittelt werden, und ein Projekt zur Weiterentwicklung eines bestehenden Stadtteils.

Diese Anwendungen führten zur schrittweisen Entwicklung von Computermethoden auf der Grundlage der mathematischen Programmierung und Datenmodellierung (im Rahmen einer anderen Dissertation), die zusammen mit SAGESSE das Planungsunterstützungssystem URB^{io} bilden. Die Ergebnisse zeigen auf, dass die Methodik effektiv zur Erforschung Hunderter von Plänen eingesetzt werden kann und Kompromisse und Synergien zwischen mehreren Zielen aufzeigt. Die konkreten Ergebnisse der Berechnungen liefern Inputs für die Festlegung politischer Ziele und die Ableitung von städtebaulichen Masterplänen.

Stichwörter. urbanes Energiesystem; Stadtplanung; multikriterielle Entscheidungsanalyse; Entscheidungsunterstützung; multikriterielle Optimierung; interaktive Optimierung; parallele Koordinaten.



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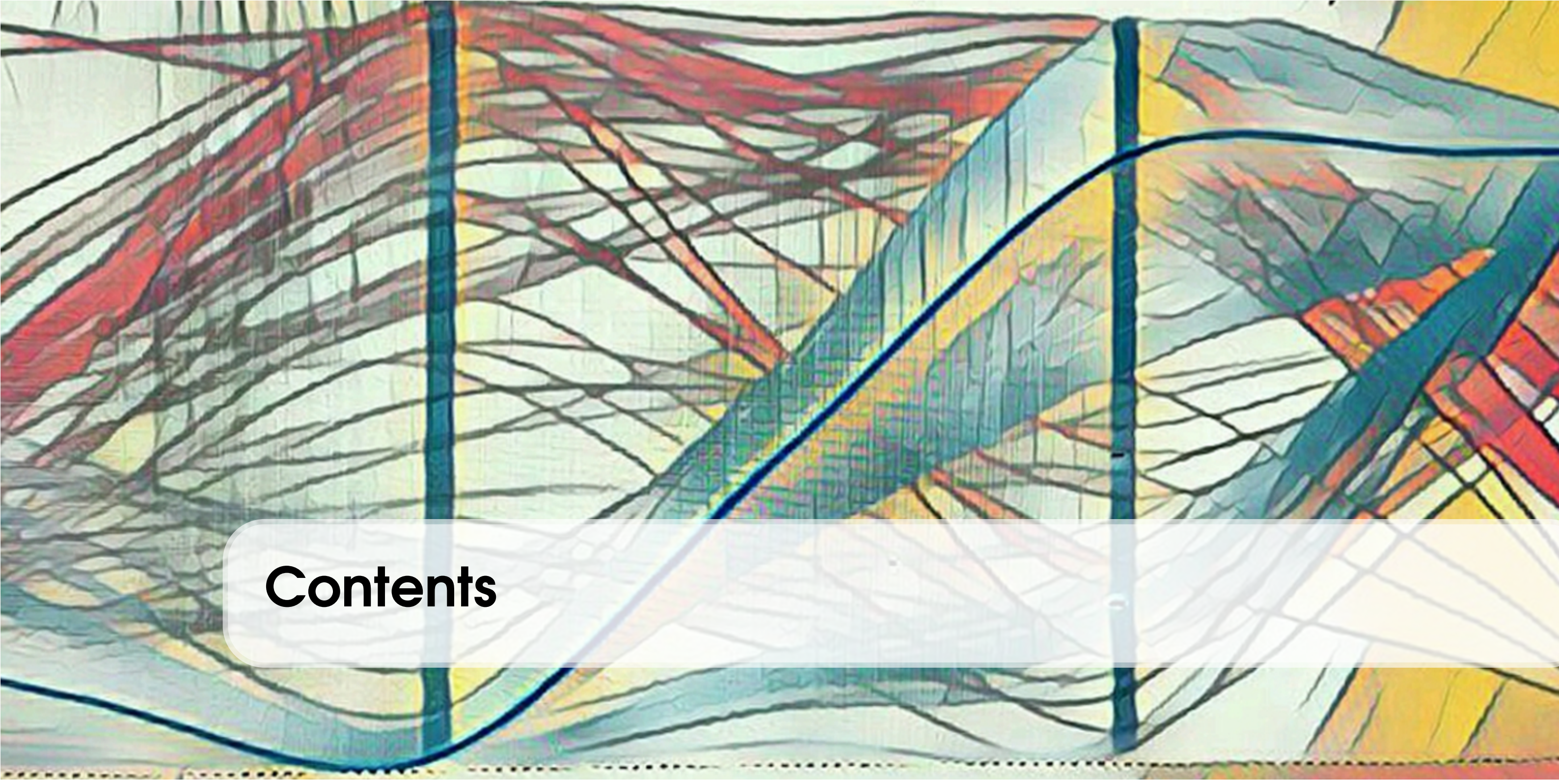

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Nomenclature

Acronyms	
AHP	Multicriteria decision analysis
ANP	Analytic network process
API	Application programming interface
ASPID	Analysis and synthesis of parameters under information deficiency
BN	Bayesian network
CBA	Cost-benefit analysis
CE	Choice experiment
CET	Concept énergétique territorial (territorial energy concept)
CHP	Combined heat and power
CoP	Communities of practice
COPRAS	Complex proportional assessment
D3	Data-driven documents
DEMATEL	Decision making trial and evaluation laboratory
DM	Decision maker
ELECTRE	Elimination et choix traduisant la réalité (from French, elimination and choice transcribing reality)
ER	Evidential reasoning
ET	Energy technology
EU	European Union
FAR	Floor area ratio
FSE	Fuzzy synthetic evaluation
FSEA	Fuzzy synthetic extent analysis
FST	Fuzzy set theory
GAIA	Geometrical analysis for interactive aid

GC	Global Criterion
GHG	Greenhouse gases
GIS	Geographic information system
GP	Goal programming
GUI	Graphical user interface
HAWM	Hierarchical additive weighting method
HEX	Heat exchanger
IEA	International energy agency
IO	Interactive optimization
IPCC	Intergovernmental panel on climate change
LVF	Landmark view factor
MADA	Multiattribute decision analysis
MAUT	Multiple attribute utility theory
MAVT	Multiple attribute value theory
MCDA	Multiple criteria decision analysis
MCDM	Multiple criteria decision making
MCS	Multiple criteria score
MEP	Mandat d'études parallèles
MEW	Multiplicative exponential weighting
MI(N)LP	Mixed integer (non) linear programming
MILP	Mixed integer linear programming
MODA	Multiobjective decision analysis
MODM	Multiple objective decision making
MOEU	Mandat de maîtrise d'œuvre urbaine
mpMILP	Multiparametric mixed integer linear programming
NAIADE	Novel approach to imprecise assessment and decision environments
NIS	Negative ideal solution
NoP	Network of problems
NSHP	Network source heat pump
OWA	Ordered weighted averaging
PDCn	Plan directeur cantonal (cantonal directive plan)
PDCom	Plan directeur communal (communal directive plan)
PDE	Plan directeur cantonal de l'énergie (cantonal energy directive plan)
PDQ	Plan directeur de quartier (neighborhood directive plan)
PG	Plan guide (guiding plan)
PIS	Positive ideal solution
PLQ	Plan localisé de quartier (localized neighborhood master plan)
PROMETHEE	Preference ranking organization method for enrichment evaluations
PWV	Pseudo-weight vector
QCBS	Quality and cost based selection
RES	Renewable energy sources
SAGESSE	Systematic analysis, generation, exploration, steering and synthesis experience
SIA	Société suisse des ingénieurs et architectes

SIMUS	Sequential interactive modelling for urban systems
SMAA	Stochastic multiobjective acceptability analysis
SODM	Single-objective decision making
SSM	Soft systems methodology
SWARA	Step-wise weight assessment ratio analysis
SWOT	Strengths, weaknesses, opportunities and threats
TOPSIS	Technique for order preference by similarity to ideal solution
UES	Urban energy system
UESP	Urban energy system planning
UN	United nations
UNCED	United nations conference on environment and development
VIKOR	Visekriterijumska optimizacija i kompromisno Resenje (from Serbian, Multicriteria optimization and compromise solution)
WASPAS	Weighted aggregated sum product assessment
WPM	Weighted product method
WSM	Weighted sum method

Introduction

Tell me and I will forget; show me and I may remember; involve me and I will understand.

— Chinese proverb

Different global and interrelated challenges such as unprecedented urbanization rates (Cohen, 2005), growing population (UN, 2014), and climate change (IPCC, 2013) are putting considerable pressure on today's urban actors. Since the symbolic tipping point which occurred in 2007 (Figure 1), humankind has become an urban species with more than half of its population living in cities (UN-DESA, 2018). This urbanization trend is expected to continue, reaching two-thirds of urban dwellers worldwide by the middle of the century (Figure 1), and up to 84% in the European Union (EU). At the same time, the total population will likely increase by 25% by 2050, reaching nearly 10 billion human beings (Figure 2). On the positive side, urbanization generally leads to better opportunities for employment, innovation, education and health care (UN-DESA, 2015). However, if poorly managed, it can lead to sprawl, environmental degradation and pollution. Furthermore, as noted by the World Urbanization Prospects, "urban dwellers tend to consume more per capita than rural dwellers", mainly because of higher incomes (UN-DESA, 2015). Consequently, the global energy demand will increase, exacerbating the effects of climate change. The International Energy Agency estimates that city dwellers represent two-thirds of the world's energy consumption and greenhouse gases (GHG) emissions, and could therefore notably curtail climate change impacts (IEA, 2008).

In response to these issues, various energy targets have been set by national or international institutions. In 2015, the signatory countries of the Paris Climate Agreement committed to take action to prevent global average temperatures to increase more than two degrees Celsius above pre-industrial values. In the EU, the 2020 climate targets (EC, 2007) are designed to reduce GHG emissions by 20% compared to 1990 levels, increase shares of renewable energy by 20%, and improve energy efficiency by 20%. By 2030, these targets should reach respectively 40%, 27% and 27% (EC, 2014), and by 2050, a decarbonized energy system is aimed. In this endeavor, many efforts in the EU have focused particularly on the built environment, as buildings represent the

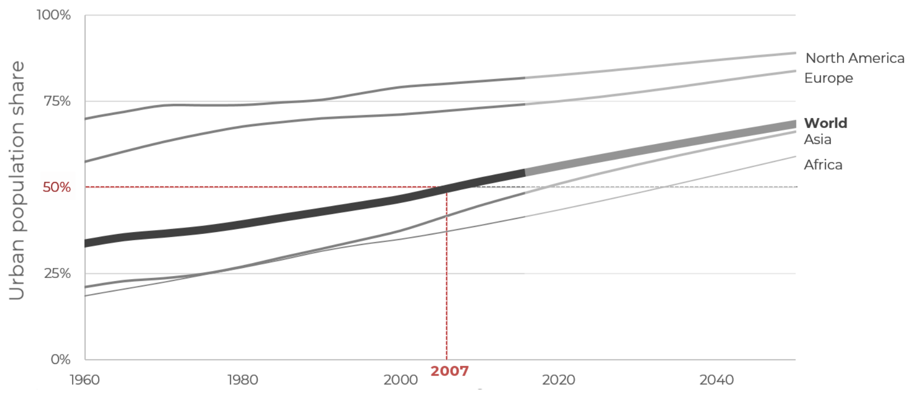


Figure 1 – Evolution of urban population shares by continent. Forecasted values from 2018 onward. Source: (UN-DESA, 2018).

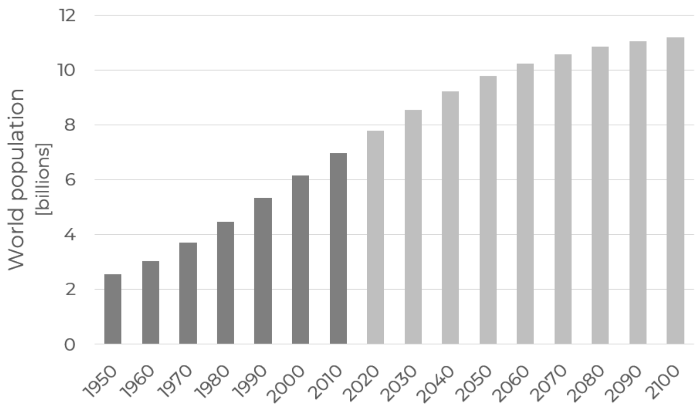


Figure 2 – Evolution of the world population. Forecasted values from 2018 onward. Source: (UN-DESA, 2018).

leading sector in final energy demand, in front of transport and industry (Figure 3).

A new role for urban planners

The active role of cities has only been progressively recognized as essential to address energy issues. Traditionally, energy planning aspects—which, in summary, encompass the identification of natural resources and energy conversion technologies which are able to satisfy the demand in an optimal way (Prasad, Bansal, and Raturi, 2014)—were managed either at the building unit level, or at the regional scale (St. Denis and Parker, 2009). Today, a wide body of literature and city-led movements support the idea of energy planning at the intermediate urban and neighborhood scales. Shortly after the global adoption of the sustainable development action plan Agenda 21 (UNCED, 1992), over 3000 cities adhered to the Aalborg charter, stating the following:

> *"We are convinced that the city or town is both the largest unit capable of initially addressing the many urban architectural, social, economic, political, natural resource and environmental imbalances damaging our modern world and the smallest scale at which problems can be meaningfully resolved in an integrated, holistic and sustainable fashion. As each city is different, we have to find our individual ways towards sustainability."* (Aalborg, 1994, p. 2)

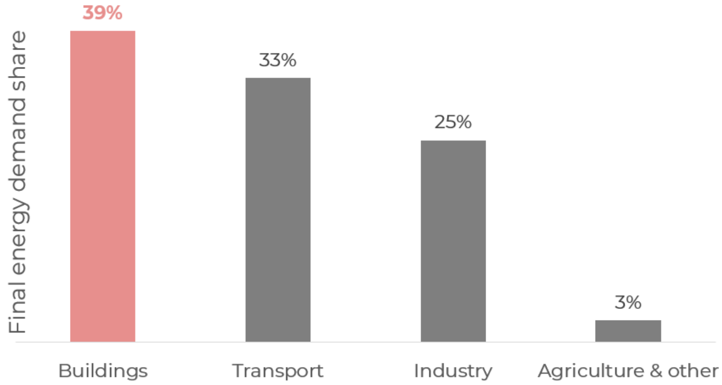


Figure 3 – Share of final energy demand by sector in the EU, 2015. Source: (EC, 2017).

More recently, the Covenent of Mayors movement has gained momentum in Europe, establishing since 2008 a vast network between cities and providing support in shaping their local energy system through the establishment of *sustainable energy action plans* (Covenant of Mayors, 2016). Also noticeable is the upscaling of different energy performance certificates—formerly developed for individual buildings—to the neighborhood scale. Examples include rating systems such as BREEAM Communities, LEED-ND or CASBEE for urban development (Sharifi and Murayama, 2014). In Switzerland, the city-scale label "Cité de l'énergie", as well as the neighborhood-scale label "Site 2000 watts" also demonstrate the recognition for considering energy at those scales (Thaler and Kellenberger, 2017).

Research also supports the idea of energy planning at the urban and neighborhood scales. For example, Rey (2012) notes that the "sustainable district" concept is still an emerging one, and emphasizes the need for "intermediate scale" approaches, located between city and building. He emphasizes that many sustainability aspects—such as low-carbon mobility or urban diversity—can only be addressed beyond individual buildings. He views the neighborhood scale as suitable to address large scale issues, while remaining in a sufficiently limited area so as to enable concrete visualization. Koch (2009) also supports action at the neighborhood level, arguing that the building scale fails to include all possible efficient energy solutions. He further notes that at this scale, already a sufficiently large and homogeneous area is available at which most efficient technologies are feasible. St. Denis and Parker (2009) identified that given recent technological advancement and better access to local knowledge, communities have become more active in planning their own energy systems. They identified several advantages, such as increased social input and participation of locals, more agile responses to opportunities and threats, more personal investment and interest of actors, and a clearer link between local consumption and generation. The United Nations Human Settlements Programme UN-Habitat (2009b) acknowledges the relevance of local governments (i.e. cities) in playing a central role in energy planning, as they are best placed to understand their citizens, know their needs and influence their behaviors. Beuzekom, Gibescu, and Slootweg (2015) advocates the urban scale to address energy issues, arguing that its increased degrees of freedom allow for increased efficiency of the resulting energy system, and better handling of multi-energy carriers, e.g. due to economies of scale, wider choice of technologies, energy balancing and demand-side management, which becomes possible in the presence of a variety of profiles.

To carry out this ambitious task, urban planners are thus expected to play a central role. Indeed, 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 (UN-Habitat, 2009a; Albers, 1986). 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 (Teriman, Yigitcanlar, and Mayere, 2010). Additionally, their strategic plans must bring together and coordinate different sectors, consider effects on multiple scales and cover long-term horizons (Huang et al., 2015; UN-Habitat, 2009a). 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 (Strasser et al., 2018). By considering energy efficiency and renewable energy integration beyond the individual building scale, urban planning can effectively help to reach energy and climate targets (Zanon and Verones, 2013; Immendoerfer, Winkelmann, and Stelzer, 2014; Parliament, 2012; IEA, 2008).

Yet, in spite of these compelling arguments, urban planning still falls short of adequate methods and tools to effectively include energy aspects in existing processes, for two main reasons.

First, because of the difficulty to clearly formulate the problems to be tackled and the goals to be achieved. The wide scope of urban planning—characterized by interrelated domains, scales, actors and temporal phases—constitutes what has been referred to as a "wicked problem" (Rittel and Webber, 1973; Levin et al., 2007). In this context, alluding to one of the central challenges of urban planning, Rittel and Webber (1973) have said:

> *"By now we are all beginning to realize that one of the most intractable problems is that of defining problems (of knowing what distinguishes an observed condition from a desired condition) and of locating problems (finding where in the complex causal networks the trouble really lies). In turn, and equally intractable, is the problem of identifying the actions that might effectively narrow the gap between what-is and what-ought-to-be."* (Rittel and Webber, 1973, p. 159)

Thus, due to the difficulty in addressing the problem exhaustively, what is commonly found in practice is a certain "taming" of the problem: the consideration of issues individually, and sequentially. As a result, energy is often still considered late in the planning process, when decisional flexibility is low, and more effort is required to adapt earlier decisions (Petersen, 2018; Schiefelbein et al., 2017; Jacobs, 1961).

Second, the complexity of urban planning implies a difficulty to anticipate—or unknowability of—the consequences of decisions (Marshall, 2012). This issue has been referred to as the "planning-design gap" (deVries, Tabak, and Achten, 2005), or the difficulty to take strategic decisions in the absence of quantified information about their practical consequences.

Decision support for urban planning

The urban planning tasks outlined in the previous section imply taking high-stake decisions in the earlier phases of a project, where multiple conflicting objectives should be met, yet where precise information about the problem and its goals may be lacking. Given the accountability of planners towards citizens, politicians or upper governmental echelons, taking such decisions represents a consequent challenge, where formal decision support methods become essential. Albers (1986) summarized this effectively by stating that:

> *...there is an uneasy relationship between politics and planning: politicians tend to hope for technical solutions to be found by planners, so that politics may avoid unpopular decisions; planners expect from politics the clarification of goals as well as*

the provision of more efficient instruments for planning and realization. Apparently, both sides expect too much. (Albers, 1986, p. 34)

Multicriteria decision analysis (MCDA) can support decision making in such cases, where informal common sense alone may not be sufficient (Keeney, 1982). MCDA can facilitate the identification of a preferred alternative by structuring the problem, and making clear the relationships between conflicting criteria or objectives. While the first branch of MCDA—known as multiattribute decision analysis (MADA)—aims at *choosing* the best alternative from a predefined set, the second branch—multiobjective decision analysis (MODA)—aims at *generating* alternatives which meet predefined objectives (Hwang and Yoon, 1981). A first fundamental benefit of MODA is its ability to foster "value-focused thinking" (Parnell, 2007). Value-focused thinking can be essentially summarized as a decision approach, which considers the governing values of a problem first, and the means to achieve them only second (Keeney, 1992). This approach is distinguished from its counterpart, "alternative-focused thinking", in the following quote:

"Value-focused thinking involves starting at the best and working to make it a reality. Alternative-focused thinking is starting with what is readily available and taking the best of the lot." (Keeney, 1992, p. 6)

While in alternative-focused thinking, better alternatives can easily be overlooked, value-focused thinking can, in principle, considerably improve the quality of complex decisions such as those found in urban energy system planning.

A second benefit of MODA is its ability to generate not only a large quantity of alternatives, but most importantly of solutions which are said "efficient", or "Pareto optimal" (Hwang and Masud, 1979). A solution is Pareto optimal if it cannot be improved in one objective without also degrading the value in at least another objective (Branke et al., 2008). Figure 4 illustrates a set of Pareto optimal solutions, known as a Pareto front, for two cost objectives, meaning a lower value in those objectives is considered desirable. In this case, assuming that both objectives fully characterize the problem, a rational decision maker would not choose one of the dominated solutions (gray dots), because there exist solutions for which both objectives can be improved (red dots).

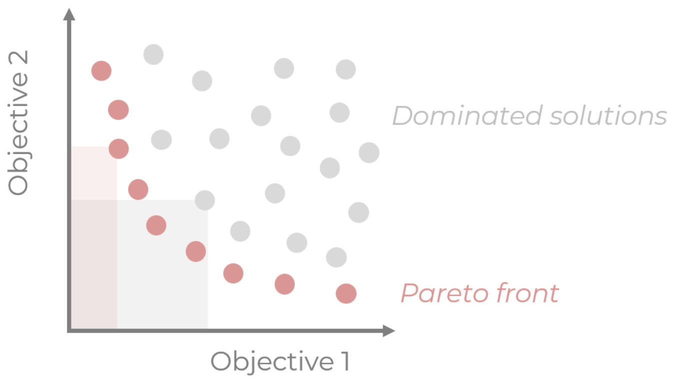


Figure 4 – Illustration of the concept of Pareto optimality for two cost objectives, whose values are to be minimized. The presence of solutions in a shaded rectangle stemming from a solution indicates it is "dominated", as solutions exist which can improve at least one of its objectives without degrading the other.

Typically, multiobjective optimization leads to multiple solutions (a Pareto front), and as such does not tell the decision maker which solution to choose, but focuses their attention on only the most promising ones (Wierzbicki, Makowski, and Wessels, 2000). The opportunity to be presented with such information, namely the tradeoffs between all (or a representative subset of) good solutions, has been shown to improve the quality and satisfaction of decisons (Balling et al., 1999; Trutnevyte, Stauffacher, and Scholz, 2011; Raphael, 2011). Indeed, the decision makers can evaluate the tradeoffs, and rationally choose a solution which is coherent with their preferences.

However, three interdependent issues arise when applying optimization to urban planning problems. First, the optimization model must overcome the inherent elusive nature of urban planning, while avoiding to adopt a too narrow and segmented representation of the different sectors (Derix, 2012; Albers, 1986; Bayliss, 1973). Second, as the model grows in complexity and size, the ability to generate the Pareto front in a reasonable amount of time decreases (Meignan et al., 2015). Finally, should a Pareto front be available, the difficulty to visualize and interpret multidimensional data becomes another barrier (Miettinen, 2014; Akle, Minel, and Yannou, 2016).

Furthermore, related to these issues is the apparent low uptake by urban planning practitioners of computer-based tools developed in academia (Geertman, 2017; Klosterman, 1999). Reported reasons for this are the difficulty to use the tools and steep learning curves, the associated mistrust, the lack of awareness that such tools exist, and in particular, the lack of collaboration between developers and planning practitioners in the development of new tools (Geertman, 2017; Jank, 2017; Pettit et al., 2017; Bayliss, 1973).

Human-computer interaction

What was described above is a problem which is likely too difficult to solve—let alone to state precisely—for a human decision maker alone. On the other hand, the difficulty to formulate the problem in precise and complete terms also makes it inadequate to solve by a computer alone. The field of human-computer interaction provides a response to this apparent dilemma, through what is known as interactive optimization (Dix, 2009; Branke et al., 2008). This type of optimization is characterized by having a "human-in-the-loop", which mutually enriches the model by providing live feedback, while the model enriches the user's understanding of the problem and of their preferences. The underlying philosophy of such an approach is that combining the human's superior intelligence and knowledge of a problem with the computer's superior computational speed "can result in better solutions than neither could produce alone" (Scott, Lesh, and Klau, 2002). In turn, solutions are better understood, and computational costs can be reduced by focusing on the most relevant solutions only (Carlsen et al., 2008).

While interactive optimization has been intensely studied in the past fifty years, their focus was predominantly on the underlying solving methods, and less on the learning potential for users (Gardiner and Vanderpooten, 1997). Indeed, users were seen essentially as a way to improve the search process, while behavioral aspects, as well as opportunities for user learning, were often neglected. In turn, this led to a low adoption of interactive optimization in practice (White, 1990; Gardiner and Vanderpooten, 1997).

In addition, many of the more recent interactive optimization methods are limited to either small application scales, or are sector-specific and capable of handling only a limited number of objectives (Allmendinger et al., 2016). Notable applications of interactive optimization are mainly performed in the academic context, and applied to a variety of problems such as medical treatment planning (Liu et al., 2018; Ripsman, Aleman, and Ghobadi, 2015), waste-water treatment plant operation (Miettinen et al., 2010), watershed conservation measure selection (Babbar-Sebens et al., 2015), fashion clothing design (Kim and Cho, 2000), industrial structure and land-use allocation (Huang and Zhao, 1998) or design of vehicle configurations (Carlsen et al., 2008).

Thesis objective and research questions

Summarizing the contextual and methodological issues described so far, what is needed is (i) a systematic way to formalize the problems encountered in urban planning, (ii) the ability to show planners the implications of their decisions before they take them, (iii) an approach which incorporates the expertise of the decision maker in the search for alternative plans, and (iv) an interface which remains accessible to lay users, i.e. the inputs required should be as simple and understandable as possible, and the methodology should convey clear insights from the resulting multidimensional data.

Accordingly, the main objective of this work is described as follows:

> *To develop a decision support methodology which enables the integration of energy issues in the early stages of urban planning.*

This objective will be achieved by progressively addressing the following research questions:

1. *Which obstacles are preventing the integration of energy issues in urban planning processes, and which improvements can be made?*
2. *What requirements do multicriteria decision analysis methods have to meet to support decisions in urban energy system planning?*
3. *How to efficiently generate and visualize a set of Pareto optimal solutions given the elusive nature of urban planning goals, and the large problem size?*
4. *Which practical questions arise in urban energy system planning, and which criteria can be used to evaluate the success of the proposed solutions ?*

Contributions

The main contribution of this thesis is the development of **an interactive optimization methodology** which can support decisions in large and ill-defined problems, implemented as a web-based platform (Chapter 3). Compared to existing approaches in the field of interactive optimization, this methodology innovates in three ways. First, the generation and exploration of solutions, as well as the steering of the search are blended together and carried out simultaneously from a parallel coordinates interface (Inselberg, 1985). Parallel coordinates are similar to radar charts, except the dimensions are displayed side-by-side, which allows the method to scale well to many dimensions, and facilitates the identification of patterns in the data (Figure 5). This allows not only to handle a large number of criteria and alternatives, but also reduces the learning curve by relying on few and concrete inputs. Second, the quasi-random sampling sequence developed by Sobol (1967) is adopted to efficiently explore the solution space in areas specified by the decision maker. While some studies use this method to enhance the quality of Pareto fronts obtained in a non-interactive way, its use in the context of interactive optimization represents a novelty. Third, multiattribute decision analysis, cluster analysis and linked data visualization techniques facilitate the interpretation of the Pareto front in real-time.

The second main contribution is the **application of the methodology to the field of urban planning** (Chapters 4–6). Urban planning literature has mostly avoided optimization models for their inability to consider the full complexity of the problems, and their impractical computational requirements. The proposed methodology makes possible the use of advanced urban planning optimization models, by mutually addressing the limitations of both the user and of the computer. Following an iterative workflow, a collaboration with practitioners led to the development of a

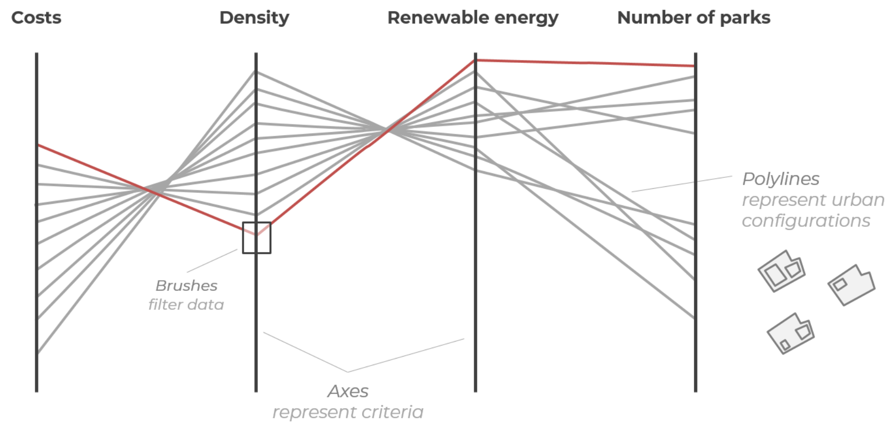


Figure 5 – Schematic depiction of parallel coordinates and their main components. Data points are represented as polylines joining the axes at their respective value. Brushes allow to filter and highlight polylines of interest. In the present work, parallel coordinates are used to explore the characteristics of urban configurations generated via multiobjective optimization techniques.

multiparametric mixed integer linear programming (mpMILP) model, which was applied to two case-studies. The implementation of the model was performed by Schüler et al. (2018b).

A third contribution is the development of a **systematic framework to characterize the challenges** hindering urban energy planning and stimulate the identification of adapted responses to those challenges (Chapter 1).

A fourth contribution includes the **review of 87 studies applying multicriteria decision analysis** (MCDA) methods in the context of urban energy system planning (Chapter 2). The main outcome of the review is a rigorous and systematic synthesis, formalized in an online parallel coordinates interface, which can be used to identify and justify the choice of MCDA methods based on the requirements of each problem.

Research approach and thesis outline

Figure 6 illustrates the adopted research approach which led to this thesis' main contributions. It consists of an iterative process which stems from a preliminary contextual planning question (e.g. how to plan a sustainable urban neighborhood), and draws from both theory and case-study specific information (i.e. workshops, master plans and legal documents) to establish the requirements of a decision support methodology which is able to answer the formulated question. The process is inherently iterative, as the progressive development of the model and the generation of results leads to a refinement of the questions asked. The practical outcome of this work was the planning support system URB^{io} , consisting of (i) a multiparametric mixed integer linear programming (mpMILP) model of the urban and energy systems and (ii) an interactive multiobjective optimization methodology based on parallel coordinates. The latter, SAGESSE (for *Systematic Analysis, Generation, Exploration, Steering and Synthesis Experience*), is the main contribution of the author, and enables urban planners both to steer the optimization procedure according to their (evolving) preferences, and to explore the solutions in real time. The former mpMILP model was developed by Schüler et al. (2018b), while the author's contribution in that work consisted mainly in providing the contextual specifications for the model.

The thesis outline is briefly described hereafter, while the main contributions of each chapter are indicated in the methodological workflow in Figure 6.

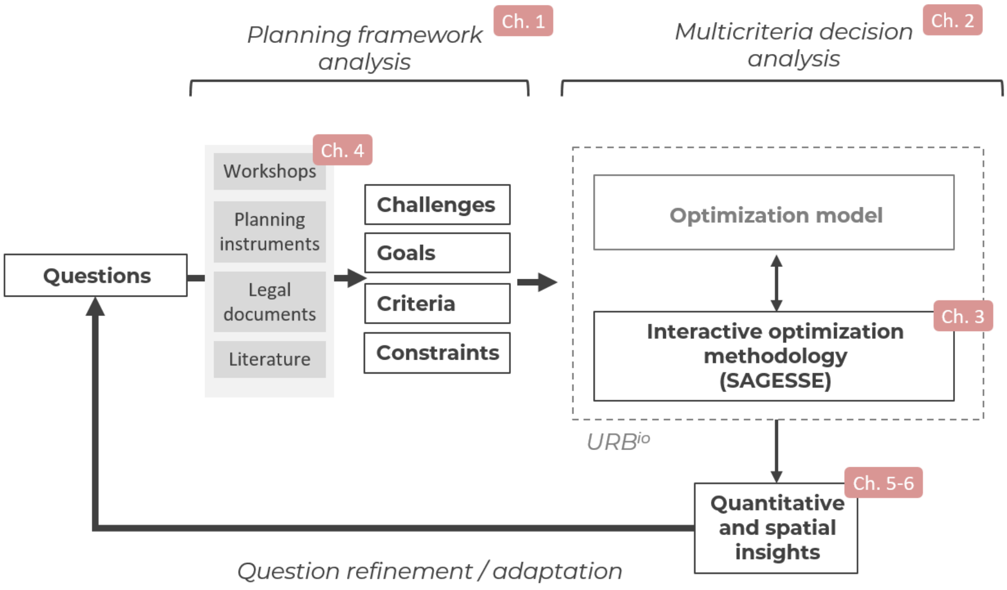


Figure 6 – Research method and thesis outline (numbered boxes correspond to chapters covering the indicated topics).

Chapter 1 lays the contextual planning background of the thesis. A review of urban planning processes is first presented, clarifying their scope and definitions. Then the concept of "wicked problem"—originally applied to social and economic aspects of planning—is extended to describe and organize the key challenges of including energy issues into urban planning. The framework is then applied to a greenfield planning project in Geneva, which will be one of the two case-studies adopted in this thesis.

Chapter 2 is a systematic review of studies applying MCDA to urban energy system planning problems. The appropriateness of different methods for specific problems is analyzed, and the findings are used to motivate the choice of methods adopted in this thesis, namely a combination of multiattribute and multiobjective decision analysis methods.

Chapter 3 contains the core methodological contribution of the thesis. After presenting the state of the art in interactive optimization, a novel methodology called SAGESSE is proposed, which addresses the open research gaps in interactive optimization, and which provides a response to the challenges identified in the first chapter.

In **Chapter 4**, the two adopted case-studies are described, and the main outcomes from the research workflow are provided. In particular, the key questions and criteria which were identified are described, while the feedback on the developed methodology collected during workshops with the planning teams is discussed.

Chapters 5 and 6 exemplify the application of the SAGESSE methodology to both case-studies. The first chapter applies the methodology in a so-called *a posteriori* mode, thereby generating the Pareto front before exploring it, while the second shows two examples of an *interactive* use of the methodology, where the decision maker progressively learns about the problem, while steering the search to generate relevant solutions.

Finally, some concluding remarks and perspectives for future work are outlined in the last chapter.

1. Challenges in urban and energy system planning

We are made wise not by the recollection of our past, but by the responsibility for our future.

— George Bernard Shaw

In this chapter, the concepts of urban and energy planning used throughout the thesis are described and discussed based on a review of literature. In particular, the main phases which constitute urban planning are presented, along with the evolution of its goals in the past decades. Then, the concept of "wicked problems" is introduced, which serves as a methodological framework to map the different challenges faced when widening the scope of urban planning to energy issues. A state-of-the-art of common responses to such seemingly intractable problems is presented. Illustrating the various concepts, the methodological framework is applied to a planning case-study from Geneva, exemplifying with practical insights the various challenges and adopted measures.

This chapter draws from materials published in Cajot et al. (2017c), Cajot et al. (2017b) and in Cajot and Schüler (2018).

1.1 Introduction

According to predictions from the United Nations (UN, 2014), two-thirds of the world's population will be urban by 2050 (Table 1.1). By concentrating people and energy consuming activities, cities currently already represent two-thirds of the world's energy consumption and GHG emitters, contributing to increase the effects of climate change (IEA, 2008). Cities, and in particular the building sector who represents 40% of the energy end-use (Pérez-Lombard, Ortiz, and Pout, 2008), are thus expected to play an important role in reaching European climate and energy targets (EC, 2014). However, to obtain cost-effective and energy-efficient building stocks, evidence suggests that the building scale may be suboptimal, and that new innovative measures involving urban planning are needed (Caputo and Pasetti, 2015; Gossop, 2011; Immendoerfer, Winkelmann, and Stelzer, 2014; Jank and Erhorn-Kluttig, 2013; Strasser, 2015; UN-Habitat, 2009a; Zanon and Verones, 2013). Addressing these issues at wider scales than the single building comes however at a price. Despite presenting possibly complex technical problems, energy planning at the building scale is facilitated by the fact that buildings are self-defined and well-understood entities, with relatively fixed life-spans, and involving fewer stakeholders with clear power relations (Peter et al., 2009; Strasser et al., 2018; Zanon and Verones, 2013). As soon as energy issues are considered at city level, these traits disappear, turning a well-defined and fairly delimited problem into an ill-defined, multi-faceted and dynamic one. Such problems have been referred to as "wicked problems", and will be a main focus of this chapter. Despite these difficulties, both the research and planning communities agree today that a new understanding of the role and form of urban planning is required to take on these pressing issues related to energy. Going beyond the traditional tasks of designing the city's spatial aspects and defining strategic targets (CEMAT, 2007), urban planning must be carefully and profoundly rethought to take ownership of, and appropriately address, energy and resource issues. This means that planners are expected to handle simultaneously both qualitative aspects such as aesthetics of urban form or quality of life, along with the more quantitative concerns of energy system design and engineering.

Table 1.1 – Urban population predictions (UN, 2014).

	Urban population [billions]	World population [billions]	Share of urban population [%]
2015	3.96	7.32	54.0
2035	5.39	8.74	61.7
2050	6.34	9.55	66.4

Barnett (1989) had already mentioned this need for urban planning to keep up with evolving challenges. As he noted:

> *"Urban design and planning techniques have to change because cities and suburbs are changing. What was true about cities as recently as ten years ago is true no longer, and the process of evolution goes on."* (Barnett, 1989, p. 131)

Furthermore, a growing number of studies support the idea that the urban context is appropriate to implement efficient and effective energy measures, and that urban planners are in a key position to coordinate and manage them. The Intergovernmental Panel on Climate Change (IPCC) has in fact recently targeted urban planning as an important mitigation measure for global warming (IPCC, 2014). Research has shown that suitable urban forms (i.e. density, building configuration and morphology) can positively affect energy demand, next to other factors such as occupant behavior, building design or systems efficiency (Ratti, Baker, and Steemers, 2005; Rode et al., 2014; Salat, 2009). Salat (2009) explicitly recommends that the results of such approaches, i.e. the identification of optimal urban form parameters in regard to energy loads and CO_2 emissions, should accompany planners when developing or transforming urban areas. Zanon and Verones (2013) argue that energy efficiencies "must be addressed by connecting the building scale with the urban one", in particular through adapted spatial planning policies and procedures. They underline how the urban form can be designed to reduce demand in buildings and transport, but also benefit energy generation. Appropriate urban form planning can, according to them, allow the development of mixed-use areas, green spaces, suitable building orientation and location, and facilitate access to renewable and district energy supply technologies. Sperling, Hvelplund, and Mathiesen (2011) discuss how the transition towards renewable energy sources requires a stronger involvement of municipalities in energy planning. They argue that the central state should set up appropriate institutional frameworks to support energy planning at the urban scale, while emphasizing the importance of a "two-way communication process through which municipalities contribute to the framing of strategic energy planning (...) at the central level". They advocate the recognition of municipalities as official energy planning authorities, in particular to facilitate the integration of administrative departments and actors. Madlener and Sunak (2011) emphasize the inextricable link between urban planning and energy planning, pointing out sustainability measures to be implemented at multiple levels. Such measures include energy-efficient appliances, architecture and retrofit on the building scale, efficient heating and cooling systems such as district heating and combined heat and power plants on the district scale, as well as energy-efficient urban design, and enabling alternative low-carbon transport modes on the metropolitan scale. Nuorkivi and Ahonen (2013) present an international project which aimed to provide urban planners with the necessary skills to include energy efficiency and renewable energies in their work. In a more technical study from Keirstead and Shah (2011), the dependencies between urban form and energy are highlighted, and an optimization approach is proposed to identify minimum energy urban layouts in regard to transportation and building energy use. They briefly review existing land-use and transportation (LUT) models, noting that many still do not focus on energy, or if so, solely considering transportation aspects. Bahu et al. (2014) show how the combination of modeling strategies, namely spatial analysis and energy system modeling, can mutually benefit urban spatial and energy planning. Detailed 3D georeferenced data was used for the assessment of building energy demand and refurbishment potential, and coupled to an agent-based modeling approach for component-level simulation, allowing to assess smart-grid measures such as demand-side management. To sum things up, this increasing body of literature on the topic shows a clear interest from both practitioners and researchers, and translates a pressing expectation for solutions. However, the consideration of energy as a central aspect of urban planning still lacks a proper framework and clearly defined methodologies (Peter et al., 2009; Strasser, 2015). This chapter expands on the results above, with the aim of exploring the different challenges and obstacles in energy planning at the urban scale, which appear to stand in the way of any satisfying solution. What is proposed here is a systematic, conceptual "map of the problematic", which can be used to better grasp the problem as a whole, and work towards the required holistic solutions.

The remaining of the chapter is structured as follows. First, a generic depiction and definition of urban planning is presented based on a systematic review of literature. Then, the evolution of urban planning goals in the past decades are discussed, providing some context to the recent widening of its scope, towards the integration of energy issues. The attempts to harmonize these requirements at the European level are briefly presented. Finally, a conceptual approach to identify and assess the challenges that are preventing the emergence of satisfactory solutions is introduced, and applied to structure the challenges encountered in an urban development project in Switzerland, and map out the different solutions proposed.

1.2 A review of urban planning processes

Masser (1983) argues that "the outcomes of planning are determined, not only by the ends that are being sought, but also by the processes that shape their implementation in practice". While the *ends* of urban planning are discussed in the next section, a simplified model of urban planning *processes* is first proposed hereafter, derived from a review of twenty scientific and practice-based references. The review methodology and its detailed results are available in Appendix A. Synthesizing the reviewed processes, the different steps and tasks involved in urban planning can be aggregated and classified into five main phases:

(1) Initiative & vision: identification of needs for action, description of a vision
(2) Strategic planning: formulation and prioritization of objectives or goals
(3) Design: elaboration, evaluation and comparison of solutions
(4) Implementation: implementation of plan
(5) Operation & monitoring: operation of infrastructure and services and monitoring

Additional information regarding the focus, iterative nature, and planning horizon of the processes was also collected (Table A.2). Nearly all references explicitly recognized the need for some form of iteration in the process, either with stepwise iterations between phases, or as an entire repetitive cycle. Even more consensual was the advocacy of public participation in urban planning. Several temporal indications show the long-term investment of planning, up to over a decade for the entire process. Six references were specifically concerned with sustainability aspects, and four with energy. Regarding physical scales, planning focus ranged from building to neighborhood, and up to regional scales.

Based on the collected information , the following definition of urban planning is proposed (Cajot and Schüler, 2018):

> *Urban planning is a continuous, iterative, layered and interconnected process of five main phases which consist in:*
>
> (i) *elaborating a common vision (initiative & vision),*
> (ii) *identifying and arbitrating corresponding objectives (strategic planning),*
> (iii) *translating the vision and objectives in alternative, concrete actions or designs, which are evaluated, compared and selected (design)*
> (iv) *implementing a plan (or passing it on to the next relevant administrative scale) (implementation)*
> (v) *operating the system of infrastructure and services, and monitoring its success until obsolescence or until a new initiative appears (operation & monitoring)*

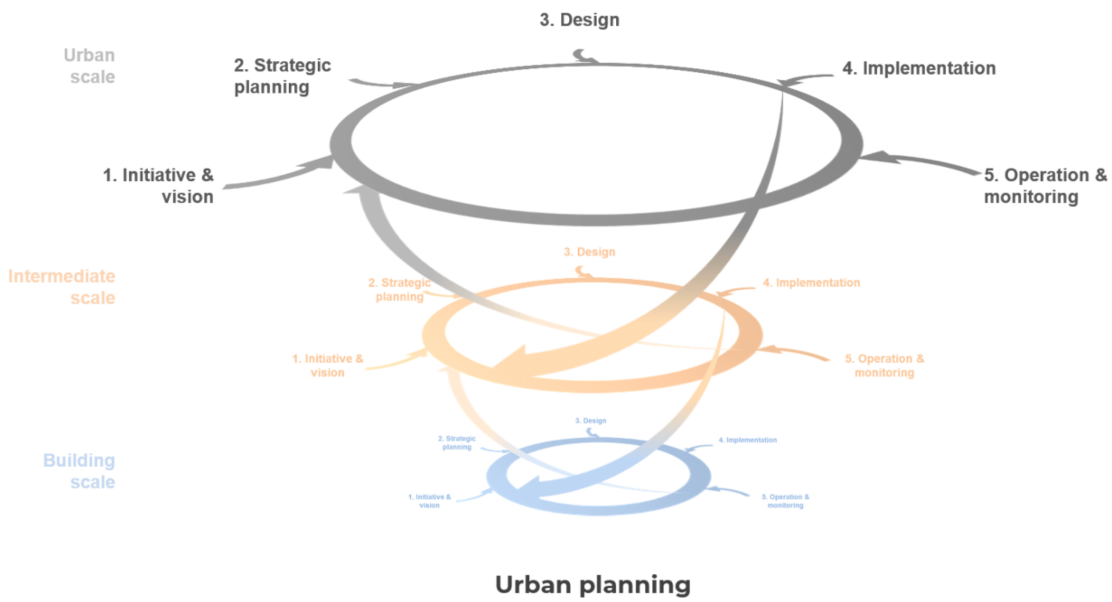


Figure 1.1 – Continuous and interconnected cycles in urban planning.

The key concepts used in the definition are illustrated in Figure 1.1, and discussed below.

Continuous and iterative. The review indicated that urban planning is frequently visualized as a linear sequence of steps. In reality, despite this linear depiction, many references emphasize the importance of *feedback loops* and *iterations* between the different steps (e.g. ensuring that proposed alternatives meet the goals identified earlier, or adapting the goals to new information collected during participative activities). Indeed, the disconnect between phases has been noted as a critical obstacle to achieving efficient plans and designs (deVries, Tabak, and Achten, 2005). Furthermore, urban planning can be viewed and understood as a *continuous*, *cyclical* process. This tendency to view planning as an ongoing activity is supported by the current reality of most planning projects in Europe. The punctual, well-delimited urban expansion and development projects (so-called "greenfield projects") of the last century have become the exception rather than the rule (Masboungi, 2014). European countries are already over three-quarters urbanized (UN, 2014), and, further conditioned by the trend for compact and dense cities, urban planning in this context consists mainly of a constant monitoring of the urban area and activities, which leads to urban renewal, redevelopment or infill/brownfield projects. Such projects possess blurred physical and temporal boundaries, where precise beginnings and endings are more difficult to define.

Layered and interconnected. These concepts refer mainly to the relationships between the physical and administrative scales at which decisions are taken. The five phases described above are purposely generic and scale independent. To some extent, they are replicable at the three key layers at which urban planning operates: the city scale, the intermediate or neighborhood scale, and the building scale. This points to the fact that urban planning is not only continuous temporally, with iterations and permeability between sequential phases and sectors, but also vertically, with reciprocal feedback between upper and lower administrative or geographical layers. Figure 1.1 illustrates how the implementation phase of the higher scales may consist in the initiation of a lower level (and thus more detailed) planning cycle, where objectives are adapted, more specific and relevant actions or physical plans are elaborated, until their implementation in the form of a construction project, or another planning cycle is attained. Likewise, each completion of a cycle leads to refined information, which in turn feeds back not only to the current scale, but also to that above.

Despite the emerging consensus on these properties of urban planning, there remains a certain confusion regarding its exact scope and sphere of action. This confusion is for example visible in the ambiguous labeling used in the reviewed material, where generic terms like "planning", "urban planning" or "plan design" are used to describe just a single step belonging to some broader, ill-defined process. In the present work, it is argued that urban planning concerns more than just the *strategic* component of the process, or the spatial *design* of the urban area. Given the necessary permeability and interdependencies between each phase, urban planning must encompass the entirety of the process.

Therefore, from the collective identification of intervention needs, down to the operation of urban infrastructure, urban planners must continuously bring together information and actors from each phase and scale, in order to best anticipate the global and local needs, and how best to satisfy them. In this context, their role becomes highly polyvalent and, to some extent, ubiquitous regarding scales and disciplines.

1.3 Towards new requirements in urban planning

1.3.1 Evolutions in planning theory

Friedmann (1987) concisely defines planning as "the attempt to connect scientific knowledge to actions in the public domain". This *connection* can follow many different methodological approaches, which are studied in the field of planning theory. Specific concerns regarding urban planning are quite recent, beginning in the 1950s (Lawrence, 2000; Schoenwandt, 2008). Among different approaches, arguably rational planning has considerably influenced current planning practices. Banfield and Meyerson (1955) describe the four main steps of rational planning as analyzing the situation, establishing goals, formulating actions and the comparative evaluation of their consequences. Due to the adaptability and the simplicity of the underlying logic, the concept has been widely accepted. Its application is based on the belief that "whatever the goals of a society, they would be more likely reached if members analyzed problems rationally" (Baum, 1996). Most importantly, rational planning can be assumed to provide psychological reassurance, as the planner's role is clearly defined as expert advisor (Baum, 1996; Lawrence, 2000; Teriman, Yigitcanlar, and Mayere, 2010). The main weakness of the concept can be seen in the difficulty to account for multiple stakeholders' opinions and interests. Indeed it includes little public participation or empirical input, while being dominated by a small number of experts (Lawrence, 2000). Also, Banfield and Meyerson (1955) recognized the idealistic limit of this model, as "no decision can be perfectly rational since no one can ever know all of the alternatives open to him at any moment or all the consequences which would follow from any action." Noble and Rittel (1988) also rejected the idea that planning and design follow a linear process, as suggested by rational planning. They deemed more appropriate to view planning as a process of argumentation between heterogeneous actors, as this helps reduce "the chances of overlooking some important aspect of the problem at hand". Finally, Albers (1986) also pointed out that strict rational planning was no guarantee of good results, for failing to incorporate the notion of creativity also necessary in planning.

Based on these main critiques, the concept evolved into more participative and holistic approaches discussed by Lawrence (2000) and Schoenwandt (2008). Current interpretations of rational planning have moved towards collaborative planning (Lawrence, 2000; Vonk and Ligtenberg, 2010; Wachs, 2001). In contrast to the initial concept, collaborative planning promotes dialogue and communication between stakeholders, leading to a broader consensus, as well as by providing a new role for planners, which shifts from technical expert, to a role of mediator coordinating all stakeholders (Teriman, Yigitcanlar, and Mayere, 2010; Zanon and Verones, 2013). Furthermore, public participation in planning and policymaking has been advocated as an alternative to mere expert-led scientific or technological approaches. Balint et al. (2011) consider public participation as a necessary but challenging process for decision makers, who need to assess interests and values which are not easily incorporated in traditional analytic techniques. They point out two shortcomings, namely the difficulty to include public participation on large geographical scales, and the failure from authorities to involve participants over long periods. Though a few practitioners still question the relevance of public participation in complex technical and scientific issues (Chilvers, 2008; Stirling, 2005), some form of public participation is generally considered beneficial in planning projects (Balint et al., 2011). For example, McLaren Loring (2007) investigated public participatory planning for wind turbines, and found that projects with higher levels of participatory planning are more widely accepted and successful. He points out that public participation is desirable and necessary in a democratic context, reduces conflict while fostering trust, and results in more robust decision-making. Based on a study of *NIMBY* (i.e. *not in my backyard*) problems, Fischer (1993) illustrates the benefits of participatory approaches. He attempts to break the idea that participatory approaches are "outrageously unscientific", and argues that collaborative citizen-expert methods might be central to solving complex environmental problems. Ultimately however, to what extent public participation should be engaged, and how their multiple and conflicting interests may be represented remain fairly open questions (Balint et al., 2011).

In parallel to the increased criticism of rational planning, as a rather rigid and technocratic approach, urban planning in the late 1900s evolved into strategic spatial planning in developed countries (UN-

Habitat, 2009a). The state accordingly became less central in urban planning processes, conferring cities and local actors more space to act. In strategic spatial planning processes, major stakeholders are identified in order to develop long-term strategies and visions. The approach is oriented towards actions and implementation in short, medium and long terms (Albrechts, 2001). Incorporating monitoring and feedback loops, decisions were from then on negotiated and deliberated by different rationalities in an iterative fashion before and during implementation. More recently, the growing complexity of urban systems and processes promoted the emergence of iterative, global and spatially defined approaches in order to replace mono-objective, linear approaches (Duarte and Seigneuret, 2011).

1.3.2 Evolutions in urban planning goals

The proposed definition in Section 1.2 emphasizes well the extensive scope of scales and topics usually associated to urban planning. Arguably, urban planning cannot be confined to merely the urban scale, as its influence is expected to extend up to the national scale and down to the building (Sperling, Hvelplund, and Mathiesen, 2011; Strasser, 2015; Zanon and Verones, 2013).

However, like many other definitions of urban planning, it avoids specifying the priorities or goals which the process aims to achieve. According to Knox (2010), these aims have ranged from "mythology and religion to geopolitics, military strategy, national identity, egalitarianism, public health, economic efficiency, profitability and sustainability". Even though aspects of sustainability and rational energy use can be identified in early concepts of urban planning, it is only in recent times that these issues take on a central role.

As modern urban planning emerged in the mid-1800s, it consisted essentially of a collection of processes to manage the sanitary and social crises which were threatening industrial cities' prosperity (Knox, 2010; Teriman, Yigitcanlar, and Mayere, 2010). This top-down, expert-led approach resulted in master-plans and land-use regulations (UN-Habitat, 2009a), favoring low-density, single-use districts as well as private cars as a means of transportation. The result was an increase in urbanization as well as a quick economic recovery that lasted until the end of World War II. After this period of urban expansion, the following decades saw a shift towards urban regeneration. Here, the goal was instead to improve existing urban areas (Duarte and Seigneuret, 2011).

In this evolving context, the oil crisis and related volatility of fossil fuel prices since the 1970s, as well as growing concerns for climate change and the emergence of the concept of sustainability (understood as a balance between social, environmental and economic interests) in the 1990s were the key drivers which progressively pushed energy issues into the focus of conventional urban planning approaches (Brundtland et al., 1987; UN-Habitat, 2009a). Today's widespread acceptance of sustainable urban planning concepts can be understood as a consequence of the described evolution in urban planning and the associated societal transformation processes. It should be noted as well that in addition to these rather environmental concerns, other global trends as well are contributing to reshape urban planning. Population growth and urbanization rates, as introduced in the opening of the chapter, raise new challenges, for example in terms of sprawl mitigation, infrastructure development, urban form and their associated impacts on quality of life (UN, 2014). Additionally, the so called "digital revolution" and increasing availability of high-resolution urban data also influence urban planning's focus and operating modes. For example, such data may shift urban planning's current long-term, strategic and rather static approaches, to a more short-term and dynamic understanding of cities (Batty, 2013). This also opens up new possibilities in terms of planning support systems and other computer-based technologies which can be used to inform and rethink planning processes (Derix, 2012; Geertman and Stillwell, 2004; Reinhart and Cerezo Davila, 2016). However, though these trends, alongside the goal of sustainable development, all contribute together to "complexify" the tasks of urban planners, their detailed analysis is out of the scope of this thesis. Instead, the focus here is more specifically on the topic of energy, as this is arguably, with its direct implications on climate change, considered one of, if not the most, pressing issues of our time (Costello et al., 2009; WEF, 2016).

1.3.3 A perspective on energy planning

A few words on the current understanding of energy planning can be useful at this point of the discussion. As a composition of a multitude of tasks, the integration of energy planning in the framework of urban planning is by its nature a fragmented and inconsistent matter. A basic problem is the lack of a common agreement on the exact definition of energy planning (Prasad, Bansal, and Raturi, 2014). For example, Thery and Zarate (2009) define energy planning as "determining the optimal mix of energy sources to satisfy a given energy demand". In this sense, the purpose of energy planning is to balance the spatially localized energy supply and demand of a given area (Keirstead, Jennings, and Sivakumar, 2012). However, this encompasses a variety of processes, energy carriers and technologies that are rarely managed together, as should be for example supply, conversion, storage and transportation technologies (Løken, 2007). Furthermore, the raising interest for local, decentralized and renewable energy technologies is currently reshaping our understanding of energy planning in cities (Adil and Ko, 2016). Cities formerly might have been considered only as "centers of passive demand which must be supplied from an ex-urban source" (Keirstead, Jennings, and Sivakumar, 2012), but today must play a more active role in organizing their energy systems from within their geographical boundaries. This change of paradigm shifts the responsibility of energy planning from a limited group of specialists, including local and national authorities, energy companies and operators, to a wider group of actors, including as well local producers, energy consumers, transportation companies, technical officers, international institutions, manufacturers of end-use appliances, financial institutions and environmentalist groups (Coelho, Antunes, and Martins, 2010). Additionally, unlike urban planning, energy planning is generally not a systematically established institution within administrative departments. Mainly for historical reasons (Merlin and Choay, 1988), the tasks described above are most often dissociated from the planning department, relegated to the management and design of networks and infrastructure by private or public actors. Caputo and Pasetti (2015) found that municipal offices often lack knowledge and authority regarding energy planning, even in the technical offices in charge of the built environment. Ideally however, energy planning – understood as the combination of tasks and actors discussed above – should be better embedded in the spatial and strategic planning processes attributed to urban planners.

The planning of energy infrastructure is not essentially new to the wide range of urban activities, however its handling by means of integrated, cross-sector and multi-actor approaches is relatively recent. Many cities are struggling to develop new methods to successfully bring together energy issues in the framework of urban planning procedures (Immendoerfer, Winkelmann, and Stelzer, 2014; Strasser, 2015; Zanon and Verones, 2013). Because of the novelty of such approaches, the term of *urban energy system planning* itself can be subject to debate and is worth clarifying. Based on a compilation of fragmented definitions of its sub-terms from literature, a synthetic definition of urban energy system planning (UESP) is put forward, in an attempt to facilitate and improve the discussion on this emerging field:

- urban energy system (UES) is defined by Keirstead, Jennings, and Sivakumar (2012) as "the combined processes of acquiring and using energy to satisfy the energy service demands of a given urban area.".
- Hopkins (2001) refers to urban planning as "intentional interventions in the urban develop-

ment process, usually by local government", and where "the term 'planning' (...) subsumes a variety of mechanisms that are in fact quite distinct: regulation, collective choice, organizational design, market correction, citizen participation, and public sector action." The concept of urban planning, previously confined to the task of designing a physical and spatial framework, has grown to serve also a more strategic function, defining and influencing the development of society (Albers, 1986). As such, urban planning is as much concerned with the spatial organization and interrelations between urban components and activities, as it is with the strategic, intersectoral and more abstract planning of a city's development, translating visions into goals, actions and investment priorities (Healey, 2004; UN-Habitat, 2009a).

- Model-based energy planning in cities or territories is defined by Mirakyan and De Guio (2013) as "an approach to find environmentally friendly, institutionally sound, socially acceptable and cost-effective solutions of the best mix of energy supply and demand options for a defined area to support long-term regional sustainable development. It is a transparent and participatory planning process, an opportunity for planners to present complex, uncertain issues in a structured, holistic and transparent way, for interested parties to review, understand and support the planning decisions".

Accordingly, the following definition and vision for urban energy system planning has been proposed in Cajot et al. (2017b), and is schematically depicted in Figure 1.2:

> *Urban energy system planning is defined as the inclusion of energy issues (related to the acquisition and use of energy) in the processes of urban planning (which strategically and spatially organize the development of a city), to find environmentally friendly, institutionally sound, socially acceptable and cost-effective solutions to satisfy the demands of an urban area.*

While this definition encapsulates the expectation of merging energy with urban planning, it lacks any explanation of how this is to be done. The next section thus elaborates on the current attempts at the European level to harmonize this question.

1.3.4 EU context: legal documents, guidelines and activities

In Europe, there is in principle no common, standard way of including and harmonizing energy issues in urban planning institutions and procedures. Following the subsidiarity principle, member states regulate and organize urban planning locally, allowing to account for local aspects and very diverse national and local planning traditions. Nonetheless, most major agreements on energy and climate goals are contracted on supranational and national levels. It is thus a consequent challenge to harmonize the allocation of targets and implementation methods on the municipal level. The European Union (EU) however does provide some guidance and common goals which indirectly influence and shape an advanced form of urban planning capable of handling the new energy issues discussed above. Through diverse legal directives and guiding documents, the EU encourages urban planning to include essentially four key features: (a) the encouragement of public participation and societal consensus, (b) the horizontal "intersectoral" coordination between disciplines and regions, (c) the vertical "multi-level" coordination following the reciprocity principle between cities, regions, countries and the EU, and (d) the sustainable consumption of natural resources (Cajot et al., 2015). Such goals have been explicitly highlighted in several documents, such as the Leipzig Charter (Charter, 2007) or the Toledo Declaration (Declaration, 2010). They propose a new urban policy based on integrated urban development, which coordinates spatial, sectoral and

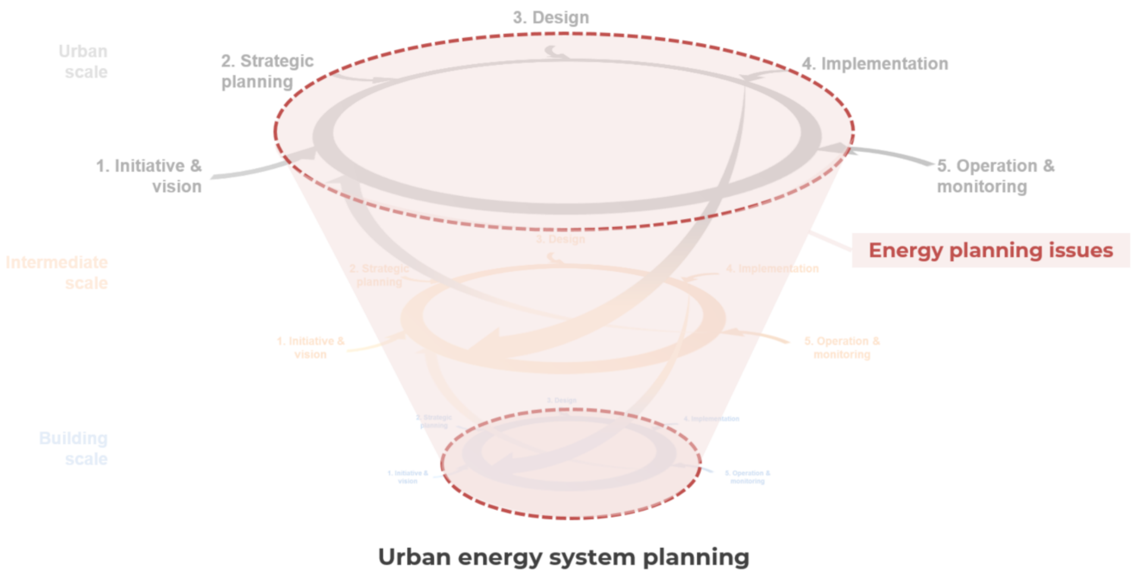


Figure 1.2 – Envisioned urban energy system planning process, as the inclusion of energy planning issues in the continuous and interconnected cycles of urban planning.

temporal aspects of urban policy. Local and regional coordination as well as citizen involvement is encouraged. The documents also call for sustainable and efficient use of resources through urban planning measures, such as compact settlements, mixed-use districts and housing renovation. The Energy Performance in Buildings Directive (European Parliament, 2010) calls Member States to "enable and encourage architects and planners to properly consider the optimal combination of improvements in energy efficiency, use of energy from renewable sources and use of district heating and cooling when planning, designing, building and renovating industrial or residential areas". The Strategic Environmental Assessment directive (Parliament, 2001) aims to ensure the "integration of environmental considerations into the preparation and adoption of plans", in particular to contribute to the rational use of natural resources based on the precautionary principle. The Energy Efficiency Directive (Parliament, 2012) also calls for citizen involvement and exchange of experiences between cities in the elaboration of sustainable energy efficiency plans. The Covenant of Mayors (Covenant of Mayors, 2016) is an initiative stemming from the EU, which precisely addresses the points from the Energy Efficiency Directive. Launched in 2008, it aims to help cities achieve the EU's 2020 climate targets (EC, 2007), by promoting the development of Sustainable Energy Action Plans (SEAP) and fostering exchange of experience between cities. Widely successful, with nearly 7000 signatory cities, the initiative now incorporates the EU's 2030 targets (EC, 2014), as well as the consideration of climate change adaptation measures in Sustainable Energy and Climate Action Plans (SECAP). In 2016, the Covenant of Mayors formed a coalition with another international initiative, the Compact of Mayors (Compact of Mayors, 2016), launched by the United Nations in 2014 to track cities' progress in acting against climate change. The merger aims in particular to increase the coordination and communication between the initiatives, and thereby facilitate the implementation of the recent Paris Climate Agreement.

Although these EU-level documents and initiatives provide helpful insights and guidelines on the overall purpose of urban planning, they do not explicitly describe how energy and urban planning processes should be integrated, which is an ongoing field of research. Aside from the Covenant of Mayors mentioned above, several European and global initiatives aim to promote research on the topic, by bringing planners and researchers together. This includes for example the Global Initiative for Resource Efficient Cities (UNEP, 2012), the Sustainable Buildings and Climate Initiative (UNEP, 2010), the European Energy Research Alliance's Smart City joint program (EERA, 2010), the Joint Programming Initiative Urban Europe (Europe, 2010) or the C40 network of megacities (C40, 2005). The International Energy Agency (IEA) is also active in this specific area through their Energy in Buildings and Communities (EBC) research program (IEA, 1977). Currently, one of the IEA-EBC projects, Annex 63 (EBC, 2013), investigates solutions to integrate energy and climate goals into common urban planning processes (Strasser, 2015).

1.3.5 Requirements, solutions and obstacles

Summarizing the discussion so far, the new requirements for urban planning have become clearer. It is understood that in order to incorporate and address energy and sustainability issues, urban planning processes must transcend former spatial, temporal or sectoral boundaries. This has been both verified in literature and is supported by the EU. Accordingly, traditional rational planning models must not only draw from and integrate aspects of collaborative and strategic planning, but also ensure sustainable development is achieved.

As discussed, shaping these new planning frameworks is an ongoing and active area of research. Several researchers have proposed solutions which begin to reflect these needs. For example, the notion of an integrated and holistic urban planning approach was developed by Gallez and Maksim (2007). They argue that the objective of urban planning is an improved coherence in public action by considering and identifying the relevant functional (rather than administrative) scales, in terms of spatial delimitations. Furthermore, the promotion of intersectoral policies as well as the integration of long-term assessments are identified as integrating factors in the planning process. Teriman, Yigitcanlar, and Mayere (2010) proposed a framework for integrated and sustainable urban planning. In particular, they advocate the early definition of goals and issues from all aspects of sustainability, the participation and accounting of all stakeholders, as well as the systematic assessment of the plan's sustainability. Sperling, Hvelplund, and Mathiesen (2011) have put forward a novel "strategic energy planning" model, promoting stronger integration between administrative scales, departments and actors, as opposed to the more silo-ed model which they refer to as "parallel energy planning".

Despite the progress done regarding the identification of needs and solutions, little attention has been dedicated specifically to the obstacles lying in between. However, the staggering task of planning for sustainable and energy-efficient cities may be better and more easily performed in the light of a systematic analysis of the obstructing challenges, which is what the remaining of the chapter will address.

1.4 A framework for describing complex problems

The discussion in the previous section started to outline the different sources of complexity in including energy issues in urban planning: multiple actors, different scales, long-term implications and uncertainty in the processes, methods and basic definitions. The formulation of the problem itself remains somewhat unclear. Scholars since the 1970s have often referred to such ill-defined problems as *wicked problems*, a notion which has been used to discuss social and environmental problems, for example regarding renewable energies or climate change (Balint et al., 2011; Boxenbaum, 2013; Levin et al., 2007; Vandenbroeck, 2012). Rittel and Webber (1973) argued that trying to formulate a wicked problem, was a problem in itself. In the present section, the main characteristics of wicked problems are adopted to frame the problem of energy planning in cities in a systematic way.

Wicked problems are essentially characterized by the presence of multiple actors with varying interests, and the difficulty to precisely define the problem statement (Boxenbaum, 2013). Additionally, what perhaps distinguishes them most from *tame problems* – their easier-to-solve counterparts – is that they “don’t have a right answer” (Camillus, 2008). Balint et al. (2011) elaborates these definitions with nine specific conditions, summarized in Table 1.2. These conditions are grouped here into three categories, whether they pertain to multiplicity and heterogeneity aspects of the problem, to related complexity and uncertainty issues, or to the instability of the context.

Initially, the notion of wicked problems referred explicitly to the intractable nature of economic and social issues in planning. Today, adding an extra layer of energy-related issues certainly amplifies the relevance of the concept. In fact, two central points raised by Levin et al. (2007) describe how the present issue exceeds the “wickedness” of dilemmas faced by urban planners in the 70s (Rittel and Webber, 1973). First, unlike before, “the central authority needed to address [the challenges] is weak or non-existent” (Levin et al., 2007). This was in particular made clear in Section 1.6.1, since energy planning is still not systematically established in most administrative structures. Second, when dealing with limited energy resources and climate change impacts, “time is running out” (Levin et al., 2007). This means that the problems faced here, if not addressed urgently, can become uncontrollable or lead to irreversible consequences.

These conditions are briefly elaborated hereafter with concrete examples, and the framework is then applied to an existing case-study in Geneva.

1.4.1 Challenges due to multiplicity and heterogeneity

As discussed in Section 1.3, urban planning requires the coordination of a multitude of fields, stakeholders and information in order to reach a diversity of generally conflicting sustainability objectives. Tradeoffs are thus necessary and lead to conflicts in decision-making. Tensions may arise as early as the problem statement itself, as multiple stakeholders, at multiple levels, will view the problem differently and favor different tactics. For example, architects and planners must rethink buildings and spaces, while local and regional authorities need to adapt organization and procedures, lawyers and politicians need to adjust legal texts and policy, and utilities must develop profitable business models.

Values are rarely properly elicited in decision-making (Keeney, 1992), which can lead to situations of so-called *split-incentives*. For example, in the landlord-tenant dilemma, low investment costs might be preferred to other social or environmental benefits (Ástmarsson, Jensen, and Maslesa, 2013), preventing any action to be taken. The balance between social, economic and environmental values, incorporated in the concept of sustainability (Brundtland et al., 1987), is thus often not respected. Another issue concerns the definition and adoption of objectives, which might appear valid when considered individually, but may conflict on short to medium terms, and thus require careful prioritizing. For example, Trutnevyte (2014) proposed a methodology to compare conflicting energy objectives, or visions, such as: carbon-free cities, cheap and affordable energy for all, regional energy self-sufficiency, job-promoting energy systems, fully renewable energy sources, highly efficient and reduced consumption. She advocates the development of visions in an inclusive, open process in presence of the legitimatized decision-makers and other relevant stakeholders. Issues related to objective and vision statements at the municipal scale have also been discussed by Sperling, Hvelplund, and Mathiesen (2011), who point out mismatches in municipal and national energy plans, attributed to uncoordinated value definition at the various scales. They interpret this phenomenon as evidence that municipalities still lack a clearly defined, and well-delimited position in terms of energy planning.

There is a priori no preferred, optimal tactic to achieve energy targets, whether it is technological, behavioral, political or economic. Furthermore, corresponding solutions and measures are

Table 1.2 – Conditions for identifying wicked problems. Adapted from Balint et al. (2011).

Category	Condition	Explanation
Multiplicity & heterogeneity	1. Lack of a single problem statement	Difficulty to agree on the exact nature of the problem, as the definition lies in the eye of the beholder.
	2. Conflicting values	The existence of conflicting values, driving the different actors, makes it difficult to assess the objective quality of any solution.
	3. Conflicting objectives	Objectives and targets set by multiple stakeholders and on multiple scales might not converge when lacking communication or consensus on the values.
	4. Multiple tactics to address the problems	The lack of consensus on the best approach to achieve similar results, is increased by the lack of clarity on objectives and values.
	5. Multiple actors with the power to assert their values	Multiple stakeholders can influence the problem and defend their interests, while the interests of third parties must also be taken into account.
Complexity and uncertainty	6. Scientific complexity and uncertainty	Decision making is hindered by uncertain or incomplete knowledge.
	7. Political complexity and uncertainty	Ambiguity among political groups and public opinion leads to a confusion in predominant values.
	8. Administrative complexity and uncertainty	Financial limitations and fragmentation of governmental institutions, across multiple levels and sectors hinders appropriate implementation of solutions.
Instability	9. Dynamic context	Evolving environmental, economic and social frameworks require flexible and adaptive solutions.

sometimes conflicting (e.g. insulating buildings may render district heating infrastructure obsolete), which makes it difficult for decision-makers to take decisions which account for these cross-effects. Kesicki and Ekins (2011) point out for example the effect of electricity decarbonization (e.g. with PV or wind power) which lowers the CO_2 abatement potential of insulating electrically heated buildings. Similarly, both insulating a home and installing a biomass boiler will reduce the carbon abatement potential of the methods, or increase their abatement cost. Tactics also can span over multiple sectors with limiting effects. Biomass planned in one region will limit the resource availability to other regions. Similarly, local resources cannot be used simultaneously for heating and transport power generation, and should be planned accordingly.

1.4.2 Challenges due to complexities and uncertainties

As identified in Table 1.2, challenges in urban energy planning arise from overlapping scientific, political and administrative complexities. One major challenge here involves data quality and access. The different physical and administrative scales and actors induce scarce, dispersed and low quality physical data, which reduces the quality of models. This quality should be assessed and followed up through the entire urban planning value chain, from planning stage to design and operation (Perez, 2014). Even if data is accessible and accurate, its access is very often hindered by privacy issues (McKenna, Richardson, and Thomson, 2012) and lack of standards (Perez, 2014). The use of existing urban data exchange standards (e.g. CityGML) may help face interoperability issues (Gröger et al., 2012). However, these standards must be adapted and extended to include specific domain applications (e.g. network utilities). Such an extension of the CityGML language core is being developed to include objects and attributes specific to the modeling of energy consumption of buildings, energy distribution infrastructure, and energy conversion technologies (Krüger and Kolbe, 2012; Nouvel et al., 2015).

Furthermore, scientific advancements in technology, and the wide range of available energy conversion technologies, make it difficult for planners to anticipate changes, and understand in which technologies they should invest (Conklin, 2006). Even if models may help simulate and optimize these choices, results are based either on present knowledge, or on assumptions regarding the future which entail uncertainties (Moret, Bierlaire, and Maréchal, 2014). Other unknowns and political disagreements slow down or block processes, for example regarding the effects and costs of climate change (Newell and Pizer, 2004).

Political and administrative limitations raise the question of identifying the relevant scale for energy planning. Optimizing the energy supply and demand of a city has often been bounded to the building scale, although higher efficiencies are usually achieved only at larger scales (Koch, 2009; Petersen, 2016; Strasser, 2015; Zanon and Verones, 2013). Koch (2009) argues that the neighborhood scale offers sufficient homogeneity in structure to apply energy efficiency measures which aren't available at the building scale, while involving socially defined groups in the planning processes, which would be more difficult at the city scale. Another recurrent challenge for cities is the translation and adaptation of global energy targets into local urban or district master plans (Caputo and Pasetti, 2015; Wiek and Binder, 2005; EBC, 2013). Finally, as raised above, the lack of a central authority responsible for energy planning in urban administrations further challenges the implementation of energy policies and plans (Caputo and Pasetti, 2015; Levin et al., 2007).

1.4.3 Challenges due to instability

Energy planning in cities is dependent on different highly time-bound and volatile parameters, such as fuel prices and operational costs, energy conversion technology investment costs, improving and emerging technologies, population growth and high urbanization rates, changing political actors and agendas, unstable international and national policy frameworks, etc. Moreover, long time frames of urban planning projects, which can span over more than a decade (Jank and Erhorn-Kluttig, 2013; Cajot et al., 2017b), with socio-economic and environmental implications lasting even longer, contrast and conflict with shorter time frames of political mandates and lifetimes of people involved in projects (Balint et al., 2011). To address some of these discontinuity issues, and in part those due to administrative fragmentation discussed in Section 1.4.2, Jank and Erhorn-Kluttig (2013) call for "smart leadership", in which a champion is systematically designated to follow the planning project and coordinate all stakeholders. Furthermore, conflicts may also arise from quick changes in societal values, for example due to external shocks (Fischer, 2015). Because of rapidly changing policy regarding renewable energy, large-scale investments are made difficult. The sudden instability following the 2011 Fukushima nuclear power plant incident illustrates this point. In many countries, the event led to rash changes in policy, including nuclear phaseout or ban, such as in Germany, Italy, Switzerland and Belgium (Schreurs, 2013). The German policy regarding nuclear energy has been particularly dynamic, shifting towards and away from a pro-nuclear policy several times in the past decades (Schreurs, 2013). This rashness is also symptomatic of the pressure and necessity to take quick decisions in order to avoid worsening climate change impacts (Levin et al., 2007). Estimates indicate that not acting soon enough to decarbonize the global economy could cost 5 to 20 times more than acting immediately, and would drastically increase human health impacts (Costello et al., 2009). In such a complex situation as urban energy planning, where more time would be valuable to take more informed decisions, time is unfortunately missing.

1.5 Managing wicked problems

If wicked problems cannot be solved in the same linear way as a well-defined problem might, they must nevertheless be tackled somehow. The studies reviewed hereafter reveal two opposite views or positions on the matter, namely, simplification, or comprehensiveness (Table 1.3). The first view realistically assumes that the only way to overcome a wicked problem is to simplify—or tame—it, by breaking it down into smaller, solvable issues. Rittel and Webber (1973) initially noted that the nature of wicked problems entails such simplifications. Because there is no "stopping rule" to wicked problems, one must at some point stop working on it for external reasons (e.g. lack of time, patience or funding) or if a sufficiently good (or 'satisficing') solution is found, even if this means the problem is left only partly addressed. They also point out other coping mind-sets, such as aggregating problems to higher scales in order to not focus on minor symptoms, or entrusting few, selected experts to arbitrate the various contradictions in values. This view is also held by Law (2014), who points out that **simplifications must necessarily happen** to handle "the indefinite extension of value clashes, political controversies, problems embedded in other problems, material heterogeneities, fluidities, and the endless and unpredictable feedback loops". He advocates for example the "homogenization" of problems (i.e. determining the extent to which they can be reduced to a single facet or metric) and "centering" of observation points (i.e. reducing the plurality of perspectives and influences in favor of centralized command-and-control). In another study, Du, Richter, and Ruhe (2006) advocate **dialog** both between humans and between humans and software as a means for cooperation and increased acceptance of solutions. They suggest that the problem must be sufficiently simplified so that the explanations (e.g. from another human or an optimization algorithm) about the relative quality of an alternative remains understandable for the decision maker. This implies an iterative process, addressing successively the different viewpoints and issues.

The second view ideally attempts to comprehend simultaneously all facets of the problem and interactions through various analysis methods. Conklin (2006) emphasizes the need for coherence

Table 1.3 – Summary of reviewed mindsets and methods recommended for tackling wicked problems.

View	Advocated mindset	Proposed methods	Reference
Realistic (simplification)	Taming the problem	-	(Law, 2014)
	Dialogue between humans and software	Optimization software Pareto analysis	(Du, Richter, and Ruhe, 2006)
	Satisficing decision-making Problem aggregation Expert-based decision-making	-	(Rittel and Webber, 1973)
Ideal (comprehensiveness)	No “taming” nor “over-studying” the problem Coherence and sharing of issues Feed-forward orientation	Dialogue Mapping	(Conklin, 2006)
	Stakeholder engagement Feed-forward orientation	Framework for Responding to Wicked Issues Pareto analysis	(Camillus, 2008)
	Argumentation Stakeholder engagement Transparency	Issue-based Information System	(Noble and Rittel, 1988)
	Knowledge-based approach Interactive group process	Mess Mapping Resolution Mapping	(Horn and Weber, 2007)
	Precautionary principle Adaptive management Participatory approaches	Learning network process	(Balint et al., 2011)
	Sensitivity to complexity and openness to simplicity Dialogue	Systems thinking Design thinking Soft systems methodology Transition Management	(Vandenbroeck, 2012)
	Web-based communication and collaboration	Collaborative innovation networks (COINs)	(Totten, 2012)
	Decision analysis	Multicriteria decision analysis	(Løken, 2007; Pohekar and Ramachandran, 2004; Strantzali and Aravossis, 2016; Wang et al., 2009; Zhou, Ang, and Poh, 2006)
	System modeling	Urban energy system modeling (simulation, optimization, LCA, rating systems, etc.)	(Huang et al., 2015; Keirstead, Jennings, and Sivakumar, 2012; Mendes, Ioakimidis, and Ferrão, 2011; Mirakyan and De Guio, 2013; Reinhart and Cerezo Davila, 2016; Sharifi and Murayama, 2014)

and shared understanding of all issues among stakeholders, to avoid the fragmentation of the problem and failing to address the overall issues at stake. To achieve this coherence, he proposes **Dialogue Mapping**, a group facilitation method to systematically represent decision making processes and increase transparency and shared understanding of the issues by all stakeholders. Dialogue Mapping is based on the Issue-based Information System developed by Noble and Rittel (1988), which was developed in response to the understanding that planning processes are in fact non-linear and may benefit from argumentation, stakeholder engagement and transparency. Horn and Weber (2007) also present a methodology to represent, understand and analyze wicked problems. The methodology includes **interactive, knowledge-based group processes and visual analytics which** enable decision makers to select actions that ameliorate the considered problem. Balint et al. (2011) studied four cases presenting wicked characteristics, including the European cap-and-trade program for greenhouse gases. They discuss in depth the benefits and limitations of three common responses to wicked problems: **the precautionary principle, adaptive management and participatory approaches**. Additionally, they propose a "**learning network process**", which seeks to identify realistic alternatives or solutions to a wicked problem by discovering the issues, preferences and values of the involved stakeholders. Vandenbroeck (2012) also emphasizes the importance of acknowledging wicked problems, and advocates the application of five methodologies, including **soft systems methodology, transition management, and design thinking**. However, he also points out a possible risk of acknowledging a problem as wicked, as it may "obscure simple and pragmatic ways of making a positive difference". Totten (2012) suggests that the rise of **web-based, self-organizing collaborative platforms** will play a role in solving global wicked problems. On one hand, by informing citizens of the risks of such problems to increase cooperation, and on the other, connecting them to generate new ideas and motivate local action. Camillus (2008) proposes a framework for coping with wicked problems in strategic business decisions. Put forward are the importance of communication and involvement of stakeholders, the identification of common corporate identity and values, focusing on few, prioritized courses of action, and a feed-forward mentality to anticipate various contextual changes and possible futures. As additional supporting solutions, to cope with the multiplicity and heterogeneity challenges, **multicriteria decision analysis (MCDA) methods** have been widely used to provide an analytical framework to facilitate discussions and mutual understanding among multiple stakeholders, and include a diversity of objectives in the decision process. Løken (2007), Pohekar and Ramachandran (2004), Wang et al. (2009), and Zhou, Ang, and Poh (2006) have reviewed studies applying MCDA specifically to energy planning situations, providing aid in understanding and choosing appropriate decision support methods. **Modeling approaches** are another common way to understand and overcome scientific complexities and uncertainties. Computer models are particularly relevant for wicked problems, for which the implementation of solutions are often associated with high costs (Du, Richter, and Ruhe, 2006), and are typically irreversible over short periods. As Rittel and Webber (1973) note in this line, "planners have no right to be wrong". Consequently, there exist many different methods and tools to predict the consequences of actions on the urban and community scales, before they are implemented. These models have been classified in various ways. Keirstead, Jennings, and Sivakumar (2012) provide a review of available tools for urban energy system modeling, distinguishing between simulation, optimization, empirical and econometric methods, as well as identifying the key areas of application for these tools (namely, technology design, building design, urban climate, systems design, and policy assessment). Mirakyan and De Guio (2013) decomposed long-term energy planning in cities and territories into four main phases, and reviewed the methods and tools available along these steps. They provide a list of common tools from the fields of simulation and optimization, system dynamics, and life-cycle analysis. On a more local scale, Mendes, Ioakimidis, and Ferrão (2011) surveyed energy models for community level energy planning, and assessed the appropriateness of different bottom-up, simulation, scenario, equilibrium, and optimization tools. Huang et al. (2015) also reviewed **bottom-up computer tools available for community energy planning**, as well as what they call **top-down methods**, which rely on upper policy and global guidelines to guide local planning. These include for example rating systems such as BREEAM Communities, LEED-ND or CASBEE for urban development, tools which have expanded, during the last decade, from the building scale to cover issues at the intermediate community scale (Sharifi and Murayama, 2014). Finally, Reinhart and Cerezo Davila (2016) review urban micro-simulation methods at the neighborhood scale. They argue that such bottom-up approaches are necessary to provide detailed information about local integrated energy systems useful to support the planning of neighborhood-sized projects.

Synthesizing the two different views mentioned above, Conklin (2006) highlights the key limitations in both extremes. On one hand, taming a wicked problem may only prove useful in the short term, but generally fails to solve the initial wicked problem in the long run, or even exacerbates it. On the other hand, overly studying the problem slows down the process, may be extremely costly, and might lead to *analysis paralysis*, in which action is needed for more information, but more information is expected in order to take action, thus freezing the process. A certain balance between the realistic and idealistic views seems desirable, and therewith some kind of iteration between a temporary reduction of the problem's scope to allow studying certain precise aspects of it, followed immediately by a recontextualization of the insights into the larger context. What is important is to not get stuck or waste resources in solving only a part of the problem, nor to be overwhelmed by the size and intractability of the whole.

These few studies provide specific mindsets and methods that can help better manage wicked problems. In the present work, the list of conditions from Table 1.2 are used as a guide to identify the issues from real-world wicked problems, and to systematically map potential responses. The main hypothesis is that a better understanding of the multi-faceted problem should foster a multi-faceted response, instead of adopting fragmented or incomplete solutions. This implies seeking a diversity of approaches, not only from the methods and mindsets reviewed above (Table 1.3), but also encouraging new creative responses, tailored to the local specificities found in real planning projects.

1.6 Application of the framework to a Swiss case-study

The framework introduced in Section 1.4 was applied to an urban development project from Geneva. The main challenges encountered by planners, as well as the proposed solutions, are identified and organized following the proposed framework. These are mapped out and summarized in Table 1.4.

1.6.1 Case-study context and description

To ensure an adequate response to population needs and achieve political targets, the canton of Geneva's development strategy relies on so-called transdisciplinary "grand projects" (Figure 1.3), through which it can coordinate and influence the urban and energy planning procedures jointly with the communes and other stakeholders. The canton being almost fully urbanized, less than 2% of its land remains for new urban development and absorption of demographic increases (Geneva, Conseil d'Etat, 2015). This sets high pressure on already built areas, but also on the few remaining greenfield development projects, who must ensure sufficient densities in order to safeguard agricultural land, and reduce impacts on landscape and ecosystems. The urban development project described hereafter is called "Les Cherpines". It is a greenfield development project located South-West of Geneva (Figure 1.3), and aims to become a mixed-use eco-district by 2030, providing 3000 dwellings and 2500 jobs over a surface of 58 hectares.

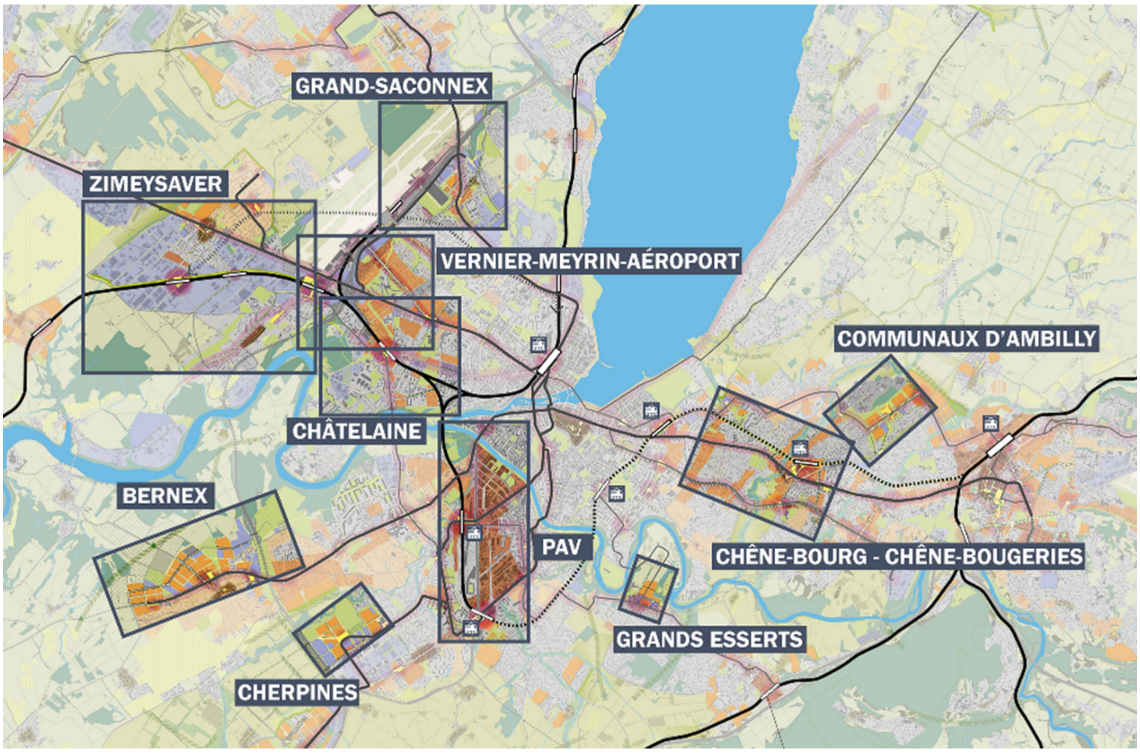


Figure 1.3 – Map of Geneva and delimitation of the ten priority "grand projects". Courtesy of Geneva, DALE (Geneva, 2013).

1.6.2 Multiple interdependent challenges

Though urban development projects such as Les Cherpines are helpful to enable the canton to achieve ambitious national and cantonal energetic goals, energy is just one among a wide range of public policies to be achieved, including in particular housing, environmental protection, public spaces, and mobility. The problem of energy is therefore somewhat diluted and intertwined with the other policies, making it difficult to state energy sustainability as an unequivocal issue. Furthermore, the multiple stakeholders involved have disagreed since the beginning on the purpose and legitimacy of the project, as reflected by the 2011 land-use modification vote, only accepted with a tight majority of 56.6% (Geneva, 2011). On one side, the canton was aiming to urbanize the land to accommodate growing population needs in a sustainable way, i.e. ensuring density, diversity and striving for energy positivity (Buchs and Norer, 2013). On the other, local agricultural and environmental associations, citizens and several political parties valued instead the preservation of agricultural land, the production of local food, food security, and the reduction of nuisances expected from increased activities. These polarized values certainly played a part in forcing the project's instigators to clarify sustainability and energy related objectives in master plans, though disagreements on their acceptability still carried on. For example, in 2013, the lack of legal or formal definition of “eco-district”, term used in the original campaign, brought discord on the number of parking places the district should guarantee (Buchs and Norer, 2013). Opponents, in this case the local green party, demanded a lower number of parking spots, arguing that an “eco-district” should be at least more ambitious than in surrounding districts (i.e. less than 1 spot per 100 m^2 of built area), and develop a multimodal transport system. Another key point of conflict revolved around the appropriate density which the district should ambition. While the canton had high expectations from this project in terms of accommodating future dwellers, the communes involved were less accepting of high densities, as these represent additional public equipment investment costs, as well as increased noise and pollution, decreasing their attractiveness and quality of life (Bernet, 2014a). The planners, caught in between this dichotomy of interests, are expected to find an acceptable value which satisfies all parties. Not only is density a highly sensible topic regarding socio-economic aspects, but as well directly influences the feasibility of the different energy strategies in line with the energy targets (Cajot et al., 2016).

Identifying the relevant scale and perimeter which should be considered when planning the district represents another key challenge. Indeed, the scales of urban planning projects, typically defined by building or administrative boundaries, rarely coincide with the wider scales across which the energy system and natural resources span. For example, the energy positivity ambition in Les Cherpines might only be achievable if boundaries wider than the neighborhood are considered, including industrial waste heat from nearby activities.

Furthermore, planning procedures on the higher scales are influencing the project as it advances. In 2015, the cantonal master plan was approved by the federal authority, but under the condition that urban development would not expand over the protected cropland, as specified in a national sectoral plan for food security (Geneva, Conseil d'Etat, 2015; Geneva, 2015c). This in turn left little scope of action to accommodate demographic growth, putting pressure on urban renewal projects, densification of villa zones, and densifying the few remaining urban development projects like Les Cherpines. Urban planners were thus required to devise a new, denser proposition, all while maintaining the general structure of the planned neighborhood, which had been validated in the project's early stages, and handling oppositions from the communes and lobbies defending villa zones (Bernet, 2014b).

Other dynamic aspects are further challenging the planners' work. The state of knowledge regarding local resources is limited, and evolves regularly. For example, a parallel ongoing project, GEothermie2020 (Geneva, 2016a), aims to evaluate the geothermal energy potential of the canton. Depending on the findings of the study, either the district heating network option could become invaluable to make efficient use of the ground's energy, or, in the case where constraining geological structures are discovered, the study could prevent the use of even individual ground source heat pumps within the boundaries of the district. As the project spans over many decades, another issue concerns the phasing of the development and construction, posing certain investment challenges. Temporally spreading the development of the neighborhood may make sense financially, but could conflict with the operational viability for a district heating alternative, which requires a minimum customer base from the start.

Another central challenge strongly hinders urban energy planning: the legitimacy that planners actually have to influence the energy system of the planned district is, in fact, fairly limited. Regarding the choice of energy technologies, in the case where no other comparable solution exists, the cantonal energy law could impose the connection of a building to the district heating network. Other measures however essentially narrow down to financial incentives, subsidies, promotion, or workarounds to influence the energy system indirectly, as will be discussed in the following section. The master plan in Les Cherpines, illustrates such a limitation, as it can only advocate – and not enforce – the Swiss building energy standard Minergie-P (stricter than the required legal standard). In practice, the adoption of the higher standard will ultimately depend on the developers, owners and constructors.

1.6.3 Towards integrated solutions in Les Cherpines and beyond

In short, the urban development project of Les Cherpines—with its various concerns for energy—displays the characteristics of a wicked problem. The various and conflicting interests at stake, pressured by scientific, political and administrative complexities, as well as an unpredictable, dynamic context, make the progress of the project a highly tedious task for planners. No ideal legal framework, improved planning process, or attempt to thoroughly model the urban system can alone overcome such challenges. Instead, planners in Geneva attempt to tackle the *wickedness* with various complementary and often innovative solutions (Table 1.4).

It was pointed out that Levin et al. (2007) considered the lack of central authority a main threat to resolving wicked problems. The Canton of Geneva addressed this issue by two main organizational evolutions. First, by creating a more autonomous energy office to carry out the energy policy, previously only tackled as part of a larger environmental direction, and second, by grouping this energy office within the same administrative department as that of town and country planning. Since 2013, this structure not only facilitates a coordinated approach between urban and energy planning, but also formalizes the legitimacy of the public authorities in regard to energy planning. Furthermore, to address the scientific and administrative uncertainties, a new energy planning instrument, the Territorial Energy Concept (TEC), was launched in 2010 to better inform the typical urban planning process with energy issues (Geneva, 2014). The TEC aims to provide a holistic overview of the natural resources availability, propose local energy strategies and relevant perimeters of study, while bringing together the stakeholders in a collaborative process. As such, it acts as a first procedural and instrumental bridge between urban planning and energy planning. Additionally, to better cope with the uncertainties and range of stakeholders involved in urban planning processes, the canton works with average-sized projects as Les Cherpines. These "grand projects" are steered by working groups which tackle the various public policies in integrated ways, and for which TECs are developed to inform the planning process with energy issues from the start. As of 2016, there are 18 such "grand projects" spread throughout the canton, with areas ranging from 12 to 380 hectares. This intermediate scale – beyond the building but below the city – can be viewed as an effective way to handle energy issues, as discussed in Section 1.4.2. Ten of these projects are already well advanced and should enter the implementation phases by 2018 (Figure 1.3). Another measure taken by the canton was the recent evolution in local planning instruments to provide more flexibility during their elaboration (Geneva, 2015b). This means that urban and architectural design can more easily be adapted throughout the process to comply with energy requirements available only at later stages, such as resource availability, exact heating demand, etc. By law, the various master plans and instruments (Figure 1.4) which intervene at different scales integrate and exchange information with adjacent scales and sectors, and are open to public consultations and opposition procedures in a fashion akin to collaborative planning. In response to the economic barriers faced by the communes, an administrative instrument was proposed to share the financial burden of densification among all communes. By means of an intercommunal funding scheme (Geneva, 2015a), those communes taking on more dwellings and public equipment are supported by communes with, for example, more economic activities or less needs for public spaces and equipment.

To overcome the limited direct legal instruments available to influence the energy system discussed above, planners can rely on some indirect workarounds. They can for example facilitate a given energy strategy (e.g. district heating, roof availability for PV, etc.) and ensure energy targets are met by identifying the adapted density, and enforcing it via the localized neighborhood plan. Planners can also rely on indirect instruments to support energy policy goals. The national sectoral plan for cropland protection, already mentioned above, is such an example. If the plan's original goal to ensure food security is nowadays debated (Ruegg, 2016), its existence nevertheless serves other more recent sustainability goals, such as limiting urban sprawl and favoring urban density, as occurred in Les Cherpines. As an ultimate (though costly) strategy, public authorities can make use of their pre-emption right, and purchase land in priority to private investors. They thereby gain control over the type of constructions to be built and can ensure that public interests are met

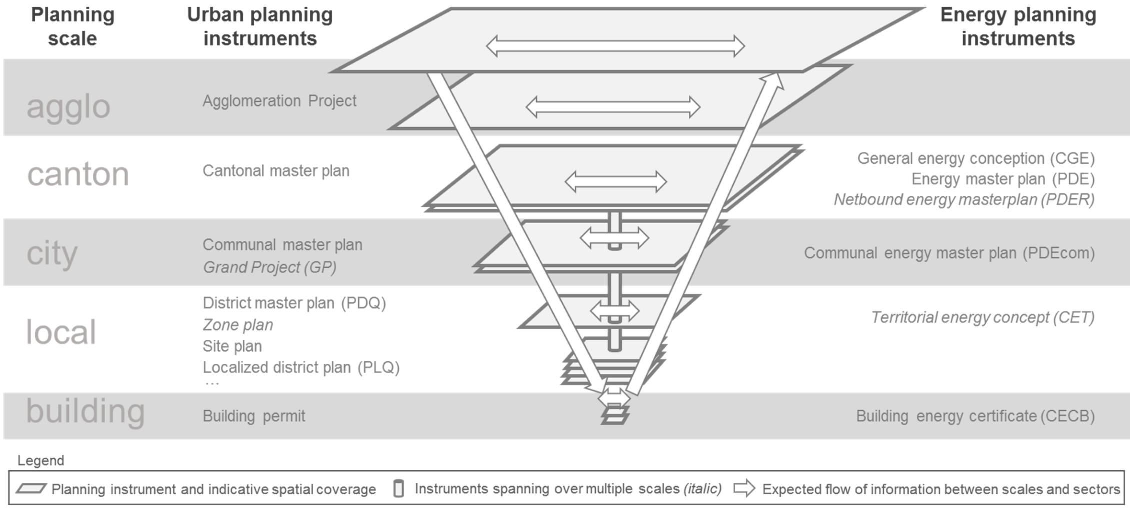


Figure 1.4 – Schematic representation of urban and energy planning instruments in Geneva. Own illustration adapted from Geneva (2003).

(Garcin, 2013).

To fill some of the known scientific gaps, data is collected and studies, such as the underground geothermal investigation mentioned previously, are financed by the canton. This information is eventually stored in an online geographic data base, partly made available to the public (Geneva, 2016b). The canton is also in search for innovative computer tools to support planners in their decisions. Their involvement in various research projects (CINERGY, 2016; INTEGRCITY, 2016) demonstrates this interest, and aims to make use of integrated multi-scale urban energy system models for simulation, optimization and multicriteria decision support.

1.7 Discussion

Urban scale energy planning

The recent evolutions in the field of urban planning, today recognized as an integrated, collaborative process, make it ideally suited to address energy and sustainability issues. As discussed however, the price for addressing these issues at wider scales than the single building is the emergence of a wicked problem, preventing the identification of any clear solution. This was the starting point and main motivation of this work: to avoid the risk of vainly tackling only sub-parts of the bigger problem, recognizing and structuring the problem's complexity should be the first step to devise appropriate solutions. By exploring the topic of energy planning at the urban scale from a challenge-oriented perspective, several insights were gained. After reviewing the new requirements for urban planning, concrete solutions on how to tackle this wicked problem were put forward. The main contribution of this chapter was then to formalize and apply the defining characteristics of wicked problems to the case of urban energy planning. As demonstrated in the case-study, the proposed set of challenges could be used as a blueprint to map the different issues, allowing the identification of holistic solutions which tackle the issues in an integrated way. Such an approach helps realize that any purely technical, or too narrow solution could not solve alone a wicked problem.

Table 1.4 – Mapping of observed issues in urban energy planning and proposed solutions adopted in Les Cherpines and canton of Geneva.

Category	Observed issue	Proposed solution
Multiplicity & heterogeneity	Multiple interdependent public policies to achieve simultaneously	Holistic master plan development on canton, commune and district scales
		Development of an energy planning instrument (Territorial Energy Concept, TEC), complementary to urban planning instruments
		Regrouping of the Town and Country planning services with those of Housing and Energy policies in a single administrative department
	Conflicting values	Clarification of public goals in master plans, TEC instrument to foster involvement of all stakeholders
		Public consultations and opposition procedures during the planning process
	Multiple interpretations of “eco-district” concept	Political “motion” (participative amendment of project proposition)
Complexity & uncertainty	Uncertain effects of key urban parameters (e.g. density, quality of life) and natural resources	Mandate external studies, use of urban energy system simulation and optimization tools
	Difficulty to identify relevant project boundaries	Definition of project scope in terms of energy resources rather than administrative boundaries, inclusion of nearby industrial zone
		Neighborhood-sized urban development projects involving public authorities and citizens (“grand projects”) TEC instrument to identify relevant scales
	Limited legitimacy of planners to influence the energy system	Application of direct and indirect measures (density targets, pre-emption right, district heating enforcement, promotion, etc.)
	Financial barriers to densification	Establishment of intercommunal funding scheme
	Data scarcity	Energy law requiring relevant actors to provide the canton with supply and demand data
		Mandate external studies and data collection (e.g. GEothermie2020)
Instability	Modification of problem’s framing conditions	Increased flexibility of localized physical plans
	Long-term project duration	Long-term “grand project” approach, steering by dedicated interdisciplinary working groups, flexible guiding plans
	Evolution of data and knowledge	Development of an online GIS data platform SITG, and CityGML model of the city

Identifying the challenges *a priori*

The mapping of the challenges was performed, in this case, *a posteriori*, and proved useful to identify and organize existing issues and solutions related to energy in an urban development project in Geneva. In the context of the European project CINERGY (2016) and the IEA-EBC Annex 63 project (EBC, 2013), discussions held between the author and urban actors from Geneva, Vienna, Lyon and Minneapolis showed encouraging responses to the framework, which was acknowledged as a comprehensive reflection of the issues encountered in their respective activities. Ideally however, what remains is for planners and researchers to apply this approach *a priori*, in order to promote the adoption and development of comprehensive solutions in ongoing planning or research projects.

A new form of urban planning

Another point of discussion concerns the expected scope and role of urban planning discussed here. As brought up in the introduction, its need to integrate energy aspects is clearly consensual, supported by various studies and different backgrounds. This change is however a profound one, still ongoing, and that will certainly require time to settle in most European cities. The examples from Geneva show well how far the urban planning paradigm must change to cope with the broadness of the issues. The case-study reveals a sincere willingness to undertake not only a deep restructuring of the urban planning concept and its administrative structures, but also to make use of and develop innovative approaches to overcome the challenges on the way. This study proposes a framework to think about the challenges and identify adapted solutions, and by doing so, also raised various examples that can serve as starting points for solutions to be applied in other cities. These starting points include the guidelines and activities stemming from the European level (Section 1.3.4), innovative planning forms (Section 1.3.5), the various methods, tools and mindsets proposed in literature to help manage wicked problem (Section 1.5), and the range of solutions and best practices illustrated by the case-study in Geneva (Section 1.6.3).

Determining the "relevant perimeter" for action

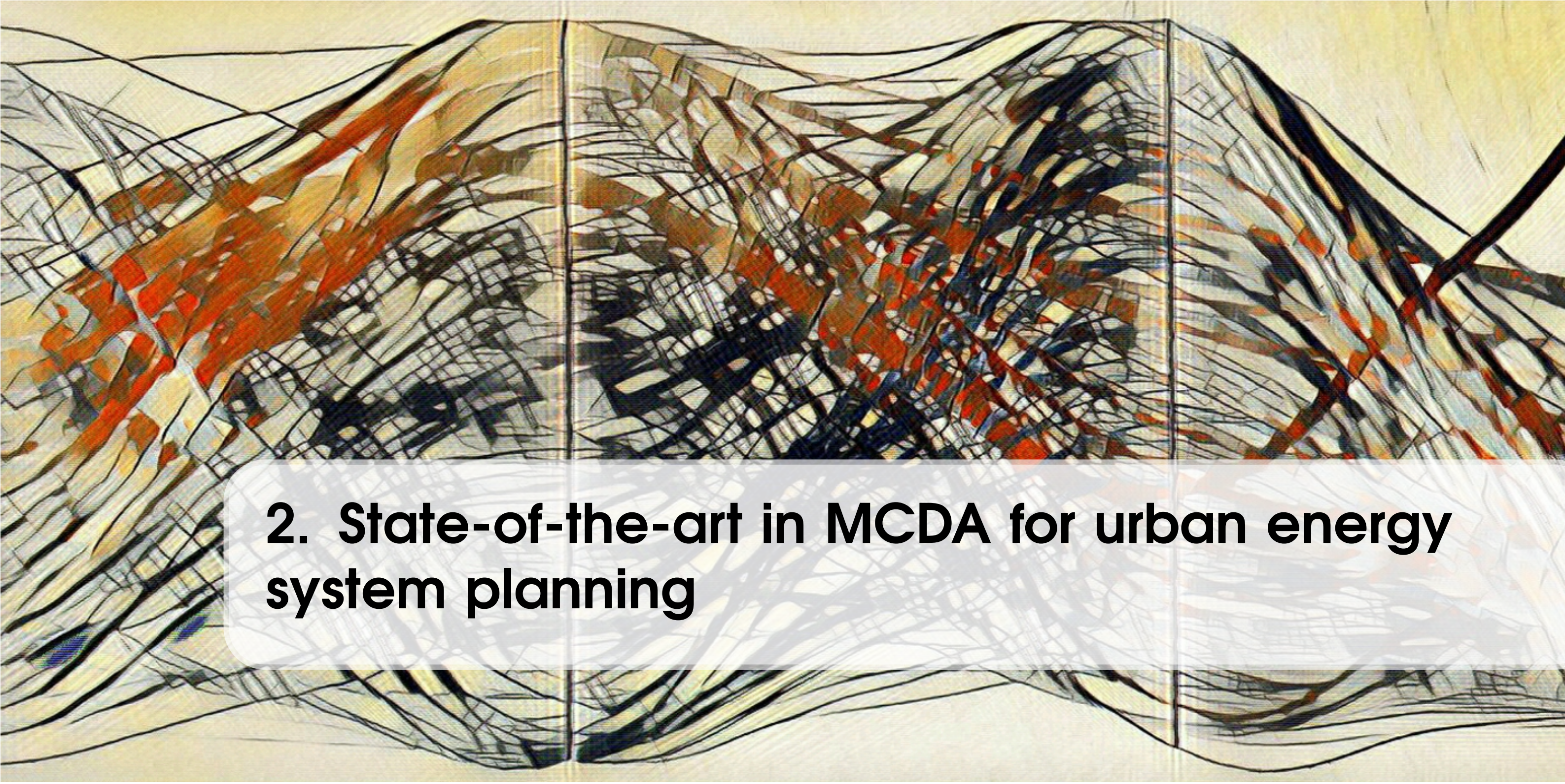
It was noted in the introduction that scale was an important contributor to the "wickedness" of energy planning in cities. The advantages of a delimited size and reduced number of actors involved at the building scale quickly vanish in the complexity of the urban scale, where lie the many opportunities of energy and cost efficiencies. Several elements pointed to the relevance of the neighborhood scale for attenuating the wickedness and thus improving results of urban energy planning. This included Geneva's focus on neighborhood-sized projects for urban development, the proliferation of tools and studies focusing on community or neighborhood energy planning, the shift of building rating systems towards the district scale, and the fact that urban quarters may already provide the critical size for most energy efficiency measures, while involving a fairly well-delimited and manageable group of stakeholders. This intermediate scale thus appears as an ideal compromise between urban and building scales. However, in spite of these arguments, some nuance should be brought to this tentative conclusion. Indeed, local specificities will always influence the need for finer or broader scale considerations, making it unclear how to set the boundaries of an urban project. The appropriate scale ultimately depends on the context and questions being asked, which are also dynamic in nature. The question of identifying the optimal scale of relevance for energy planning should thus be regarded as an open one, where further research must be carried out to provide planners with rigorous and systematic tools, able to quantify the gains and losses of considering different boundaries.

Other challenging trends

This point goes back to what makes planning a wicked problem. It was already pointed out how originally the term was used to describe the new social considerations brought into planning and discussed by Rittel and Webber (1973) in the 70s, and how today, new concerns (including climate change, urbanization, population growth, availability of digital material, and more generally, aspirations towards sustainable development) are further pressuring urban planners to conciliate always broader perspectives and conflicting goals. The emphasis in this chapter was deliberately set on energy issues, mainly for the urgency argument evoked by Levin et al. (2007) regarding climate change, and the top prioritization of this issue worldwide (Costello et al., 2009; WEF, 2016). Indeed, cities are to act promptly and effectively if they are to adequately support their nation's commitment to the Paris Agreement on climate change (Rogelj et al., 2016) and other national energy strategies. In this broader perspective of sustainability however, the approach proposed here, as applied to energy questions, may well be just a first step. Further research and applications of the approach could extend the focus to the other trends mentioned in Section 1.3.2, highlighting more specifically the issues related to quick urbanization, population growth, digitalization, and other trends to come.

Optimization for understanding cities

In 1986, Albers (1986) concluded his discussion on urban planning by referring to an "uncomfortable situation", brought up by the new understanding of urban systems as complex and uncertain entities. He noted the unevenness and unpredictability of planning measures in achieving political goals, and the inability of mathematical models to fully represent such systems. Thirty years later, despite notable progress in computers and urban models, it seems the situation remains somewhat uncomfortable. There is still a divide between sectors, scales and people, and the development of appropriate solutions thus entails a close collaboration between researchers and practitioners. This is in line with the *symmetry of ignorance* discussed by Noble and Rittel (1988), which assumes that "knowledge is distributed in unknowable ways", and dismisses the fact that "there could be such a thing as *experts* who know more about how a problem ought to be solved than those directly affected by the problem". Undoubtedly, among all urban actors, planners have the most accurate and comprehensive understanding of the problems, and their experience, creativity and intuition will remain central in handling the more qualitative and wicked aspects of planning. However, the true contribution of novel quantitative solutions, including urban scale simulation and optimization tools, has yet to be fully understood and established in planning practices. In this context, the pressing issues related to energy might represent a convenient opportunity to rethink how such tools could be used to inform planning. Perhaps indeed, as Albers (1986) implied, *optimizing* a system as wicked as a city remains a fallacy. This does not mean, however, that optimization methods could not be harnessed to provide planners with new quantitative insights regarding the many concurring tradeoffs taking place in cities. And therewith, provide new understandings of the wicked challenges of our time, and how to adequately address them.



2. State-of-the-art in MCDA for urban energy system planning

If you know exactly what you are going to do, what is the point of doing it?
— Pablo Picasso

Urban energy system planning (UESP) being a highly multi-sectoral and multi-actor task, multi-criteria decision analysis (MCDA) methods are frequently used to support the decision processes. These methods may provide support in organizing and identifying solutions to problems with conflicting objectives. However, knowing which method to use is generally not straightforward, as the appropriateness of a method or combination of methods depends on the context of the decision problem. In this chapter, a review of scientific papers is performed to characterize and analyze MCDA problems and methods in the context of UESP. The review systematically explores issues such as the scope of the problems, the alternatives and criteria considered, the expected decision outcomes, the decision analysis methods and the rationales for selecting and combining them, and the role of values in driving the decision problems. The final outcome is a synthesis of the data and insights obtained, which may help potential users identify appropriate decision analysis methods based on given problem characteristics.

This chapter is an adapted version of (Cajot et al., 2017b).

2.1 Introduction

In the past decades, the energy sector has undergone profound changes and is currently facing new challenges. Concerns for climate change, linked to GHG emissions and fossil fuel consumption, have led many countries to actively decrease their energy demand, reduce dependency on fossil fuels, and increase the share of decentralized and renewable energy (IEA, 2008). While the deregulation of the energy market in many countries has offered new opportunities in achieving this transition, it also increased the complexity and scope of energy planning (Makkonen, 2005). In this context, cities play an important role, by reshaping the urban form and their energy infrastructure. Since the rise of environmental and social concerns in the end of the previous century (Rittel and Webber, 1973; UNCED, 1992), the field of urban planning has opened up to include these issues. Urban planners thus play a considerable role, as they must mediate and account for the many interests at stake when making decisions (Teriman, Yigitcanlar, and Mayere, 2010). While it has been demonstrated that the lack of analytical support may lead to the use of simplified and contradictory decision rules (Keeney, 1992; Pedrycz, Ekel, and Parreiras, 2011), mono-criterion approaches are most likely sub-optimal when considering a wider range of objectives and attributes, and thus support long-term sustainable development only partially (Mirakyan and De Guio, 2013). Several methods focusing essentially on monetary aspects, such as cost-benefit analysis, cost-effectiveness analysis or financial analysis, have been qualified as "reductionist" techniques for failing to capture the multiple facets of a problem (Browne, O'Regan, and Moles, 2010; Dodgson et al., 2009). For these reasons, multicriteria decision analysis (MCDA) methods have become increasingly popular in the field of energy planning (Løken, 2007; Pohekar and Ramachandran, 2004; Wang et al., 2009; Zhou, Ang, and Poh, 2006), enabling decision makers to better understand the decision problem they face, negotiate, quantify and communicate preferences, and make decisions more explicit and rational (Ghafghazi et al., 2010; Pohekar and Ramachandran, 2004).

Several reviews of MCDA methods have been realized, some with more specific focus on energy related problems. The initial review of MCDA applications in energy and environmental studies by Huang, Poh, and Ang (1995) was later updated by Zhou, Ang, and Poh (2006), who underlined the important increase in applications. Pohekar and Ramachandran (2004) classified and reviewed more than 90 papers on MCDA applications to sustainable energy planning, aiming to highlight the suitability of methods to different application areas, namely "renewable energy planning, energy resource allocation, building energy management, transportation energy management, planning for energy projects, electric utility planning and other miscellaneous areas". Polatidis et al. (2006) proposed a framework to help select suited MCDA methods for decisions related to renewable energy sources (RES). Løken (2007) discusses and classifies energy planning studies which adopted various MCDA methods including value measurement models, goal, aspiration and reference models, and outranking models. Wang et al. (2009) reviewed the most frequent criteria used in MCDA for energy system sustainability, as well as corresponding methods for criteria weighting, evaluation and aggregation. Dodgson et al. (2009) provide an overview of MCDA techniques, as well as practical guidelines for their application in various areas of government decision making, including energy issues. Strantzali and Aravossis (2016) reviewed papers which applied various decision support methods (MCDA, cost-benefit analysis and life-cycle analysis) to renewable energy investment studies, classifying them by year, application area and geographic distribution. Greco, Ehrgott, and Figueira (2016) present a historical context for MCDA, as well as in-depth descriptions of outranking methods, multi-attribute utility and value theory methods, non-classical methods to cope with uncertainties and fuzzy measures, and multi-objective optimization methods.

Given the current needs for urban areas and their energy systems to help solve the climate and energy challenges discussed above, the present review examines more specifically the studies making use of MCDA in this area. Several lacks identified in the literature have in particular motivated this work and its focus on the urban scale. First, it has been noted how MCDA studies so far have rather focused on the macro scale (national and regional) or the micro scale (single building or user), and avoided the intermediate urban and neighborhood scales (Løken, 2007; Makkonen, 2005). Furthermore, it is particularly relevant to tackle this research gap in the light of the increasing interest in planning energy at the neighborhood to urban scale, discussed in Chapter 1. Løken (2007) also observed a lack of studies covering simultaneously multiple sectors and energy carriers, advocating more integrated approaches. More generally, he and Hobbs and Horn (1997) further advocated the combination of multiple MCDA methods, as the choice of a method strongly influences the decision outcome. Stemming from these lacks, as well as other open issues impacting decision outcomes (Section 2.2.3), this review investigated the literature on UESP involving MCDA, with the aim of achieving the two following objectives:

1. To characterize and classify the nature and types of MCDA problems related specifically to UESP, investigating aspects such as the problem's scope (localization, spatial scales, temporal scales, topics and planning focus), alternative generation methods, criteria used, decision problematic, and planning driver.
2. To survey the MCDA methods (and supporting methods) used to solve these problems, the reasons for selecting them, and when applicable, the rationales for combining them.

After addressing these objectives by analyzing the reviewed papers, a synthesis is performed by combining the data into a multicriteria decision support framework in order to facilitate the choice of appropriate MCDA methods in the area of UESP. As a simple and intuitive way to explore multi-variate data, parallel coordinates are adopted to visualize and interactively select relevant methods. In fact, several authors previously noted that choosing an appropriate MCDA method was a MCDA problem in itself (Al-Shemmeri, Al-Kloub, and Pearman, 1997; Ghafghazi et al., 2010; Løken, 2007). Guitouni and Martel (1998) however recommend avoiding the “vicious circle” of using an MCDA method to choose an MCDA method, advocating instead the definition of methodological principles and decision making situation typologies to help choose appropriate methods. A review-based approach as proposed here, which characterizes the decision problems and corresponding decision support methods, therefore offers a framework to help choose methods according to various problem characteristics.

The present review can be useful for both researchers in the fields of urban planning and decision science, and to practitioners. To the latter, it offers an overview of existing methods and a means to identify those most suited to their problems and decision contexts. To the former, several research priorities and topics, based on the findings, are addressed and proposed in the concluding section.

The chapter is structured as follows. First, core concepts and definitions used throughout this study are presented, as well as the review methodology, and describing in particular the review questions (Section 2.2). Next, the results gathered from the review of all papers are analyzed, and a synthesis is performed by combining the data into a decision support framework (Section 2.3). Finally, main insights and findings are summarized and discussed in Section 2.4.

2.2 Definitions and methodology

2.2.1 Multicriteria decision analysis

MCDA allows to organize and structure complex decision problems characterized by multiple, often conflicting objectives. Several scholars in the field of MCDA have stressed that MCDA should not be mistaken for decision *making* techniques, but rather techniques for analysis and aid (Belton and Stewart, 2002; Keeney, 1982; Roy, 1996). Keeney (1982) for example wrote that “decision analysis will not solve a decision problem, nor is it intended to”. Belton and Stewart (2002) stated that the main goal of MCDA should be “to facilitate decision makers' learning about and understanding of the problem faced, about their own, other parties' and organizational priorities, values and objectives and through exploring these in the context of the problem to guide them in identifying a preferred course of action". As discussed by Dodgson et al. (2009) and Wang et al. (2009), from the definition of the problem to the desired decision analysis outcome, four mains steps should be followed (Figure 2.1). This process is not necessarily sequential, and may have iterations (Guitouni and Martel, 1998).

A multicriteria decision problem thus essentially consists of a set of m alternatives A_i that are

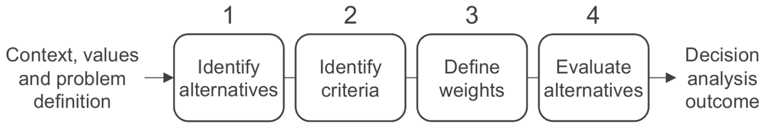


Figure 2.1 – Main steps involved in MCDA.

evaluated on the basis of n conflicting and incommensurate criteria C_j. For an effective application in decision analysis, the selected criteria should in principle respect the following characteristics to adequately represent the problem (Malczewski and Rinner, 2015; Keeney and Raiffa, 1976; Belton, Ackermann, and Shepherd, 1997; Chankong and Haimes, 2008): complete (i.e. covering all facets of the problem), operational (i.e. supporting the analysis in an meaningful, understandable and measurable way), decomposable (i.e. allowing to analyze different parts of the problem separately to simplify the process), non-redundant (i.e. avoiding to bias the analysis), and minimal (the number of criteria should be kept as small as possible).

The decision maker can further specify weights w_j indicating the relative importance of each criterion. This problem is typically organized in what is referred to as a decision matrix (Malczewski and Rinner, 2015; Dodgson et al., 2009; Zanakis et al., 1998):

$$\begin{array}{c} \\ \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & \dots & C_j & \dots & C_n \\ w_1 & w_2 & \dots & w_j & \dots & w_n \end{array} \\ \begin{pmatrix} z_{11} & z_{12} & \dots & z_{1j} & \dots & z_{1n} \\ z_{21} & z_{22} & \dots & z_{2j} & \dots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{i1} & z_{i2} & \dots & z_{ij} & \dots & z_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & \dots & z_{3j} & \dots & z_{mn} \end{pmatrix} \end{array} \tag{2.1}$$

where z_{ij} is the measure of performance of alternative A_i for criterion C_j. In most cases, normalization of the z_{ij} must be performed to obtain criteria with comparable scales. Various normalization techniques can be used, depending on the needs of the DM and the nature of the data set, for example vector normalization, or linear scale normalizations (Hwang and Yoon, 1981; Chakraborty and Yeh, 2009). Similarly, weights are usually normalized so that $\sum_{j=1}^{n} w_j = 1$.

As shown in Figure 2.1, values are at the basis of the MCDA process, which stem from the actors involved in the problem, and should influence the identification of both alternatives and criteria. These four concepts – values, alternatives, criteria and actors – are described next. Values can be defined as principles or beliefs, held by individuals or groups, which reflect their conception of what are good or desirable states or behaviors (Balint et al., 2011; Connelly and Richardson, 2005). In this sense, they rationalize actions and guide the selection or evaluation of behaviors and events. According, to Keeney (1992), values are typically indicated in seven different forms (ethics, traits, characteristics, guidelines, priorities, value tradeoffs, attitude toward risk). To be of use in decision making, they are made explicit through associated statements, criteria, objectives and weights. Values are rather ends in given time horizon, and should not be confused with means. As proposed by Keeney, Renn, and von Winterfeldt (1987), a ‘value tree’ can be established to elicit the values of stakeholders, and derive an organized hierarchy of corresponding criteria which achieve or describe the given values.

An alternative is a means towards the satisfaction of the values and criteria. In some cases, it is the aim of MCDA to short-list a wide range of existing alternatives. In other cases, the identification of alternatives is itself a necessary and active process (Dodgson et al., 2009). As suggested by Keeney (1992), alternatives are only important in the way that they satisfy the values (and the criteria involved), and their identification should therefore be driven by these values. Alternatives can be generated either automatically (as is the case in multiobjective optimization), or manually (Pedrycz, Ekel, and Parreiras, 2011).

Though there is no standard definition of the expression "criteria" (Nijkamp, Rietveld, and Voogd, 1990), generally speaking, a criterion represents a standard of judgement to test the acceptability of an alternative (Pedrycz, Ekel, and Parreiras, 2011). In multicriteria literature, it is used to describe two distinct concepts: objectives and attributes. Objectives indicate the desired direction towards which a DM wishes to move (for example, minimum cost, or maximum energy efficiency) (Pedrycz, Ekel, and Parreiras, 2011). Objectives can be distinguished from goals, which represent a threshold or target level to reach, in terms of a specific state in space and time, while the objective gives the desired direction (Hwang and Masud, 1979). Attributes are a set of characteristics chosen by DMs that measure the performance of an alternative (e.g. how it impacts employment, quality of life, environmental parameters...) (Hwang and Masud, 1979; Pedrycz, Ekel, and Parreiras, 2011). Weights are determined to indicate the relative importance or preference of criteria (Wang et al., 2009).

The DM is but one among several types of actors in a decision process. Roy (1996) describes three main types of actors: *stakeholders, third-parties and analysts*. The former are those who have an important interest in the decision and directly intervene in the decision process. They consist either of individuals, a clearly defined group of individuals (an elected body, a panel of experts...), or a group with less well-defined boundaries (a lobby, public opinion...). Usually, the objectives and values of the different stakeholders are diverse and conflicting. Because the decision aid cannot simultaneously benefit all stakeholders comprehensively, one stakeholder is generally identified as the DM. The second type of actors are referred to as *third-parties*, as they do not actively take part in the decision process, but are affected by its consequences, and thus whose preferences must be taken into account (typically the citizens, end-users, consumers...). A third type of actor is the analyst, who plays a role in supporting the decision maker. In some cases, the DMs may develop the decision aid themselves, but generally this task is performed by an analyst different from the DM. This is in particular the case when the DM does not possess the technical or methodological background, or when an external party is desired to ensure a neutral and more objective approach. In summary, stakeholders are the actors who actively take part in the decision process and include the DM. These can be assisted by an analyst whose role is to provide methodological support to help answer questions posed by a stakeholder in a decision process. This support must take into account not only the interests of the stakeholders, but also of third-parties who are affected by the decision.

Rationales for using MCDA in energy planning have been discussed and compared to other decision support methods (cost-benefit approach (CBA), cost-effectiveness approach (CEA), energy ecological footprint, etc.) or simply to informal judgement unsupported by such methods (Dodgson et al., 2009; Wang, Xu, and Song, 2011). The main arguments in favor of MCDA from Browne, O'Regan, and Moles (2010), Coelho, Antunes, and Martins (2010), Dodgson et al. (2009), Ghafghazi et al. (2010), Pohekar and Ramachandran (2004), and Wang, Xu, and Song (2011) can be summarized as follows:

- Useful to resolve conflicting interests and reach compromises
- Transparent, explicit and flexible
- Promotes public participation in decision making processes

- Can be process-oriented (rather than results-oriented) to favor understanding of the problem
- Synthesizes multiple aspects in a single decision output
- Facilitates multi-disciplinarity
- Can represent the preferences of multiple stakeholders by varying weights
- Can analyze incommensurable or uncertain criteria
- Can handle and aggregate qualitative and quantitative information
- Can complement a reductionist approach by providing a more holistic approach

Browne, O'Regan, and Moles (2010) nevertheless point out two key drawbacks of MCDA in energy planning, namely the dependency on subjective judgment in qualitative approaches, and the difficulty to quantify environmental or social impacts precisely. MCDA has also been criticized for providing inconsistent results, being highly dependent on method choice and subjective stakeholder preferences (Guitouni and Martel, 1998).

2.2.2 Review methodology and scope

The review presented hereafter analyzed papers obtained by searching the Scopus database. The search included papers ranging back as far as the database allowed (the oldest paper surveyed going back to 1990), up to 2016–the date of writing of the original review article (Cajot et al., 2017b). The search query performed in the database aimed at identifying all papers dealing with MCDA in urban and energy planning by searching titles, abstracts and keywords. Search terms were selected according to the following aspects. Literature on multicriteria decision analysis frequently replaces the latter term with 'making' or 'aid'. To avoid missing any entries, only the key-words 'multi criteria' were employed. The keywords 'energy', 'planning' and 'decision', were included to narrow the search to the topic of interest. 'Urban planning' can be interchangeably referred to as 'city planning' or 'town planning'. The latter did not influence the search results and was not included in the query. Furthermore, urban planning spans across several administrative scales, and therefore the keywords 'district' and 'neighborhood' were included to reflect this.

After testing the sensitivity of the different key-words and of logical operators AND/OR, the final query included all studies published both in journals and conference proceedings, leading to 127 papers. Papers were only kept for the review if they explicitly discussed or applied MCDA in urban or urban-related contexts. From the 127 papers identified, 23 were thus discarded as being off-topic, and 17 were unavailable, leaving 87 reviewable papers. Two of the papers included 2 distinct MCDA studies. The identified sample of 89 MCDA studies is deemed sufficient to address the present review's objectives (Section 2.1).

The relevant studies applying MCDA for UESP were found in a total of 58 different journals and conference proceedings and are well dispersed across the various sources. The journal Energy contains the majority of studies (10), followed by Applied Energy and Energy Policy (4 studies each).

Figure 2.2 reveals the increasing popularity in MCDA applications in UESP, which took off in the 2000s, with an average of 1.7 papers published per year until 2010, and an average of around 11 papers per year since.

2.2.3 Review questions

Seven review questions were defined to address the two review objectives stated in the introduction. The first objective of characterizing UESP problems was achieved by analyzing the following five questions for each study:

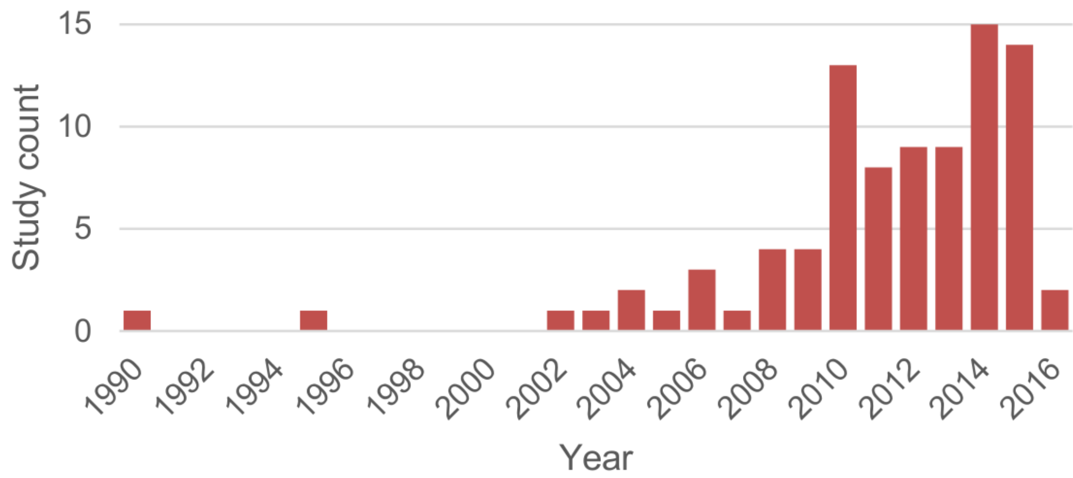


Figure 2.2 – Distribution of publication dates for the 87 papers reviewed involving MCDA in UESP.

(i) What was the problem's scope (including geographical location, physical scale, temporal scale, topic and planning focus)?
(ii) How many alternatives were considered, and how were they elicited?
(iii) How many criteria were used, and how were they selected?
(iv) What was the expected decision outcome or problematic?
(v) Was the problem driven by values or by alternatives?

The second objective of characterizing the MCDA methods was done by exploring the following two questions:

(i) How many MCDA and supporting methods were adopted, which ones, and why were they chosen?
(ii) Which methods were combined, and for what purpose?

Each question is further described in the following sections.

Problem scope

In each reviewed study, the general scope of the problem was hereby investigated, considering the geographical location in which the problem was set (classified by continent), the physical scales bounding the problem (whether the focus of the planning was set on the building, neighborhood, city, regional, state or country scale), and the temporal scale covered by the problem (noting any temporal horizon considered by the authors in their study). The different studies were also classified according to topic and planning focus. Concerning the topics, six broad themes were found sufficient to cover the extent of the reviewed papers, as follows: (1) heating and cooling, (2) power, (3) mobility, (4) environment, (5) waste, (6) water/wastewater. The papers were further classified according to their planning focus as follows:

a. System specific planning: when only a sub-part of the UES is considered, e.g. heating system, electrical system, demand side analysis in residential sector, etc.
b. Integrated or master planning: when different energy carriers, sectors, or demand and supply systems are considered
c. Operative planning and management: when the main focus is not on long-term system design and investment, but rather on operative aspects, e.g. optimization of energy supply or energy use.

Alternatives

This review question counted the number of alternatives analyzed by each study, and the methods used to identify them. Keeney (1992) emphasizes the importance of alternative creation, writing that it "may be more important to create alternatives than to evaluate readily available ones". He blames decision methodologies for often neglecting this aspect, or inhibiting it. If many MCDA problems in literature may lead to believe that the typical application involves a predefined set of alternatives, this is often not the case (Belton and Stewart, 2002), and the more complex problems such as those found in UESP require careful thought in the structuring of the problem and identification of alternatives. For example, Feng and Lin (1999) point out the limitations of conventional approaches for generating new urban layout plans. They argue that the urban development process should begin with a systematic generation of physical layout alternatives, but deplore that conventional processes for generating alternatives are usually considered "a 'black box' inside which planners are subjective and alternatives are few." In response, they propose an optimization model to systematically elicit alternatives maximizing public comfort and convenience, with which they were able to identify 4 alternatives performing better than the original plan. Typical methodologies which can be used to support alternative generation are discussed by Siebert and Keeney (2015), who review existing methodological approaches for creating alternatives (structured techniques, creativity techniques, value-focused thinking, etc.). Mirakyan and De Guio (2014) reviewed the main methods which can support alternative identification, including brainstorming, soft systems methodology (SSM), strengths, weaknesses, opportunities and threats (SWOT) approach, Delphi, means-ends objective network, and network of problems (NoP). They further proposed a methodology for finding innovative alternatives in planning, where common solutions may not be satisfactory, but where satisfying solutions are not obvious. Belton and Stewart (2002) present various methods for idea generation, some of which can help think about and identify alternatives. These include checklists to stimulate idea generation, alternative-based thinking methods, where users analyze and compare alternatives to stimulate the generation of new ones, and value-focused thinking using means-ends objective network, introduced by Keeney (1992), where value elicitation is performed prior to alternative identification. Despite the advancement of research in this field, the reviewed studies usually remained implicit or fairly superficial in describing how the alternatives were generated. In this context, the review distinguished the following cases for alternative generation: by the authors themselves, based on literature, by external experts or actors, by relying on heuristic approaches such as mathematical multi-objective optimization, systematic combinations and enumeration, or simply externally defined (e.g. the evaluation of grant requests submitted). When specified, any supporting method used by experts or actors was noted (including GIS software, SWOT analysis, Communities of Practice (CoP), or interactive user selection).

Criteria

This question considered the number of criteria used in the analysis, and any explicit references to their selection process. These approaches included: author's judgement, literature or predefined sets of indicators, experts' recommendations, and, when specified, other supporting methods (Delphi, CoP), or any combination of these approaches.

Decision problematic

The problem type, as posed in the study, was surveyed. This question is of particular interest in the field of MCDA, and can even be considered as the first and most important step in MCDA (Chen, 2006): when addressing complex decision problems, analysts must initially consider what type of result or outcome is expected. Roy (1996) first used the term "problematic" to describe the main types of outcomes MCDA can provide. In this review, we investigated which problematics were adopted, based on the most relevant problematics proposed by Roy (1996) and Belton and Stewart (2002). According to their typologies (Figure 2.3), an MCDA approach can be applied to:

- select or choose a "best" alternative, by reducing the set of alternatives to a smallest sub-set (**choice problematic**)
- rank the alternatives by order of preference, enabling the DM to think about the problem and discuss with all stakeholders (**ranking problematic**)
- help sort alternatives according to predefined categories, that shall help the DM know which treatment to give to the grouped alternatives (**sorting problematic**)
- choose a subset of alternatives, that can be combined and account for interactions and positive or negative synergies between them (**portfolio problematic**)
- search for, identify or create new alternatives based on the insights gained from the MCDA process (**design problematic**)
- gain a greater understanding of the problem, in particular what may or may not be achievable (**description problematic**).

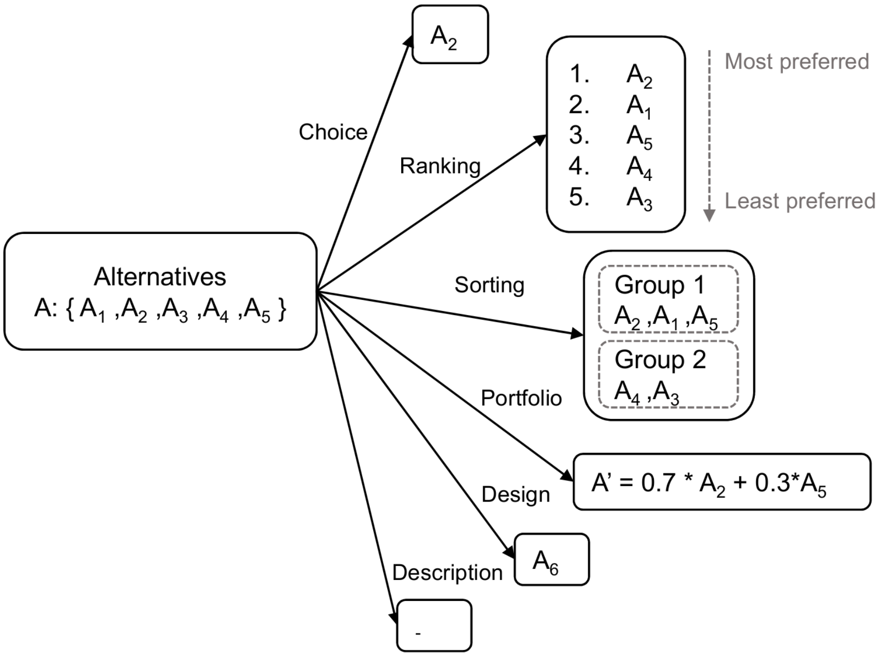


Figure 2.3 – Schematic overview of the MCDA problematics investigated in the review. Adapted from Belton and Stewart (2002) and Chen (2006).

It should be noted that the delimitation between problematics is not always absolute, and that a certain hierarchy can exist among them. For example, a first expected outcome may be *ranking*, followed by the *choice* of a single alternative. Similarly, the *portfolio* problematic can be considered a specific type of the *design* problematic, in which alternatives are created by combining various sub-components–this was generally the case for studies designing alternatives through multiobjective optimization. In turn, the newly created *portfolios* can further be *ranked*, *sorted*, *described* or *chosen* from. In the reviewed studies where multiple problematics concurred, the predominant one was retained, relying when possible on explicit statements from the authors.

Analysts must be aware of the type of results they aim to provide (a best single solution, a ranking of all solutions, the identification of original alternatives, etc.). Often however, this appeared to be only implicitly considered, or not considered at all. As the method used may constrain the type of result, this reinforces the argument of carefully identifying the expected decision outcome early in the decision process, in order to avoid the generation of undesired information, and associated waste of time, effort and cost.

Planning driver

This question investigated the extent to which the planning problems were driven by values, rather than means or resources readily available. In the reviewed papers, values most often took the form of "characteristics of consequences that matter" stated in the introductory sections of the papers, or as "priorities" and "value tradeoffs" when establishing criteria and weights.

This question is particularly relevant in the light of the recent changes in urban planning, which shifted from physical, expert-led approaches, to a wider, strategic and collaborative form (Albers, 1986; Scherrer, 2008; Wachs, 2001). A wider scope, including in particular energy issues as well as public participation, implies that planners must cope with a wider range of values than previously, which poses a series of challenges such as their systematic incorporation in decision making, or gathering information about the values (Balint et al., 2011; O'brien, 2003). Connelly and Richardson (2005) and O'brien (2003) point out the general lack of explicit acknowledgment of – and distinction between – the different values which should influence and drive planning. According to them, omitting values, assuming they are known, or underestimating their diversity may lead to unacceptable outcomes. As a response to these issues, Keeney (1992) originally advocated "value-focused" thinking, as opposed to what can be called "alternative-" or "resource-focused" thinking. According to him, failing to elicit values before defining alternatives leads to a constrained vision of the problem, which "anchors the thought process, stifling creativity and innovation". Additionally, how alternatives are identified also directly influences how well the values shall be satisfied. Often, decision makers do not spend enough effort on alternative creation, missing many alternatives, including important ones, hindering the achievement of the objectives (Siebert and Keeney, 2015). Exploring how values were involved in the reviewed studies, these were classified as either value-driven or alternative-driven, following loosely the framework from Keeney (1992). This classification is not meant to be an absolute one, but rather to foster thinking about values in MCDA and how these could improve the final outcomes. Based solely on the reported elements in the final publication, and without the full knowledge of how the decision problem was actually addressed, the problem cannot easily be declared either purely value-driven, or purely alternative-driven. Instead, it lies within a continuum between both ends (Figure 2.4), depending on the reported information regarding values, and alternatives.

Several characteristics of value-driven approaches were used to evaluate the reviewed studies (Figure 2.4). As such, the studies which were more explicit in their elicitation of values, whose values in turn appeared to influence the identification of criteria and alternatives, and which considered a broader range of alternatives, or motivated the narrow set evaluated, were marked as value-driven. Those who only moderately exposed the guiding values, or which values didn't appear to influence the decision analysis, or which didn't motivate the choice of alternatives were marked as alternative-driven. To help in the classification, three types of alternative sets were used to describe the studies:

- Type 1: The study includes and compares different categories of alternatives (e.g. renewable energy technologies, refurbishment, funding options, spatial alternatives, information and incentives)
- Type 2: The study includes and compares alternatives from one category (e.g. different renewable technological alternatives, such as solar PV and wind; or different locations for a waste disposal)
- Type 3: The study includes and compares alternatives belonging to a single sub-category (e.g. different solar PV cell types).

Three specific approaches for alternative generation (previously mentioned in Section 2.2.3) were also found to be particularly in line with value-driven thinking, as they enable a transparent and comprehensive way to identify alternatives, with little a priori in their construction. The first approach was multi-objective decision making (MODM)-based heuristics, in which a wider range of alternatives are automatically generated by combining decision variables to best achieve predefined objectives, allowing more informed, and more rational decisions (Cohon, 1978). Similarly, some geographic information system (GIS) approaches also assumed a broad, continuous range of locations as possible solutions, as opposed to a comparison of a limited subset of pre-selected sites. Other systematic combinatorial approaches were found, in which theoretically all possible alternatives of a category were considered a priori. This was for example the case when enumerating all possible priority sequences for restoration of district heating pipe segments (Rochas, Kuzņecova, and Romagnoli, 2015). Finally, to complete the assessment of planning drivers, the stated rationales for selecting the set of alternatives, if available, were also used to classify the studies (e.g. authors who provided strong justifications for the choice of alternatives were more likely to be classified as value-driven as if the alternatives were not justified or appeared to be selected arbitrarily).

It should be noted that the value- or alternative-driven nature of a problem should not necessarily be regarded as "good" or "bad". Indeed, the problem context may simply be conditioning an alternative-driven approach, as for example in Hsueh and Yan (2011), where a method for comparing urban development projects which had applied for governmental grants is proposed. Similarly, some studies might not claim to find the best possible alternative to achieve a valued goal, but rather purposely aim to answer a more specific question about a given technology. This is for example the case of De Feo, De Gisi, and Galasso (2008), who compare various coagulants for urban wastewater treatment.

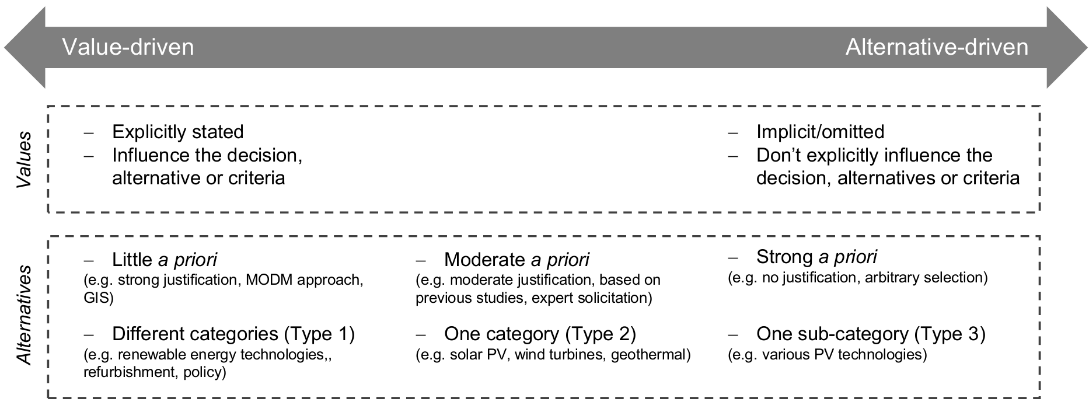


Figure 2.4 – Considered characteristics for classifying the studies as value- or alternative-driven.

MCDA methods

This section aimed at identifying the MCDA methods, as well as the supporting methods, employed to address the different problems, and the rationales behind their choice. There are many ways to categorize MCDA methods. In this study, they have been divided in five main groups, loosely based on classifications proposed by Belton and Stewart (2002), Hwang and Yoon (1981), Løken (2007), Mardani et al. (2015), and Zhou, Ang, and Poh (2006):

1. **Value measurement models** assign numerical scores to each alternative, by aggregating criteria and weights. Among the most common approaches include the Weighted Sum Method (WSM), or the Analytical Hierarchy Process (AHP).

2. **Goal, aspiration and reference level models** are often gathered under the expression goal programming, and a typical example is the Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS). The intuitive underlying principle in these models is that alternatives which are closest to an ideal solution are selected.
3. **Outranking models** distinguishes alternatives in a pairwise fashion for each criterion, as in the PROMETHEE or ELECTRE methods. For example, with ELECTRE, pairwise comparisons are performed between alternatives for each criterion. Intuitively, the approach can be viewed as a voting procedure, in which each criterion can vote for or against an alternative, and where the value of the vote depends on the weight of the criterion (Pasanisi, 2014). Unlike for the previous models, the outcome of this process is ordinal, e.g. an outranking relation such as $A_2 > A_1 > A_3$. This group is also referred to as the French school of MCDA methods, namely because of the pioneering work on the ELECTRE methods from Roy (1996).
4. **Multi-objective decision making** (MODM) relies either on deterministic approaches (e.g. linear programming techniques) or on stochastic heuristics (e.g. evolutionary algorithms). This group also contained methods which were referred to as single-objective decision making (SODM). Though in most cases SODM considers just a single objective, providing a somewhat limited interpretation of a problem, their name can be in some cases misleading. SODM can indeed handle multicriteria aspects of a problem by resorting to various techniques (Savic, 2002). This can be achieved by means of scalarizing functions (Branke et al., 2008), e.g. aggregating various objectives into a single objective function through a weighted sum (Karmellos, Kiprakis, and Mavrotas, 2015; Ma, 2012; Yokoyama and Ito, 1995), or by setting different constraints on criteria to evaluate trade-offs with the objective, as in the ε-constraint method (Pérez-Fortes et al., 2012; Haimes, Lasdon, and Wismer, 1971), or simply by varying the criteria being optimized and comparing outcomes (Ayoub et al., 2009).
5. The fifth group included methods which do not belong exclusively to any of the other groups, relying e.g. on fuzzy set theory, and other methods developed more recently, and referred to as "decision making aggregation methods" in Mardani et al. (2015). Fuzzy set theory (FST) can indeed be either used to extend existing MCDA methods (Mardani et al., 2015; Wang et al., 2009), or used independently for criteria aggregation (Greco, Ehrgott, and Figueira, 2016).

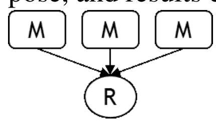
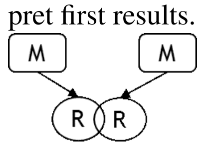
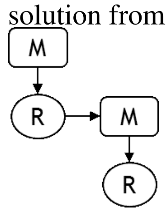
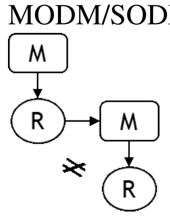
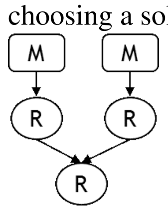
Several auxiliary methods are frequently found supporting the MCDA process. Referred to in this paper as "supporting methods", these include for example fuzzy set theory (FST), the Delphi method, SWOT analysis, GIS tools (cf. Figure 2.11 or Table B.1 for an exhaustive list).

Furthermore, the stated arguments for choosing an MCDA or their supporting methods were collected during the review. These arguments can be compared to the requirements and "quality factors" discussed by Mirakyan and De Guio (2015) for choosing decision methods.

Combination of MCDA methods

The combined use of methods, as well as the rationale for doing so, were also investigated. Strantzali and Aravossis (2016) have recently pointed out the growing trend in combination and comparison of different methods' results. As mentioned in the introduction (Section 2.1), Løken (2007) and Hobbs and Horn (1997) have advocated using multiple MCDA methods to tackle a similar problem, as its solution may strongly depend on the method choice. Crump and Logan (2008), Greene, Caracelli, and Graham (1989), and Mirakyan and De Guio (2015) have discussed the various purposes and motivations for combining methods. Greene, Caracelli, and Graham (1989) initially noted five key purposes for mixing methods, which include triangulation, complementarity, development, initiation and expansion (Table 2.1). The reviewed studies indeed often involved multiple methods, and the stated or inferred purposes were systematically monitored. As already encountered by Greene, Caracelli, and Graham (1989), the purpose stated by the authors may differ from the definitions proposed, in which case, for better coherence, the inferred purpose matching the definitions was noted. In several occurrences, several purposes were identified, and noted as primary, secondary and tertiary purpose, by order of importance in the study.

Table 2.1 – Purposes for combining multiple methods.

Purpose	Reasons	Example and depiction (M = method, R = result)
Triangulation	Seek convergence and corroboration of results across different methods	E.g. (Ribau, Sousa, and Silva, 2015), where 3 methods were applied for the same purpose, and results compared. 
Complementarity	Different methods used to measure overlapping but distinct facets, to enhance, illustrate or clarify results from one another.	E.g. (Nowak, Bortz, and Roclawski, 2015), where a navigation tool is proposed to interpret first results. 
Development	Different methods used sequentially to use results from one to develop or inform another	E.g. (Koo and Ariaratnam, 2008), where AHP is used to aggregate first qualitative criteria, to be used in a WSM, or (Zheng et al., 2015) where ER is used to select a solution from MODM results. 
Initiation	Also uses methods sequentially, with the aim to identify contradictions or new perspectives, and learn why these exist (rarely intentional).	E.g. where an obvious optimal solution from MODM/SODM would not be satisfactory 
Expansion	Applies different methods for different inquiry components, increasing the breadth and quality of the results by applying the most suitable method for each task.	E.g. where SWOT analysis is used to analyze the situation, value tree approach to identify values and criteria, and MCDA for choosing a solution. 

2.3 Results

2.3.1 Problem scope

This section presents the general results concerning the scope of the studies, as described above. A majority of papers were published by European (44 studies), Asian (23) and North American (15) institutions.

Regarding the scale at which the studies took place, a spread from country to building level was observed. 48 studies covered the city scale, 14 the neighborhood, 10 the regional scale, 7 the building, 6 the country and 2 the state. It should be noted that this spread appeared despite narrowing the search to the urban and neighborhood scales, illustrating the tendency of urban planning to also impinge upon broader and smaller scales.

Papers were grouped according to the typologies in Section 2.2.3. The sub-topics were tackled as follows: heating and cooling (43 studies), power (41 studies) and mobility or water/wastewater projects (20 studies each). This reflects the importance of the stakes associated with heating and cooling in buildings, the leading sector regarding GHG emissions and primary energy use (IEA, 2008; ODYSSEE-MURE, 2015).

Regarding the planning focus of the studies, 63 were dealing with system specific aspects, whereas 18 handled the issues in an integrated way, considering multiple subtopics, energy carriers or types of infrastructure, and 8 focused on operative planning aspects. The temporal horizons covered by each study are plotted in Figure 2.5, classified by planning focus. The sampled studies showed that planning projects which focused on specific aspects of the system coped on average with longer time horizons than projects considering the system as a whole (24 and 21 years respectively). The operative planning and management studies considered time horizons of days to several years, on average considering the year as time perspective. These temporal horizons are closely in line with those of the planning tasks and decision making levels discussed by Makkonen (2005) and Mirakyan and De Guio (2015), which distinguish strategic decisions (spanning over more than 10 years), tactical decisions (between 1 and 10 years) and operational (less than a year).

2.3.2 Alternatives

The review showed that a majority of studies (44) considered 5 or less alternatives (Figure 2.6A). 9 studies handled over 30 alternatives, and 5 studied a continuous range of possible alternatives in GIS-based approaches. In practice, the types of alternatives considered in the UESP problems were widely diverse, ranging from the evaluation of *geographic locations* (e.g. siting of hazardous waste landfills (Feo and De Gisi, 2014) or PV recycling plants (Goe, Gaustad, and Tomaszewski, 2015)), *development scenarios* (e.g. comparing environmental-, technology- and economic-driven energy use scenarios of urban areas (Wang, Xu, and Song, 2011) or policy scenarios (Phdungsilp, 2010)), *actions or measures* to be implemented by urban actors (e.g. building renovation measures (Medineckiene and Björk, 2011)), or *technologies and infrastructure* (e.g. community scale renewable energy sources and technologies, such as solar PV or thermal, wind turbines, geothermal, micro-hydro (Nigim, Munier, and Green, 2004), or residential heating systems (Kontu et al., 2015). Alternatives were most often generated or selected by the authors of the studies themselves, followed by alternatives generated by means of optimization methods, expert solicitation, GIS and literature (Figure 2.6B). In the context of planning community-scale renewable energy projects, Nigim, Munier, and Green (2004) write that "an ideal decision environment would include all possible information (...) and every possible alternative". Due to limited time and resources, they note that one must generally deal with limited alternatives. As expressed in other studies however, this constraint shouldn't prevent the consideration of as many alternatives as possible in the definition

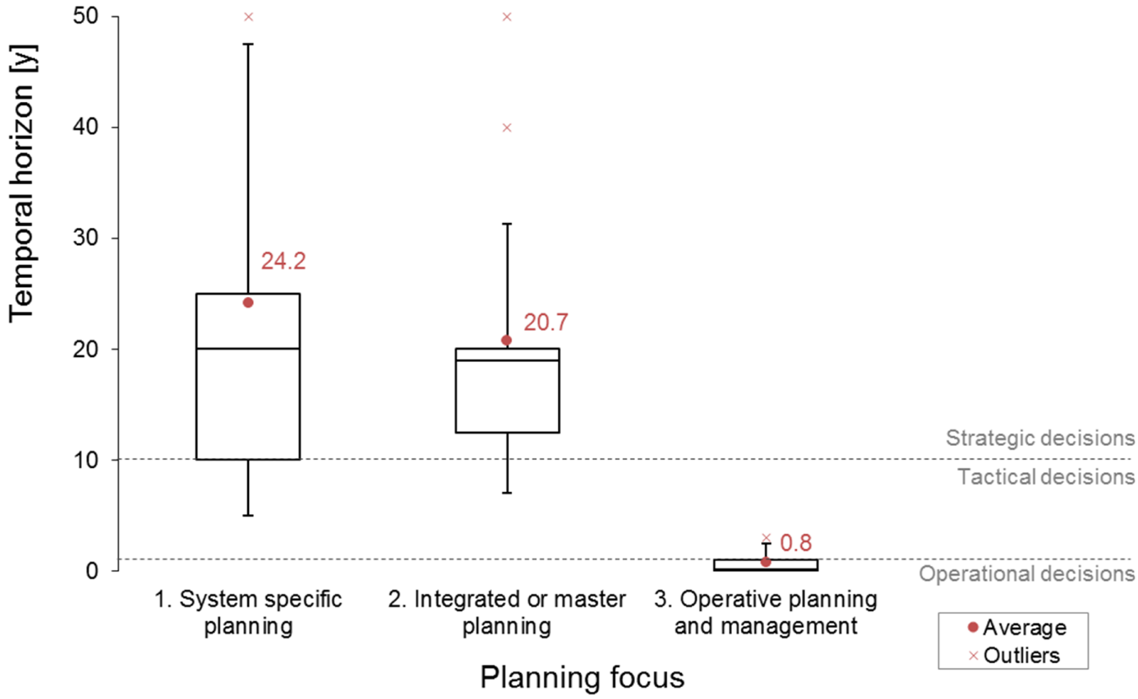


Figure 2.5 – Boxplots of the temporal planning horizons covered by the studies in each planning focus category. The average values for each category are based respectively from left to right on 63, 18 and 8 studies. Tukey style whiskers extend to points within 1.5 times the interquartile range.

of the problem context. When selecting sustainable energy resources, Kaya and Kahraman (2010) and Kontu et al. (2015) underline for example the importance of initially considering a broader set of alternative energy resources, including possibly less popular or less sustainable options such as fossil or nuclear fuels. Ghafghazi et al. (2010) also consider extended energy sources for a district heating project, explicitly motivating – based on values or problem boundaries – why they keep or reject them in the study.

2.3.3 Criteria

The typical number of criteria used in the MCDA studies reviewed is between 6 and 10 criteria (Figure 2.7A). Only two studies used more than 40 criteria. When these were not proposed or developed by the authors themselves, which was found to be the leading approach for criteria elicitation (51), criteria were taken from literature (32), including readily available criteria sets, identified and selected by external experts (17), and occasionally adopting more formalized methods such as Delphi (3) or CoP (1) (Figure 2.7B). In a study evaluating the appropriateness of technologies for reducing heating costs of impoverished communities (Bauer and Brown, 2014), 49 criteria were ranked according to their prevalence in literature, considering this prevalence as “a proxy for importance”. The most cited criteria included e.g. community input, affordability, autonomy or adaptability of the technology. In a second step, the study also ranked these criteria according to local stakeholders, whose ranking differed from the literature-based ranking. Among the top 8 selected criteria were for example efficiency of resource use, job creation, simplicity and autonomy of the technology. This indicates that a literature-based listing of common criteria could be useful as a first step to identify prevalent and possibly important criteria (such a list is for example provided by Wang et al. (2009) for energy supply systems analysis). However, its practical usability would require further classification and analysis of the criteria by topic and scale. For example, it has been

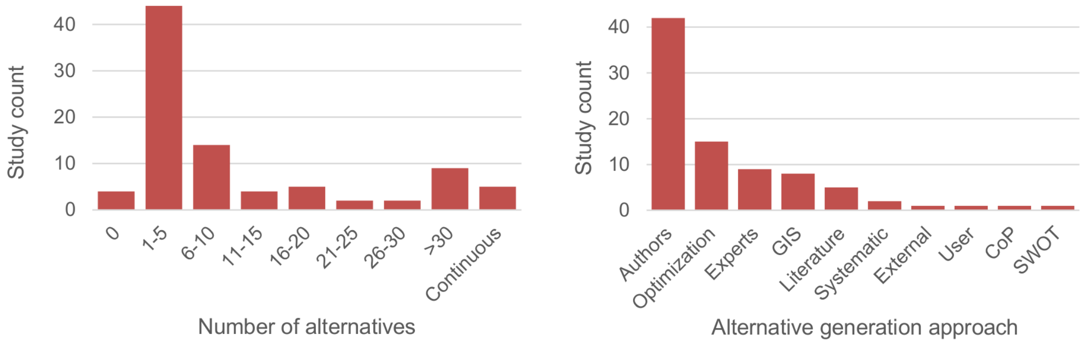


Figure 2.6 – Results regarding number of alternatives and generation approaches in reviewed studies. (A) Number of alternatives analyzed by the reviewed studies. The bin ‘>30’ includes numbers of alternatives between 30 and 7000, whereas ‘Continuous’ includes studies which relied on GIS methods. (B) Distribution of alternative generation approaches adopted by the reviewed studies.

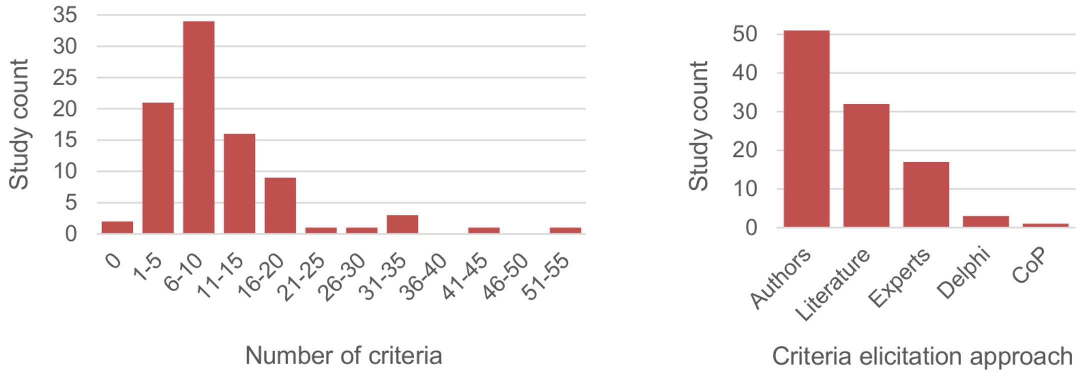


Figure 2.7 – Results regarding the number of criteria and elicitation approaches in reviewed studies. (A) Distribution of criteria number used in the reviewed studies. (B) Distribution of criteria elicitation approaches adopted in the reviewed studies.

noted that the relevance and perceived importance of criteria such as noise or dust emissions may be higher for small problem boundaries and scales than more global criteria such as CO_2 emissions or energy efficiency (Koo and Ariaratnam, 2008; Macoun, 2005). Eventually, some adaptation and extension of the list to meet local specificities is anyway advised (Bauer and Brown, 2014).

2.3.4 Decision problematic

The types and number of decision problematics found in the reviewed papers are displayed in Figure 2.8. Most of the studies aimed at choosing a single best option (i.e. 32 choice problematics), followed by the goal of ranking the alternatives (22). 16 studies didn’t aim to make a decision per se, but rather learn about the decision problem and alternatives involved (description problematic). Bauer and Brown (2014) for example illustrates a description problematic, as the approach doesn’t necessarily aim to choose or rank alternatives, but instead to assess even individual solutions, and give them a score which could serve as general advice regarding any solution’s quality or “appropriateness”. Browne, O’Regan, and Moles (2010) provide another example of the description problematic, using NAIADE to assess and compare the impacts of energy policy scenarios. They write that the “purpose of NAIADE is not to produce a definitive ranking of alternatives, but to rationalize the problem and provide a framework for communication among stakeholders." Respectively 13 and 6 studies were of the portfolio and sorting types. Notable portfolio examples consisted for example in combining energy efficiency measures in buildings, choosing from various envelope components and configurations (doors, windows, wall materials), lighting systems and other electrical appliances, and heating systems (Karatas and El-Rayes, 2014; Karmellos, Kiprakis, and Mavrotas, 2015), or combining different waste recovery pathways to create municipal recycling programs (Banar, Özkan, and Kulaç, 2010). Li, Parriaux, and Thalmann (2013) propose a method to sort urban zones according to their potential of underground exploitation, distinguishing high potential zones for short-term exploitation, moderate potential zones to be reserved for long-term projects, and prohibited zones where underground exploitation would conflict with environmental or economic goals.

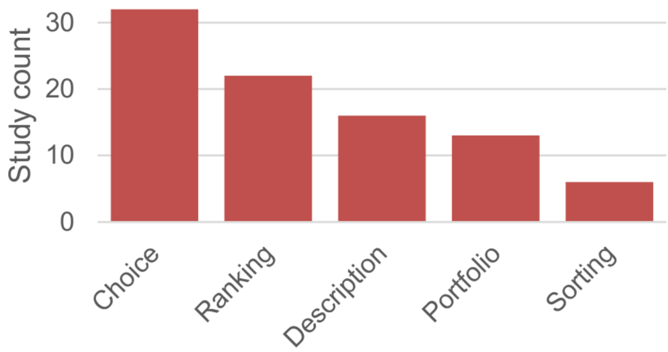


Figure 2.8 – Distribution of decision problematic types in the reviewed studies.

In Figure 2.9, the most common MCDA methods used for each decision problematic are shown. Aside from the sorting type, most problematics were addressed with a variety of methods. A few trends can nonetheless be pointed out. MODM methods were predominant in addressing the portfolio problematics. MODM indeed usually works by searching optimal combinations of decision or control variables, which combined form an optimal (or Pareto optimal) solution as regard to the objectives. As noted earlier, this problematic can typically be followed by any other decision problematic. Notable examples were offered by Karmellos, Kiprakis, and Mavrotas (2015), Pérez-Fortes et al. (2012), and Zheng et al. (2015) who followed up with choice, or Karatas and El-Rayes (2013) and Yokoyama and Ito (1995) with description. MODM also proved popular in describing decision problems, as used in one-third of the description problems. A second third is handled with AHP and WSM methods. Single choices were performed predominantly with AHP, WSM and TOPSIS, whereas ranking also was carried out in 25% of the cases by ELECTRE III, PROMETHEE and VIKOR methods.

Regarding supporting methods, Delphi was found particularly often in description problematics, GIS in choice and sorting problematics, and FST was found in all 4 problematics, except portfolio (see appendix, Figure B.5).

Several authors expressed particular comments regarding desired decision outcome and corresponding choice of methods. Zhang, Pan, and Kumaraswamy (2014) for example pointed out that depending on the expected outcome, decision makers could choose between ELECTRE I when aiming for a choice problematic, or ELECTRE II for a ranking problematic. Medineckiene and Björk (2011) noted that DMs seeking to learn about worst performing alternatives should avoid resorting to MEW, as this method relies on multiplicative aggregation and tends to rank alternatives at 0, though these might not be the worst performing over all criteria.

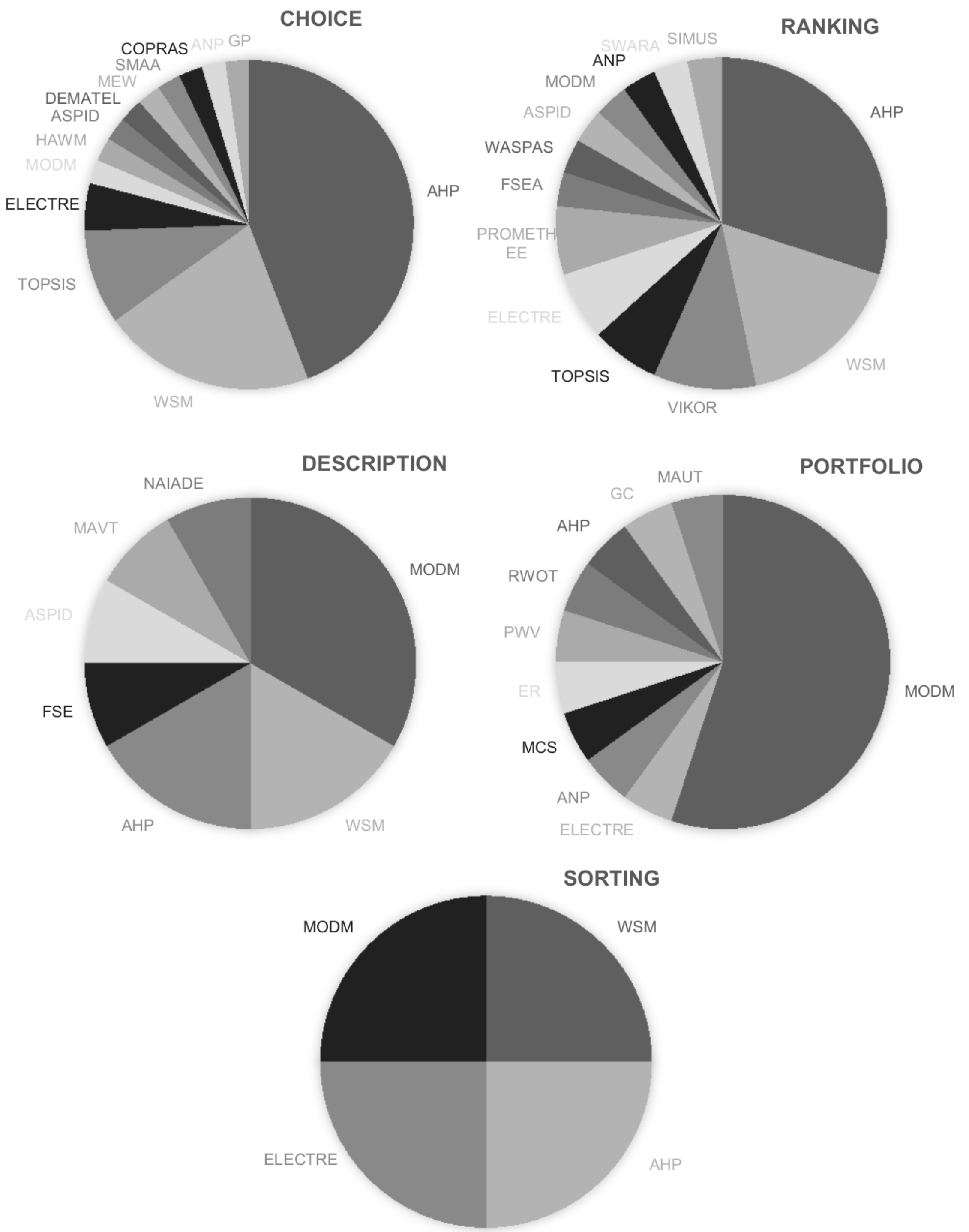


Figure 2.9 – Distribution of MCDA methods used per decision problematic as follows: (A) Choice, (B) Ranking, (C) Description, (D) Portfolio, (E) Sorting.

2.3.5 Planning driver

According to the characteristics presented above (Figure 2.4), two-thirds of the studies (60) were found to adopt rather value-driven approaches, while the remaining (29 studies) were rather alternative-driven. Kontu et al. (2015) illustrates well a value-driven approach, in which values are clearly stated (e.g. sustainable development of energy system, reduced environmental impacts, safeguard economic and social opportunities) and guide the identification of criteria and alternatives (performed in a collaboration between sustainable energy experts and practitioners). The authors also point out explicitly that alternatives were kept intentionally broad in the beginning, including also fossil fuel based solutions, only to let the values' associated criteria assess their relevance. The alternatives were of type 2, meaning various heating and electricity components were assessed. Another value-driven example is provided by González et al. (2013), in which values are clearly expressed and prioritized (sustainable urban development, promotion of positive changes in the urban context, sparing of natural resources, enhancing environmental protection, etc.), and explicitly shaped both the study's objectives, criteria, and alternatives. The alternatives in turn included comprehensive planning measures suited to achieving the values (brownfield rehabilitation, energy efficient housing construction, green space development, etc.).

2.3.6 MCDA methods

Similar to previous findings (Mardani et al., 2015; Strantzali and Aravossis, 2016; Wang et al., 2009; Zhou, Ang, and Poh, 2006), AHP is found to be the most popular method used for energy related problems (Figure 2.10). This can in part be explained by its frequent use not only as an MCDA method for criteria aggregation, but also as a method to elicit preference weights. Figure 2.10 further illustrates the great diversity of methods being used: nearly 30 different MCDA methods have been applied in the 89 studies considered. Besides AHP, only WSM, MODM, TOPSIS, ELECTRE methods, ASPID, VIKOR, PROMETHE methods and MAUT/MAVT were used more than once. A detailed classification and count of studies per method category is available in Appendix B, Table B.1. It was found that value measurements models are the most popular, used in 69% of the reviewed studies. Second most popular are the MODM methods (19%), followed by aspiration models (13%), others (12%) and outranking methods (10%).

Similarly to the main MCDA methods, Figure 2.10 also shows the frequency of supporting methods used in the studies, revealing in particular the common use of fuzzy set theory (14), of GIS (12) and Delphi (7).

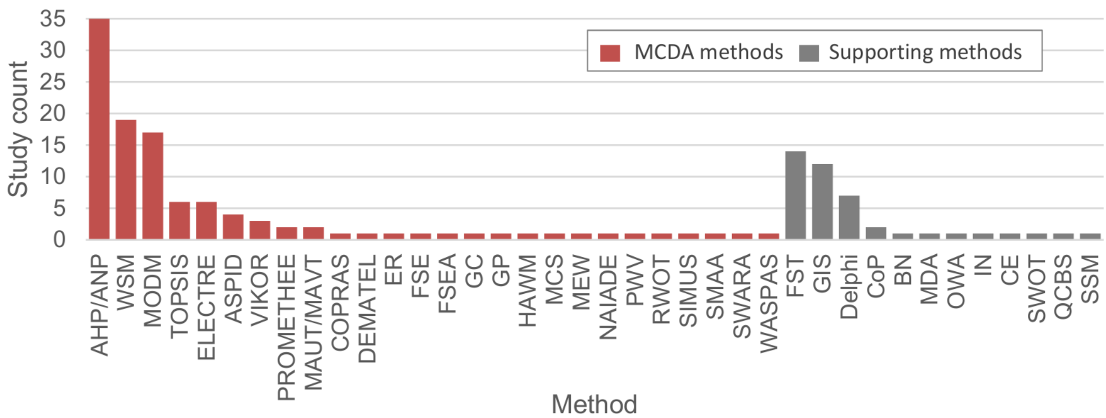


Figure 2.10 – MCDA and supporting methods used in the reviewed studies. Note: ELECTRE encompasses also ELECTRE III and TRI; PROMETHEE encompasses also PROMETHEE-GAIA.

Figure 2.11 illustrates the predominantly stated arguments for MCDA and supporting methods (the detailed information and references can be found in the appendix, Table B.1). It can be seen that the choice of an MCDA method was due most frequently to its perceived popularity, stated most often for AHP, WSM and MODM. The second most frequent argument stated was that of simplicity, which was also expressed as intuitiveness, straightforwardness, transparency or pragmatism. This argument applied most often to AHP, WSM, TOPSIS, and VIKOR. Equally frequent was the ability to handle qualitative and quantitative information, mainly for AHP and ASPID.

Regarding arguments for choosing supporting methods (Figure 2.11), the two principle reasons stated were to help in collecting and incorporating human experience and knowledge (applicable by decreasing importance to FST, CoP, Delphi and OWA), and to cope with incomplete, uncertain, non-measurable, vague or estimated information (stated for FST and OWA). Other reasons, essentially attributed to Delphi, were to assist in evaluating criteria and weights, as well as eliciting the criteria and alternatives. GIS tools were used mainly for their ability to quickly and simultaneously display multiple data-sets, but also for efficient display of information, handling of multiple spatial and temporal scales, and flexibility in combining various tools.

2.3.7 Method combinations

Figure 2.12, shows that a majority of studies (54) rely on a single main MCDA method, followed by 20 which combine 2 main methods, and 3 combining 3 main methods. 2 studies included up to 4 main MCDA methods. 10 studies did not include any main MCDA method, which is partly explained by those relying solely on GIS (4 studies). When considering also the combination of main and supporting methods together, then a majority of studies (46) appear to contain more than one method.

The most frequent reason for combining methods was the development rationale (26 studies), followed by complementarity (11) and triangulation (9). Secondary rationales were development (8), complementarity (8) and triangulation (1). Though it could be argued that several of the development cases also achieved the purpose of expansion, increasing the breadth of results by application of various specific methods (e.g. those involving Delphi (Bauer and Brown, 2014; Haruvy and Shalhevet, 2007; Hsueh and Yan, 2011; Jain et al., 2014; Vafaeipour et al., 2014), or SWOT (Öztürk, 2015), their sequential flow of information – characteristic of the development type – was deemed most relevant than this latter aspect. As such, no studies involved expansion, nor initiation.

The most common development combination was the use of AHP to elicit the weighting of criteria, to be used in other MCDA methods, such as TOPSIS (Ekmekçioĝlu, Kaya, and Kahraman, 2010; Khoshsolat et al., 2012; Tzeng, Lin, and Opricovic, 2005; Ziemele et al., 2014), WSM (Medineckiene and Björk, 2011; Rochas, Kuzņecova, and Romagnoli, 2015), and others (Beccali, Cellura, and Mistretta, 2002; Duan, Pang, and Wang, 2011; Fetanat and Khorasaninejad, 2015; Hsu and Lin, 2011; Karatas and El-Rayes, 2013; Kaya and Kahraman, 2010; Medineckiene and Björk, 2011). The Delphi approach was used in five instances to analyze the decision context while using AHP (Hsueh and Yan, 2011; Jain et al., 2014), WSM (Bauer and Brown, 2014; Haruvy and Shalhevet, 2007) and WASPAS (Vafaeipour et al., 2014) for alternative comparison. Development was also found between MODM/SODM and other MCDA methods in four studies, where WSM (Aydin, Mays, and Schmitt, 2014; Fonseca et al., 2016; Ribau, Sousa, and Silva, 2015), ER (Zheng et al., 2015) and PWV and GC (Ribau, Sousa, and Silva, 2015) helped select solutions resulting from optimization calculations. This was also stated as a reason for choosing these methods. One study inverted this pattern, instead making first use of a GIS-based analysis to short-list nine potential locations, which were than incorporated in an MINLP model as decision variables for the optimization calculation (Goe, Gaustad, and Tomaszewski, 2015). With nine instances, WSM was the most frequently used as a follow-up method to AHP (Koo and Ariaratnam, 2008; Medineckiene and Björk, 2011; Rochas, Kuzņecova, and Romagnoli, 2015), optimization (Aydin, Mays, and Schmitt, 2014; Fonseca et al., 2016), Delphi (Bauer and Brown, 2014; Haruvy and Shalhevet,

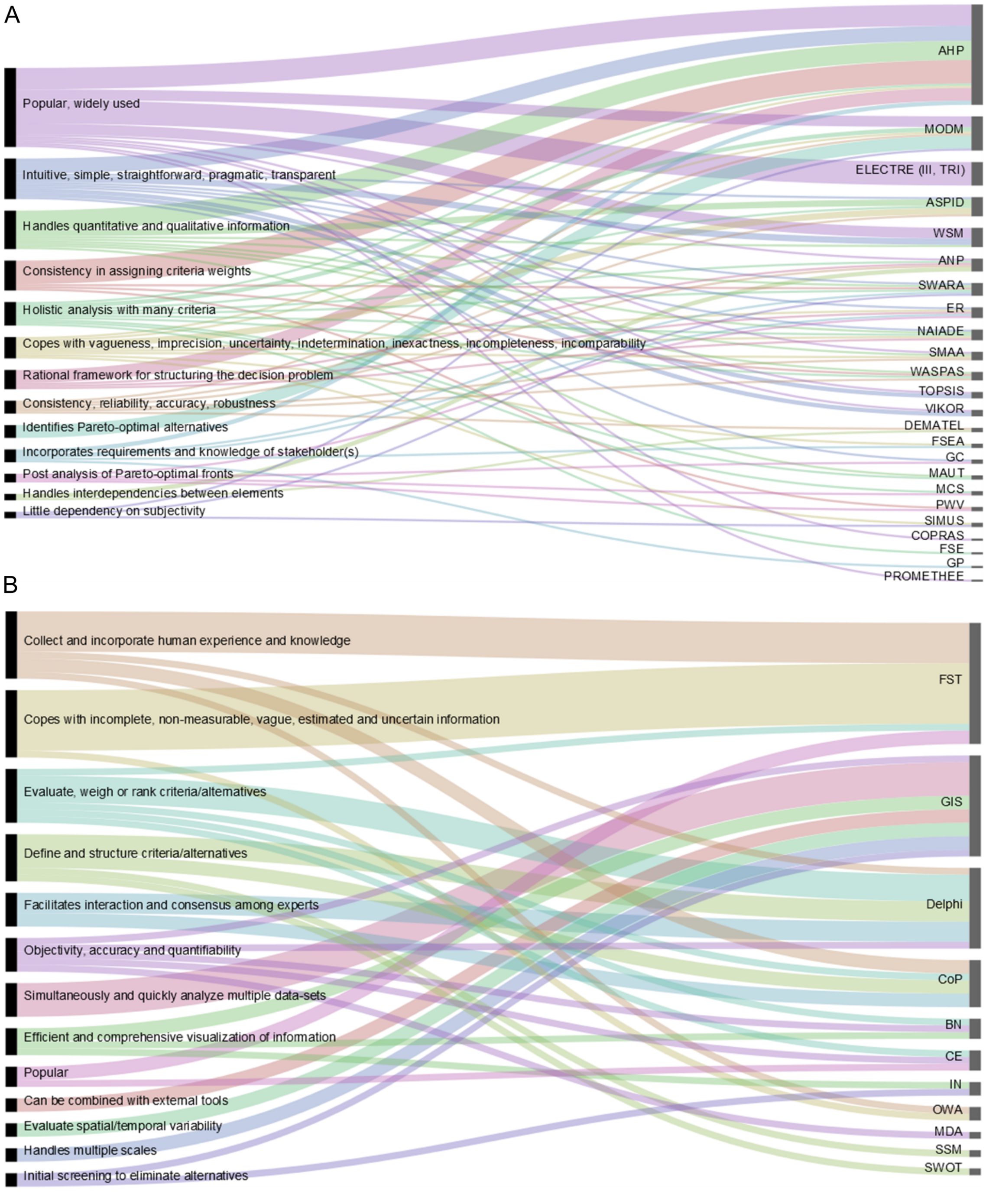


Figure 2.11 – Stated arguments for selecting the respective (A) MCDA methods and (B) supporting methods. Note: HAWM, MAVT, MEW, RWOT and QCBS are not represented, as no explicit arguments were provided in the studies.

2007), CE (Dombi, Kuti, and Balogh, 2014) and GIS (Feo and De Gisi, 2014). AHP was also used in a second step in seven studies, benefiting from prior applications of methods such as GIS (Feo and De Gisi, 2014; Idris and Abd. Latif, 2012), Delphi as noted above (Hsueh and Yan, 2011; Jain et al., 2014), CoP (Chrysoulakis et al., 2013; González et al., 2013) and FSEA (Wang, Xu, and Song, 2011).

In 12 papers, complementarity was related to the adoption of fuzzy set theory (Al-Yahyai et al., 2012;

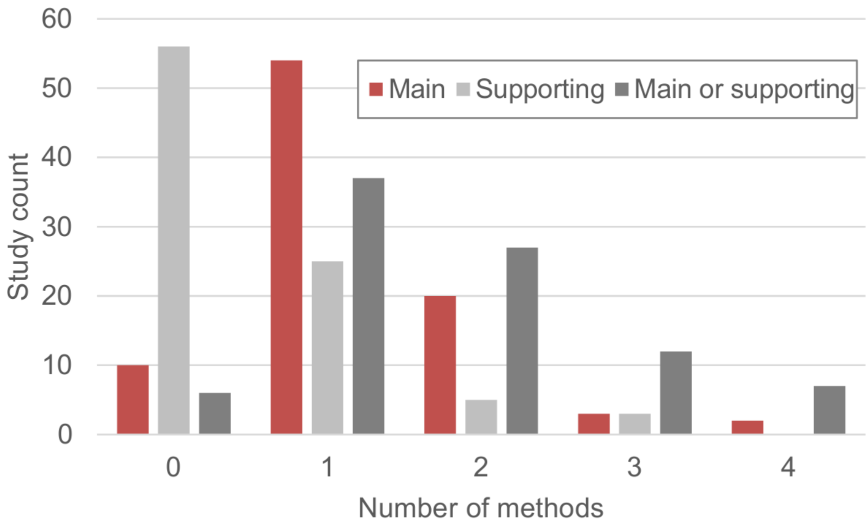


Figure 2.12 – Number of methods used per study.

Al-Yahyai and Charabi, 2015; Colantoni et al., 2016; Duan, Pang, and Wang, 2011; Ekmekçioĝlu, Kaya, and Kahraman, 2010; Fetanat and Khorasaninejad, 2015; Guo and Zhao, 2015; Hsu and Lin, 2011; Hsueh and Yan, 2011; Kaya and Kahraman, 2010; Khoshsolat et al., 2012; Wang, Xu, and Song, 2011), combining FST with existing methods such as AHP (Al-Yahyai et al., 2012; Duan, Pang, and Wang, 2011; Ekmekçioĝlu, Kaya, and Kahraman, 2010; Hsu and Lin, 2011; Hsueh and Yan, 2011; Kaya and Kahraman, 2010; Khoshsolat et al., 2012; Wang, Xu, and Song, 2011), ANP, DEMATEL, ELECTRE (Fetanat and Khorasaninejad, 2015), TOPSIS (Ekmekçioĝlu, Kaya, and Kahraman, 2010; Guo and Zhao, 2015; Khoshsolat et al., 2012), GIS (Al-Yahyai et al., 2012; Al-Yahyai and Charabi, 2015; Colantoni et al., 2016; Hsu and Lin, 2011) and VIKOR (Kaya and Kahraman, 2010). In 3 papers, GIS was used, mutually enhancing WSM (Arampatzis et al., 2004), AHP (Al-Yahyai et al., 2012; González et al., 2013), and OWA (Al-Yahyai et al., 2012). MODM was enhanced by MAUT for the aggregation of the objective function (Karatas and El-Rayes, 2013), and by use of an interactive result exploration tool (Nowak, Bortz, and Roclawski, 2015). In one case, BN and WSM were combined (Awad-Núñez et al., 2015).

It is well understood that the choice of MCDA method can influence the final results. Several of the reviewed studies triangulated various methods to compare outcomes either between two common methods (e.g. between ELECTRE III and WSM (Carriço et al., 2014; Frijns et al., 2015) or ANP (Banar, Özkan, and Kulaç, 2010), AHP and WSM (Feo and De Gisi, 2014), or to compare the results of less common or self-designed methods with more common ones (e.g. between TOPSIS and VIKOR (Tzeng, Lin, and Opricovic, 2005), WSM and QCBS (Vadiati et al., 2012), AHP and a variant of WSM (De Feo, De Gisi, and Galasso, 2008), AHP and SIMUS, comparing more specifically differences in subjectivity accounting (Nigim, Munier, and Green, 2004), or WSM with MEW and COPRAS (Medineckiene and Björk, 2011)).

Carriço et al. (2014) and Frijns et al. (2015) observed nearly similar results and pointed out that in general, MCDA literature does not discuss which method is most suited for which case, nor why results would differ using different methods with same input data. They underline the fact that selecting appropriate methods for different problem types is still an open research question. Feo and De Gisi (2014) compared AHP and WSM variants, and were able to obtain similar ranking of the solutions, observing however differences between the relative position of the ranked solutions.

Vafaeipour et al. (2014) did not compare the results of WSM and WPM, but relied on a combination of both, arguing it to be more robust. They explicitly recommend in their conclusion to compare results with other well-known MCDA methods.

2.3.8 Synthesis of the review

While the previous sections were concerned with the *analysis* of the reviewed studies, namely examining in detail the various constituents of the multicriteria problem, the present section proposes a *synthesis* of the present work. A synthesis can be defined as "the combination of components or elements to form a coherent whole" (Oxford Dictionary of English, 2005), and indeed, the elements of information collected in the review are brought together, and their relationships are made coherent by use of parallel coordinates (Figure 2.13). Parallel coordinates are a convenient and powerful way to handle multi-variate data and provide interactive decision support (Inselberg, 2009; Heinrich and Weiskopf, 2013; Johansson and Forsell, 2016; Packham et al., 2005). Their use can help identify which methods have been applied in various contexts, providing a guide to select a suitable method. Parallel coordinates consist of vertical axes–representing the criteria–and of polylines–representing individual studies–flowing across each axis. Six main criteria have been selected here to represent the characteristics of the MCDA process steps (Figure 2.1), while the associated MCDA and supporting methods used are presented in the last four axes. Therefore, the correspondence of methods with problem scope, number of alternatives, and criteria is established, allowing end-users to find methods most relevant to their situation. The axes values of temporal scale, number of alternatives, and number of criteria have been clustered for better readability, e.g. temporal scales are represented by the 3 temporal horizons discussed in Section 2.3.1. The charts in Figure 2.13 provide a static illustration of the online interactive framework (Appendix B.1). By color coding the various MCDA categories, it becomes clear which methods were predominant for different cases. For example, the following questions can be visually answered by exploring and filtering the parallel coordinates:

- Which methods were most adopted for handling many criteria or alternatives?
- Which methods depended the least on supporting methods?
- Which methods were used for which scales and planning focuses?
- Which methods supported which decision problematics?
- Which methods were combined?

Highlighting some of the insights observed in Figure 2.13, we note that value measurement methods were very eclectic, as altogether they were adopted for nearly scales and decision outcomes (Figure 2.13B). Goal, aspiration and reference level methods were essentially used for the urban and neighborhood scales, whereas they were never used for integrated planning or description and sorting problematics (Figure 13C). These methods handled limited number of criteria, never exceeding 20. The outranking group was also fairly eclectic in terms of supporting all decision problematics, and rarely required or relied on supporting methods (Figure 2.13D). They were combined with methods from other groups, including ANP, DEMATEL, and WSM. MODM methods handled multiple scales and planning focuses, while tackling many alternatives, but not more than 20 criteria (Figure 2.13E). The newer MCDA methods labeled "others" are also fairly broad on all criteria, avoiding however operative planning focus and temporal horizons (Figure 2.13F). Finally, the studies which did not involve any main MCDA method, were also the ones handling the largest amount of alternatives and criteria, in particular because of the use of GIS approaches (Figure 2.13G).

Figure 2.13H presents a concrete example illustrating how the parallel coordinates can be used to filter the solutions to match a user's problem context (see Appendix B for accessing the online

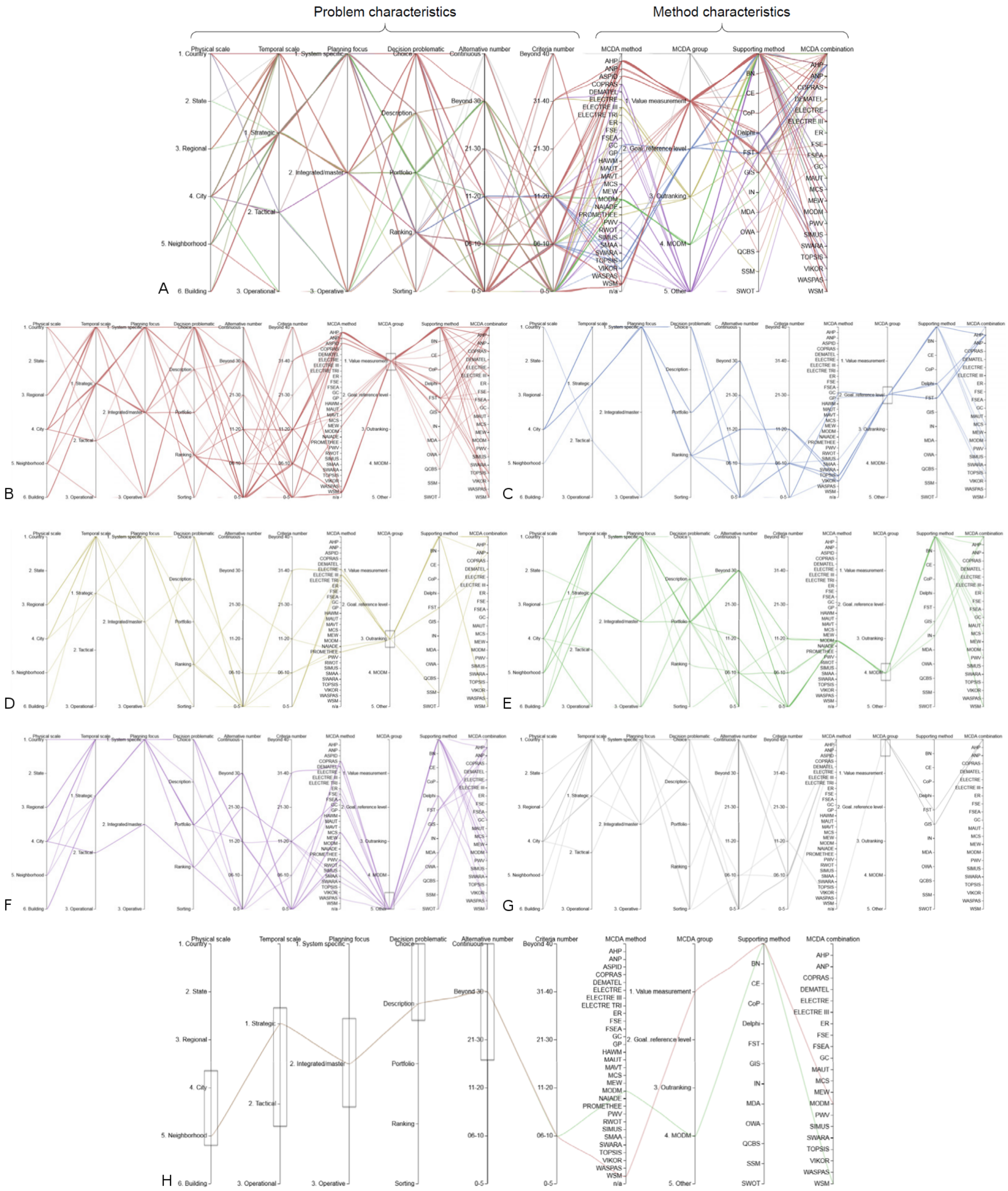


Figure 2.13 – Synthesis of data collected from the reviewed papers, depicted in parallel coordinates. (A) All methods displayed with their corresponding characteristics. (B-G) Filtering of the methods by MCDA group. (H) Identification of the methods matching a user-defined planning problem, by brushing the corresponding axes. Charts based on the interactive framework available in Appendix B.1.

version). In the example, the context is defined by "brushing" the axes in the areas of interest, namely to support a planning problem at the urban to district scale, to tackle the system holistically, and to provide either a description of the issues at stake, or to provide support in choosing from a large quantity of alternatives. The chart reveals two methods which faced similar conditions: WSM and MODM.

2.4 Discussion

A proliferation of MCDA

The review has revealed several trends and insights on the ongoing applications of MCDA in UESP. The first and most notable trend is the increasing use and popularity of these methods in urban energy planning contexts, which can be interpreted in at least two ways. First, this demand for decision analysis and support may reflect the increasing complexity and intractability of issues related to urban energy planning (Cajot et al., 2017c), alongside the expectation of accountability and transparency in public authorities' decision making (Keeney, 1982). MCDA appears in these regards as an appropriate response to support the decision makers involved and make their decisions more clear and justifiable. Another interpretation is the growing literature on MCDA, which reinforces its visibility, recognition, validity and trustworthiness, thus facilitating its dissemination. As Strantzali and Aravossis (2016) also point out, decision makers now tend to resort to a wider variety of methods than before, also building their own methods, when appropriate, to better face their specific issues. If the more traditional methods like AHP, WSM, MODM and TOPSIS are still the most popular, a broad range of less common methods are tested and applied in attempts to facilitate decisions of urban actors. This was clearly demonstrated in the present selection of studies, as illustrated by the broad range of methods adopted, around 30 MCDA methods found in 89 studies.

Choice of MCDA methods

The second key finding was the main rationale observed for choosing a method: in nearly 30 papers, one of the main arguments for choosing a method was its popularity. This seems to indicate that DMs are more likely to trust a method which has been intensively studied and applied by peers. In this regard, reviews such as this one help identify these common and popular methods.

However, it could be argued that the *appropriateness* of a method does not merely depend on the number of previous applications. The present study thus strived to provide a deeper context to these applications, underlining not only the most popular methods, but also the the characteristics of the decision problems in which they have been applied. An interactive parallel coordinates interface has been developed here to synthesize the collected review information, and published online to provide a means to support analysts and decision-makers in selecting appropriate methods (Cajot et al., 2017b).

Additionally, if the present results explored in the parallel coordinates may guide end-users in selecting methods, they serve a complementary purpose for decision scientists and researchers, by revealing possible research gaps. Future research may therefore explore the lacks made visible by the parallel coordinates. It was out of the scope of this study to question why, for example, goal and aspiration level methods tended to include only limited criteria compared to other MCDA categories, or avoided the more integrated planning or operative planning problems. Similarly, it was not explored why outranking methods compared fewer alternatives than the other categories. The visual support and comprehensiveness offered by parallel coordinates facilitates this identification of trends, lacks and subsequent questions which could be explored in future work.

Combining MCDA

The review has also looked at the reasons for combining various methods. It became clear that MCDA can benefit from multi-method approaches, as more than half of the studies relied on a combination of MCDA and supporting methods, and about a third used a combination of two or more MCDA methods. The leading rationale for combining methods was development, with AHP frequently used for weight elicitation, Delphi for analyzing the decision context, and between

MODA and MADA methods. Ten studies explicitly aimed to triangulate and compare different MCDA methods, and two trends were observed here. First, triangulation which aimed at comparing common methods, and second, triangulation between a common method and a less known one. This tends to show that users of MCDA are fairly cautious in their adoption of existing or new methods, and do realize the advantages of comparing several methods for an enhanced understanding of the problems.

Another noticeable trend was the combination of MCDA with various supporting methods like Delphi, CoP or SWOT, which help structure the problem, identify alternatives and criteria, and prioritize them. In turn, this helped decision-makers better focus on values. Even without the use of supporting methods to elicit values, a majority of studies were considered driven by values, rather than alternatives. This is rather encouraging, as it reflects a more productive approach to decision analysis and problem solving, by promoting the analysis of many alternatives, leading to better decisions. Nevertheless, still one-third of the studies focused on alternatives, possibly failing to identify better, more adapted solutions.

Insights into urban energy system planning

The review focused on the context of UESP, thereby providing useful information about an emerging topic. The studies revealed that urban energy questions indeed span over decades, increasing the challenges and uncertainties in the decision process. Most planning questions concerned temporal horizons of over 20 years, meaning investments and effects will last at least that long, and are worthy of analytical decision support. It was also found that though the leading topics of study were heating, cooling and power, a wider balance with topics of mobility, water, environment and waste also exists. However, as was already pointed out by Løken (2007), the integration of carriers and technologies is still fairly rare, as a majority of studies remain system specific. Few studies dealt with operative planning, and, here as well, future work to better link the specific planning and design studies with effects at the operative stage would prove useful. Regarding the lack of studies on the urban and local scale also noted in the introduction, the number of studies found in the context of this review seems to indicate that the awareness of the importance of this topic has grown in the past decade, and will certainly continue expanding.

Optimization beyond the building scale: an underexplored area

Two general and critical limitations of the reviewed studies are recalled here:

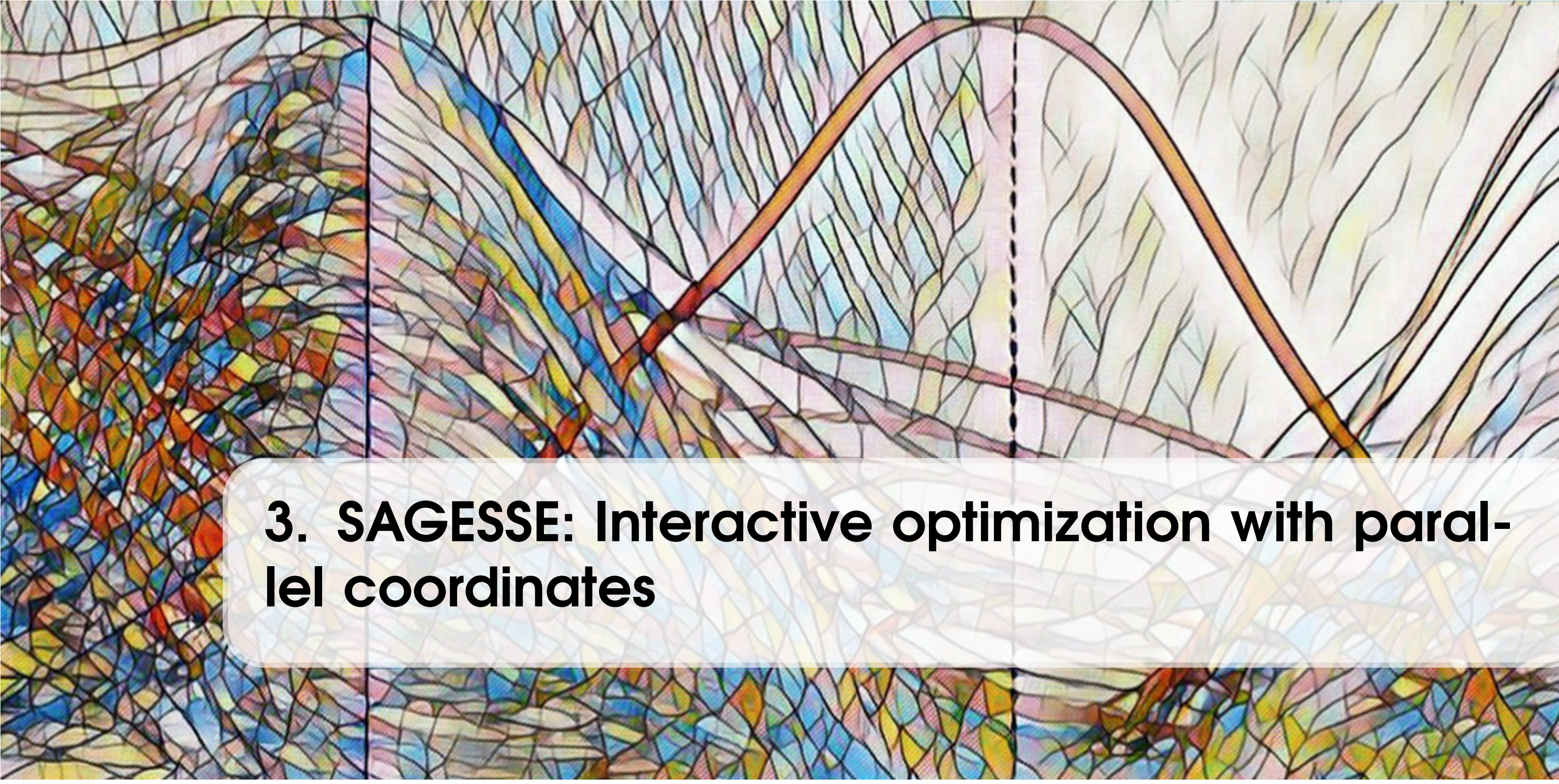
- **Lack of integrated approaches.** A majority of studies (63) tackled the problem in a system specific way, while only 18 covered simultaneously multiple sectors.
- **Limited number of criteria and alternatives.** The tendency to consider narrow scopes is further reflected by the fact that 64% of studies considered 10 criteria or less, and only 8% considered more than 20 criteria. Regarding the number of alternatives, 70% of studies compared 10 alternatives or less, while 20% compared more than 20. This is supported by Allmendinger et al. (2016), Xiao, Bennett, and Armstrong (2007), and Balling et al. (1999) who also report low number of objectives and alternatives in multiobjective optimization studies.

Despite the beneficial role of multiobjective optimization methods to foster value-focused decisions and consider a large amount of alternatives (Section 2.2.3), particularly few applications were found for the integrated planning studies, only 2 of which where done beyond the building scale (Fonseca et al., 2016; Rager, Dorsaz, and Maréchal, 2013). While a few other applications which were not identified in this review can be noted (e.g. (Keirstead and Shah, 2011; Weber and Shah, 2011; Kämpf et al., 2010; Best, Flager, and Lepech, 2015)), in general one can say that this field is still fairly underexplored.

Some ambivalent critiques of optimization by urban planners can explain in part these limited applications. On the positive side, Brill (1979) recognize that optimization can promote creativity and inventiveness, which are required for the generation of original and efficient plans. He also notes how the limitations of optimization models can be to some extent complemented by the use of more detailed simulation models in subsequent stages. Additionally, Keirstead and Shah (2013) underline that the simplified level of detail in optimization models can in fact be considered an asset in early stages of planning, where "their reduced data requirements enables models to be tested quickly against multiple scenarios". Balling et al. (1999) notes that in practice planners generally rely on "a mere handful of candidate plans", although it is likely that better plans could be considered. They argue that optimization "keeps the decision makers focused on competitive plans and divert their attention away from wasteful dominated plans" (Balling et al., 2000). However, the main reluctance of adopting such models to support urban planning can be loosely summarized by the three following limitations (Bayliss, 1973; Albers, 1986; Rittel and Webber, 1973; Brill, 1979; Keen, 1977; Kok, 1986):

1. The tendency of existing optimization models to focus on one or few different sectors simultaneously
2. The difficulty to weigh objectives objectively in presence of multiple actors
3. The difficulty to define "optimal conditions" with simple objective functions, only valid in sector-specific approaches

Interactive optimization—which was not addressed in any of the reviewed papers—is known to partly improve some of these limitations by exploiting the expertise of decision makers to overcome the model and computational limitations (Meignan et al., 2015). However, there are still gaps in existing interactive methodologies preventing their application in the context of urban and energy planning. These gaps, and how to address them, are the focus of the next chapter.



3. SAGESSE: Interactive optimization with parallel coordinates

My senses of space, of distance, and of direction entirely vanished. I thought I was very high up when I would suddenly be thrown to earth in a near vertical spin. I thought I was very low to the ground and I was pulled up to one thousand meters in two minutes by the 500-horsepower motor. It danced, it pushed, it tossed...

— Antoine de Saint-Exupéry (1921)

Interactive optimization methods are particularly suited for letting human decision makers learn about a problem, while iteratively providing feedback to steer the optimization process. For such methods to be adopted in practice, computational frameworks are required, which can handle and visualize many objectives simultaneously, provide optimal solutions quickly and representatively, all while remaining simple and intuitive to use and understand by practitioners. Addressing these issues, this chapter introduces SAGESSE (Systematic Analysis, Generation, Exploration, Steering and Synthesis Experience), a decision support methodology, which relies on interactive multiobjective optimization. Its innovative aspects reside in the combination of (i) parallel coordinates as a means to simultaneously explore and steer the underlying alternative generation process, (ii) a Sobol sequence to efficiently sample the points to explore in the solution space, and (iii) on-the-fly application of multiattribute decision analysis, cluster analysis and other data visualization techniques linked to the parallel coordinates.

This chapter is based on material from Cajot et al. (submitted).

3.1 Introduction

Making a decision generally involves balancing multiple competing criteria in order to identify a most-preferred alternative. For simple, day-to-day decisions, this can usually be done by relying on intuition and common sense alone. For larger, more complex decisions, common sense may not suffice, and multicriteria decision analysis (MCDA) can be used to formalize the problem, both improving the decision and making it more transparent (Keeney, 1982).

To make better decisions requires a clear knowledge of the available alternatives. However, research has shown that without adequate support, the identification of alternatives is difficult and often incomplete, even for experts in a field (Bond, Carlson, and Keeney, 2008; León, 1999; Malczewski and Rinner, 2015). MCDA adopts two distinct perspectives on alternatives, depending on the considered branch (Cohon, 1978; Hwang and Masud, 1979). Multiattribute decision analysis (MADA) aims to help select the best alternative from a predetermined subset (Malczewski and Rinner, 2015; Chankong and Haimes, 2008). Such *alternative-focused* methods have the risk of omitting important alternatives and leading to suboptimal solutions (Siebert and Keeney, 2015; Beach, 1993; Feng and Lin, 1999; Keeney, 1992; Belton and Stewart, 2002; Belton, Ackermann, and Shepherd, 1997). Multiobjective decision analysis (MODA) methods, on the other hand, systematically generate the alternatives based on the decision maker's (DM) objectives. They can thus be considered to promote *value-focused thinking*, because they require the DM to think about the driving values first, and consider the means to achieve them only second (Keeney, 1992).

However, solving multiobjective problems implies that, contrary to single-objective problems, not one well-defined solution is found, but a set of equally interesting *Pareto optimal* solutions. Such solutions cannot be improved in one objective without depreciating the value of another objective. When considered collectively as a *Pareto front*, they inform about optimal tradeoffs between objectives. In order to make use of such results, some preferences must be articulated by the DM in order to identify a most satisfactory solution from the Pareto front. The articulation of preferences, consisting e.g. in acceptable ranges, tradeoff information, or relative weights of objectives, can be done in one of three ways (Hwang and Masud, 1979; Branke et al., 2008):

i. **A posteriori**, once all the Pareto optimal solutions have been identified. The advantage is that the decision maker has a complete overview of the available options. On the other hand, the calculation can be extremely long if the solution space is vast, the decision maker may not have the time to wait, and the process will certainly compute many wasteful solutions which are of little interest. Even if time were not an issue, the difficulty to visualize, interpret and understand the Pareto optimal results can compromise the trust from the DM, especially when more than three objectives are considered.
ii. **A priori**, before starting any calculations. This is the most efficient approach, as theoretically only one solution is calculated. However, it is also probably the most difficult from the decision maker's point of view, as it assumes that they are perfectly aware of their preferences and acceptable tradeoffs, and are able to formulate them precisely. In practice, when dealing with complex and interdisciplinary problems, this knowledge is generally unavailable until the solutions are calculated, and therefore the risk of reaching an infeasible or unsatisfactory solution is high (Piemonti, Macuga, and Babbar-Sebens, 2017; Meignan et al., 2015).
iii. **Interactively**, as the optimization progresses. This is a common response to the limitations of a priori and a posteriori approaches. By involving the human decision maker directly in the search process, interactive optimization (IO) allows the user to learn from solutions as they are produced, refine their preferences, and in turn restrict the search to the most relevant areas of the solution space (Kok, 1986).

3.1.1 Background of interactive optimization

Interactive optimization consists of four main components which are combined to form a human-computer interaction system: a user, a graphical user interface (GUI), a solution generator and an analyst (Figure 3.1).

During a preparatory *analysis phase*, the user describes the problem and criteria to the best of their knowledge, and the analyst develops the model accordingly. A feedback loop, which can overlap

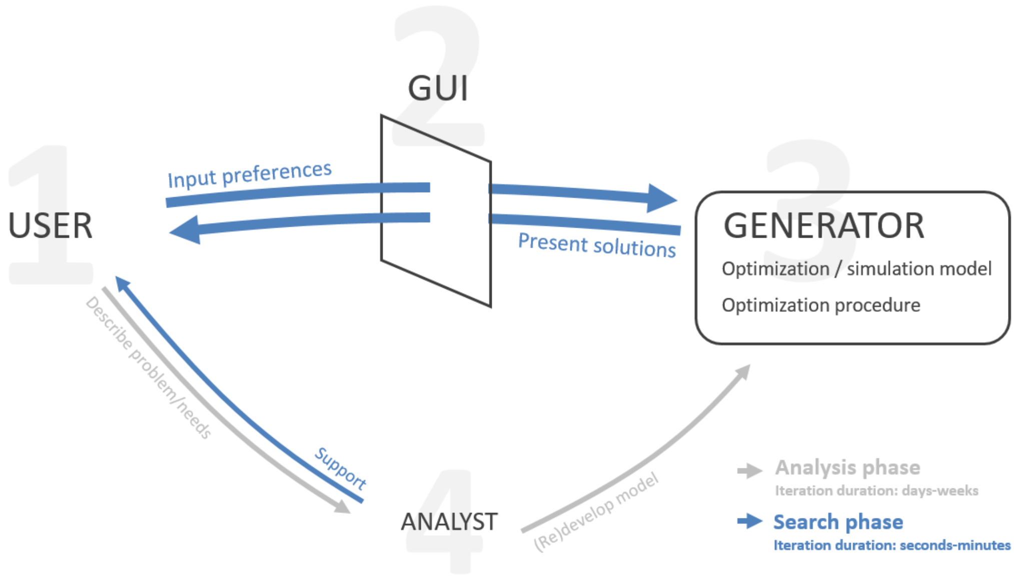


Figure 3.1 – Main components and flows of information in interactive optimization. GUI: graphical user interface. Adapted from Spronk (1981) and Meignan et al. (2015).

with the search phase, ensures the model captures the user's requirements as these evolve (Fisher, 1985). During the *search phase*, the user steers the generation of solutions through the GUI. Here, the role of the analyst becomes more passive (Spronk, 1981). The basic mechanism of IO consists in the oscillation between a generation phase, an exploration phase, and a steering phase. Typically, the process begins by *generating* and presenting one or several predetermined solutions for the user to *explore*. They study and compare their characteristics which are presented in the GUI, and react to them by communicating their likes or dislikes, also formalized through the GUI. These inputs are used to *steer* the subsequent calculations towards desired areas of the solution space. The process repeats until the user is convinced to have found the most satisfactory solution.

The main premise for human-computer interaction is that complex problems can be better solved by harnessing the respective strengths of each party (do Nascimento and Eades, 2005; Fisher, 1985; Hamel et al., 2012). The relatively superior human capabilities are in the expertise of the problem and subjective evaluations, as well as skills in strategic thinking, learning, pattern recognition and breaking rules consciously (Babbar-Sebens et al., 2015; Fisher, 1985; Klau et al., 2010; Shneiderman, 2010; Wierzbicki, 2010).

The relative strengths of the computer are in counting or combining physical quantities, storing and displaying detailed information and performing repetitive tasks rapidly and simultaneously over long periods of time (Shneiderman, 2010). In IO, the interface, or graphical user interface (GUI), allows to dialog with the user, both displaying results visually and receiving the user's preferences as inputs via mouse events or textual entries. The solution generator component consists of an optimization or simulation model describing the problem by its decision variables, objective functions and constraints, and an optimization procedure, which can be either an exact or a heuristic-based algorithm searching for solutions to the optimization problem (Collette and Siarry, 2004; Meignan et al., 2015). Some of the widely used meta-heuristic procedures include evolutionary algorithms, simulated annealing, and swarm particle optimization. Such algorithms mimic natural phenomena to explore a solution space towards optimal solutions. Unlike exact methods, they rely on stochastic exploration of solutions, searching for combinations of variables which lead to the best performance of a fitness function, or objective. This makes their implementation often simpler, but at the price of requiring many iterations to reach what is often only an approximation of the Pareto front. In the case of exact methods, the solution space is explored in a deterministic way, making the procedure overall more efficient and guaranteeing to find (at least weakly) Pareto optimal solutions. When dealing with many objectives, a parametrized scalarization function is commonly used to convert the multiple objective problem into several single objective ones, making it possible to use widely available and rapid single-objective solvers. By varying the parameters in the scalarization function, a range of Pareto optimal solutions to the initial multiobjective problem can be generated (Branke et al., 2008; Chankong and Haimes, 2008) . Together, the optimizer and GUI provide an efficient and systematic framework to generate and represent a large number of Pareto optimal solutions which are most relevant to the user.

There are several compelling benefits of involving a human user in the interactive optimization process. First, the incorporation of expert knowledge, intuition and experience can compensate the unavoidable simplifications induced by the model (Meignan et al., 2015; Liu et al., 2018; Piemonti et al., 2017). Second, computational effort is reduced by focusing on only the most promising regions of the solution space (Balling et al., 1999; Liu et al., 2018; do Nascimento and Eades, 2005). Third, the interaction process promotes trust, facilitates learning, and increases the user's confidence in the solutions and thus their likelihood of actually implementing them (Liu et al., 2018; Hwang and Masud, 1979; Spronk, 1981; Shin and Ravindran, 1991). Finally, this approach avoids the need to specify any explicit *a priori* preference information (Hwang and Masud, 1979; Allmendinger et al., 2016).

On the other hand, the main drawbacks are that IO methods rely on the assumptions that a human DM is available, that they are willing to devote time to the solution process, and that they are able to understand the process, inputs asked of them, and resulting outcomes (Liu et al., 2018; Hwang and Masud, 1979; Spronk, 1981; Branke et al., 2008; Collette and Siarry, 2004). This implies that developed methodologies should be both easily understandable, and able to quickly generate representative Pareto optimal solutions for the user to explore.

3.1.2 Related work

Review of interactive optimization procedures

Over the past decades, a variety of interactive optimization methods have been developed, with efforts both in improving the underlying search procedures, and interaction mechanisms. (Vanderpooten, 1989; Kok, 1986) provided an early attempt at describing and organizing IO methods. They distinguished between search-based methods, in which the DM's preference structure is supposed stable and preexisting, and learning-based methods, which promotes the discovery of preferences in problems where these are not known or difficult to express.

Many efforts have been done to review and synthesize the technical developments in the field of interactive optimization. The earlier developments of search-based methods are described by Branke et al. (2008), Chankong and Haimes (2008), Hwang and Masud (1979), and Collette and Siarry (2004). These are often classified according to the preference structures required from the DM (e.g. reference points, weights, bounds, tradeoff quantification) and the implications these have on generating Pareto optimal solutions. More recently, Meignan et al. (2015) provided an extensive review of the technical aspects of existing methods. They classified interactive methods based on the following features: the type of optimization procedure used (exact, heuristic or metaheuristic approaches), the user's contribution to the optimization process (affecting either the model or the procedure), and the characteristics of the optimization system (direct or indirect user feedback integration). Regarding optimization procedures, they found that heuristic- or metaheuristic-based approaches were predominant (25 out 32 surveyed studies), while exact approaches were the minority. A possible explanation for the popularity of metaheuristics is that in interactive methods, approximations of global optima may be good enough given the expected inaccuracies of the model. Another perspective favors however exact methods, especially for large problems with thousands of variables. Chircop and Zammit-Mangion (2013) argue that for unconstrained search spaces, stochastic search procedures will require a large number of objective function evaluations, leading to computationally intensive algorithms. Conversely, exact methods, by relying on scalarization techniques and efficient deterministic single objective approaches can quickly find optima of even large scale multiobjective problems (Williams, 2013; Schüler et al., 2018b) (Branke et al., 2008, p. 61, 64). This efficiency is critical because the number of solutions required to explore the solution space grows exponentially with the number of objectives (Copado-Méndez et al., 2016; Cohon, 1978). Ultimately however, the question of whether exact or heuristic methods are most efficient is debatable, and depends on the problem considered. For structured, convex, linear or quadratic programming problems, metaheuristics may not be more competitive than exact, gradient-based methods. On the other hand, because they rely on multiple solutions per iteration, evolutionary algorithms can easily benefit from parallel processing to achieve greater search efficiency. For these reasons, Branke et al. (2008, p. 64) nuance their conclusion by suggesting further research to understand the respective niches of each procedure, and to develop hybrid approaches exploiting their respective strengths.

Beyond the underlying technical aspects of interactive optimization, growing interest has been devoted to the learning opportunities which it provides. In this vein, Klau et al. (2010) argued that promoting effective interaction and learning mechanisms is more important than efficient algorithms. The reasoning is that whichever solution is produced, it ultimately is a simplification of reality which isn't directly usable. It is thus crucial that the user is able to correctly interpret and recontextualize the results. Therefore, the insights gained during the process, about the tradeoffs, synergies and feasible boundaries are eventually more useful outcomes than the solution itself.

Allmendinger et al. (2016) employ the term "navigation" to encompass not only the optimization procedure, but also the efforts made on real-time exploration of optimization results. However, among the six so-called navigation methods reviewed in (Allmendinger et al., 2016), four are *a posteriori* methods (meaning solutions are precalculated), while only two are interactive (Korhonen and Wallenius, 1988; Miettinen et al., 2010). Their review further reveals that most of these methods tend to handle only five or less objectives, and do not consider problems with more objectives or highly uncertain conditions. They call for the development of new methods which can easily handle complex problems with many objectives, and which provide more intuitive GUIs and interaction mechanisms.

Interfaces for multiobjective interactive optimization

The need for intuitive visualization of multiobjective optimization results and interaction with the optimizer has been recognized as a central issue (Xiao, Bennett, and Armstrong, 2007; Branke et al., 2008, p. 15). Meignan et al. (2015) conclude that "the development of more natural and intuitive forms of interaction with the optimization system is essential for the integration of advanced optimization methods in decision support tools". Branke et al. (2008, p. 52) explicitly mention the importance of user-friendliness in IO as a topic for future research. This is also true for the representation of interaction with the problem, e.g. how the DM inputs their preferences (Miettinen and Kaario, 2003), and the representation of the preferences themselves (Branke et al., 2008, p. 201). Liu et al. (2018) note that despite interactive optimization being "essentially a visual analytics task", literature is rather silent on the specifics of visuals and interaction approaches, focusing rather on optimization procedures and preference models.

Much attention has been given to advanced visualization methods for results of *a posteriori* multiobjective optimization methods, although their adoption in interactive methods is still low. Efforts in this area are mainly motivated by the fact that while Pareto fronts up to three objectives can be mapped in traditional planar or three dimensional representations, problems with many-objectives (i.e. more than three) are more challenging due to both the complexity of data to display, and the space required. Among the many available techniques reviewed by Miettinen (2014) and Branke et al. (2008), parallel coordinates stand out as an intuitive and scalable alternative. Introduced by Inselberg (1985) and extensively described by Inselberg (1997) and Inselberg (2009), parallel coordinates are similar to radar charts, except the dimensions are displayed as vertical side-by-side axes instead of radially. This allows the method to scale well to many dimensions, and facilitates the comparison of values and identification of tradeoffs, trends and clusters in the data (Shenfield, Fleming, and Alkarouri, 2007; Akle, Minel, and Yannou, 2016). Data points are depicted as polygonal lines (or polylines), which intersect the axes at their corresponding values. The main drawbacks of parallel coordinates include cluttering of the chart when displaying many alternatives, and the impossibility to visualize all pairwise relationships between dimensions in a single chart (Johansson and Forsell, 2016; Heinrich and Weiskopf, 2013). Studies also emphasize the need for users to receive basic training to better harness parallel coordinates (Wolf, Simpson, and Zhang, 2009; Akle, Minel, and Yannou, 2016; Johansson and Forsell, 2016; Shneiderman, 1996). The recent developments of interactive data visualizations have greatly alleviated these limitations by allowing the user to filter the displayed solutions, reorder axes by dragging them to explore specific pairwise relationships, or change the visual aspect of lines such as color or opacity to reveal patterns across all dimensions (Bostock, Ogievetsky, and Heer, 2011; Fieldsend, 2016). Heinrich and Weiskopf (2013) provide an extensive review of parallel coordinates and recent developments in their interactive features.

Several studies investigated the practical applicability of parallel coordinates in the context of multiobjective optimization. Akle, Minel, and Yannou (2016) studied their effectiveness in comparison to radar charts and combined tables for the balancing of multiple criteria and selection of preferred solutions. They found parallel coordinates to be the most effective and engaging approach for exploration, requiring less cognitive load and stress than the other charts. They also remark that parallel coordinates were the least known method, and suggest that training users could further improve the performance and usability of the approach. (Stump et al., 2009) also encountered this need, and undertook a study comparing the understanding of users who never used their tool with those who had previous experience (Wolf, Simpson, and Zhang, 2009). They found that novice users showed less certainty in which visualizations to use or actions to perform, and concluded that more training prior to using the tool would be necessary. They also suggest that a simplified interface with less steering and visualization features, as well as less densely packed alternatives might help users focus on relevant information and actions (Shneiderman, 2010). It has furthermore been suggested that parallel coordinates cannot display certain kinds of information and should be complemented (e.g. with spatial representations) for a more complete representation of alternatives (Xiao, Bennett, and Armstrong, 2007). Bandaru, Ng, and Deb (2017b), Sato, Tomita, and Miyakawa (2015) and Kok (1986) point out that when DMs only have a vague understanding of their preferences, it may be easier to specify loose ranges of preferences in the objective space, rather than exact points of preferences. The action of “brushing” available in interactive parallel coordinates charts addresses this issue. Brushing is a common action in interactive data visualization, where the user selects and highlights a subset of data, typically by dragging the pointer over the area of interest (Martin and Ward, 1995). One limitation of parallel coordinates is the visualization of Pareto fronts. It is however possible to make some interpretations, though these differ from traditional 2D plots and require familiarity with the charts. Li, Zhen, and Yao (2017) provide some insights on how to translate Cartesian representations of Pareto fronts into parallel coordinates.

Given the widespread attention received by parallel coordinates, their adoption in the context of multiobjective optimization is not surprising. However, their use remains predominantly confined to *a posteriori* exploration of precalculated solutions (Raphael, 2011; Miettinen, 2014; Xiao, Bennett, and Armstrong, 2007; Fieldsend, 2016; Rosenberg, 2012; Kipouros, Mleczko, and Savill, 2008; Bagajewicz and Cabrera, 2003; Ashour and Kolarevic, 2015; Akle, Minel, and Yannou, 2016; Bandaru, Ng, and Deb, 2017a; Franken, 2009). Only a few studies suggested using parallel coordinates to steer the optimization procedures, but all adopt meta-heuristic approaches, limiting their applicability to smaller problems with few variables (Stump et al., 2009; Fleming, Purshouse, and Lygoe, 2005; Sato, Tomita, and Miyakawa, 2015; Hernández Gómez, Coello Coello, and Alba Torres, 2016).

Overview of existing interactive optimization methods

A selected number of methods are described hereafter, outlining their responses to the issues above as well as the remaining gaps. For a more extensive overview of existing approaches, we refer to (Meignan et al., 2015; Allmendinger et al., 2016; Branke et al., 2008)

Korhonen and Wallenius (1988)'s Pareto Race is considered a multiobjective linear programming navigation method (Allmendinger et al., 2016; Greco, Ehrgott, and Figueira, 2016), and uses a visual interactive method to steer the search freely, in real-time. Much effort was dedicated to make the use of the software simple and intuitive to lay users, for example simplifying the preference input to “faster", or “more/less of this objective", and letting the program translate this into corresponding parameters (increments, aspiration levels, choice of goals). A later adaptation of the tool allowed handling also non-linear (i.e. quadratic-linear) problems, improving the efficiency of generating a continuous and representative portion of the Pareto front (Korhonen and Yu, 2000). The display in Pareto Race consists in bar charts reflecting the last computed solution, from which the user can request more or less of any of the objectives in the next iteration. The main limitation of this simple and intuitive method lies in the underlying iterative nature: displaying only one solution at a time prevents gaining a clear overview of all solutions and relationships between objectives. Therefore, for large problems with many objectives, the user may not be able to explore all potentially interesting solutions in a realistic amount of time. The larger the problem, the less freedom the user has to change their mind frequently (Korhonen, 1996), which limits the applicability of this method for large problems.

Another navigation method is Pareto Navigation (Monz et al., 2008), however to achieve quick and responsive interaction between the user and the tool, solutions are precalculated, while the user can then explore them, or request recombinations of existing plans which require less time to compute.

The approach developed by Miettinen and Mäkelä (2000) was allegedly the first interactive optimization method made available online. WWW-NIMBUS is a classification-based interactive multiobjective optimization method, which asks the user to classify the objectives whether they should be improved, remain identical or be relaxed. The principle is that in each iteration, the current solution should be improved according to the user's specifications. Because the process produces Pareto optimal solutions, it is necessary that at least one objective is allowed to diminish. While the original implementation was technically limited to relatively small problems, subsequent versions improved both the optimization procedures and the GUI. Hakanen et al. (2007) developed IND-NIMBUS, which included a new nonlinear solver to tackle large-scale problems such as simulated moving beds, and provided new visualizations to compare results, including 3D histograms and parallel coordinates. In A-GAMS-NIMBUS, Laukkanen et al. (2012) combined linear and nonlinear solvers, as well as a bi-level decomposition for a heat exchanger network synthesis problem in industrial processes. The ambition was to provide quick resolution of solutions, which ranged between 1 and 43 minutes per iteration.

In a separate work, Miettinen et al. (2010) proposed a reference-point interactive method, NAUTILUS, addressing two behavioral biases, namely loss aversion and anchoring effects, by encouraging the user to not interrupt the search before finding a most preferred solution. To do so, the very first solution presented to the user is a dominated one, so that each iteration does not necessarily imply sacrificing one objective in favor of another, as happens in most IO methods, where tradeoffs necessarily occur when moving from one non-dominated solution to another.

Babbar-Sebens et al. (2015) developed WRESTORE, an interactive evolutionary algorithm tool to search for preferred watershed conservation measures. The process follows a predetermined sequence of interactive "sessions" during which the user is presented with maps and quantitative indicators for different alternatives. During a session, the user either explores and learns from previously generated alternatives, is asked to rate the new alternatives with a psychometric scale (e.g. "good", "bad", etc.), or is supported by an automated search procedure which relieves the user from providing inputs by relying on deep learning models which mimic the user's preference model. In addition, the tool is web-based and aims to enable multiple users to explore alternatives and steer the search jointly. The visualization of the alternatives is done essentially by displaying decision variables on maps with colored layers and icons, and providing quantitative performance indicators via histogram charts. The authors concluded on the relevance of surrogate models to reduce latencies due to computational time. In their study, they report durations of around 10 minutes per solution using the current watershed model, and total experiment durations spanning over several hours or days. A follow-up work from Piemonti, Macuga, and Babbar-Sebens (2017), the authors studied the usability of the tool, and identified three main improvement points: (i) time dedicated to preference elicitation should be minimized to avoid user fatigue, (ii) the interface should facilitate the access and comparison of detailed information in areas of interest, and (iii) that the accumulated findings of the user should be recapitulated at the end of the process.

Stump et al. (2009) present a trade-space visualization (ATSV) tool, which aims to help designers explore the design space in search of preferred solution. This is an adaptation of the a posteriori exploration of a precalculated trade-space which Balling et al. (2000) first coined "design by shopping". This feature-rich tool proposes various multidimensional visualizations (scatterplots, parallel coordinates, 3D glyph plots) to explore the trade space and steer the search for new solutions. The visualization tool is coupled to a simulation model by means of an evolutionary algorithm, and the search is influenced by user inputs consisting in reference points or preference ranges. The tool provides a very flexible exploration of the design space, including infeasible and dominated solutions. While this allows a more exhaustive exploration, this necessarily is done at the expense of additional computation time, and therefore the approach is limited to computationally inexpensive simulation models, or dependent on intermediate calculation phases which rely on low-fidelity surrogate models to narrow the design space before initiating more intensive calculations.

3.1.3 Research gaps and objectives

A wide variety of preference types, procedures and interfaces for interactive methods emerge from the existing literature. However, in spite of the early efforts in developing effective search-based procedures, and the more recent efforts in making tools which enable user learning, there remains a slow progression of "application-oriented" methods which succeed in being adopted outside of academia (Gardiner and Vanderpooten, 1997). Four interconnected requirements, which remain only partially achieved in existing methods, can explain this gap (Fig. 3.2):

- First and foremost, methods must have the ability to handle many objectives, and produce many efficient alternatives reflecting the complexity of real-world problems. Xiao, Bennett, and Armstrong (2007, p. 235) noted that most interactive methods still rely on a relatively

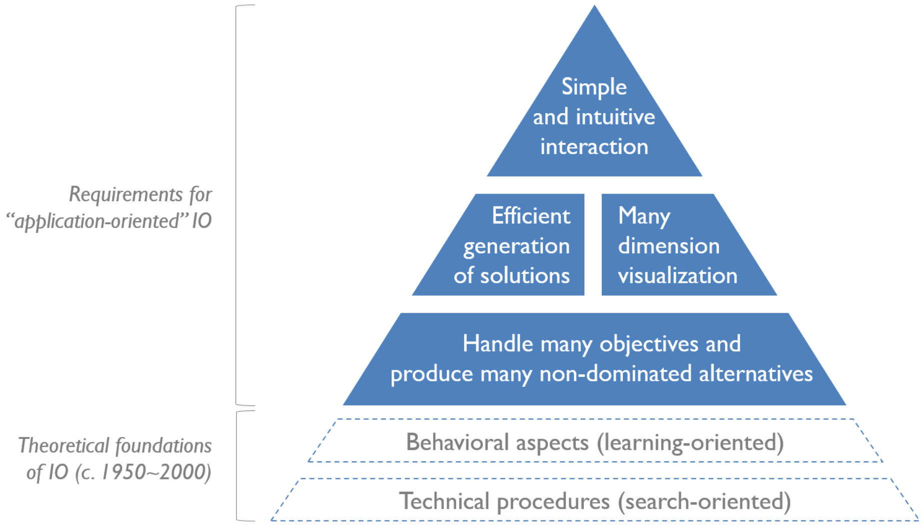


Figure 3.2 – Summary of requirements for interactive optimization.

limited number of solutions, possibly overlooking important Pareto optimal ones, while Allmendinger et al. (2016) found that they typically involve a limited number of objectives, rarely exceeding five. The notion of efficient, or Pareto optimal is also essential, because the goal is to focus the attention of decision makers on the most competitive solutions, and avoid wasting time on less interesting ones (Balling et al., 2000).

- The previous requirement leads to the need for methods which are capable of overcoming the associated computational burden. It is crucial that results are delivered promptly to reduce latency time for users, whose willingness to participate might otherwise be compromised (Branke et al., 2008; Miettinen et al., 2010; Collette and Siarry, 2004). This entails not only that individual solutions are rapidly calculated, but also that they efficiently provide a representative overview of the Pareto optimal front. So far, it appears the underlying trade-off with computational speed has been between either addressing only computationally inexpensive problems (or relying on low-fidelity approximations, e.g. (Stump et al., 2009)), or facing longer calculation times, possibly disrupting the search and learning experience (e.g. (Babbar-Sebens et al., 2015)).
- Visualization approaches for multiobjective optimization results are equally important, and have been extensively reviewed by Miettinen (2014), Packham et al. (2005), and Fieldsend (2016), clarifying the advantages and limits of the available options (scatterplot matrices, spider charts, Chernoff faces, glyphs...). Among these, parallel coordinates increasingly stand out among the most efficient approaches. They are known for their intuitive representations (Packham et al., 2005; Akle, Minel, and Yannou, 2016), as well as for occupying the least amount of space per criterion, making them highly scalable to many criteria (Fleming, Purshouse, and Lygoe, 2005). Despite these strengths, like other visualizations, parallel coordinates also suffer from a lack of readability when displaying many solutions, and the difficulty to view all pairwise relationships in a single chart. The development of interactive visualization methods such as the data-driven documents (D3) library has allowed to partly overcome these issues by filtering solutions and rearranging axes (Bostock, Ogievetsky, and Heer, 2011; Heinrich and Weiskopf, 2013). While Inselberg (1997) provided valuable guidelines in how to effectively interpret relationships in parallel coordinates, recent studies considered more closely the interpretation of Pareto optimal solutions (Li, Zhen, and Yao, 2017; Unal, Warn, and Simpson, 2017). Furthermore, the display of quantitative criteria

may not always suffice to take informed decision, and augmenting the traditional display of results with, for example, maps (Xiao, Bennett, and Armstrong, 2007), depictions of physical geometries (Stump et al., 2009), values of decision variables (Gardiner and Vanderpooten, 1997) or qualitative criteria (Cohon, 1978) is advised.

- Finally, a simple and intuitive interface is necessary to top the aforementioned requirements. The user must be able to not only easily understand the results, but also steer the process with minimal effort. However, the use of complex jargon, and difficult inputs are still considered barriers against a wider adoption of interactive methods in practice (Cohon, 1978; Wolf, Simpson, and Zhang, 2009; Akle, Minel, and Yannou, 2016). Meignan et al. (2015), Allmendinger et al. (2016) and Branke et al. (2008, p. 52) all conclude their reviews with a call for improvements in the development of user-friendly interfaces and methods.

While the methods reviewed above address one or several of these requirements, none addresses them all simultaneously. The objective of this chapter is thus to introduce a new interactive optimization methodology addressing the requirements in Figure 3.2. Its applicability to urban planning problems is demonstrated in Chapters 5 and 6.

3.2 Description of the SAGESSE methodology

SAGESSE – for *Systematic Analysis, Generation, Exploration, Steering and Synthesis Experience* – is an interactive optimization methodology designed to address the requirements summarized in Fig. 3.2. It differs from most traditional sequential or alternating paradigms found in interactive optimization, as the steps of *generation*, *exploration* and *steering* blend together to form a single, continuous, interactive search process capable of tackling large problems (Fig. 3.3). This is made possible by combining in particular three main elements: (i) parallel coordinates as a means to simultaneously explore and steer the underlying alternative generation process, (ii) deterministic optimization methods coupled with a quasi-random sampling method to efficiently capture large solution spaces, and (iii) on-the-fly application of multiattribute decision analysis, cluster analysis and the physical representation of Pareto optimal solutions to support decisions. Preceding the interactive search, an *analysis* phase is performed by the user and the analyst to translate the constituents of the real-world problem into an optimization model (decision variables, objectives, constraints). Following the interactive search, the methodology provides a way to *synthesize* the gained knowledge by extracting the subset of most preferred solutions and key criteria. Overall, SAGESSE consists in an *experience*: a practical contact with facts, which leaves an impression on its user (Oxford, 2018). This means the user doesn't merely obtain a final solution suggested by the model, but rather acquires the knowledge and confidence of why certain solutions are preferable to them. As noted by French (1984), "a good decision aid should help the decision maker explore not just the problem, but also himself". Finally, the confidence is reinforced by the *systematic* nature of the methodology, exploring the solution space with an optimization model and rigorous sampling technique, and reducing the chances of missing a better alternative.

3.2.1 Overview of workflow

Figure 3.4 describes the general workflow of the methodology, which consists of six main steps. While in principle steps 1 to 5 all occur simultaneously (i.e. generation, exploration and steering tasks happen at the same time), their methodological aspects are explained hereafter sequentially.

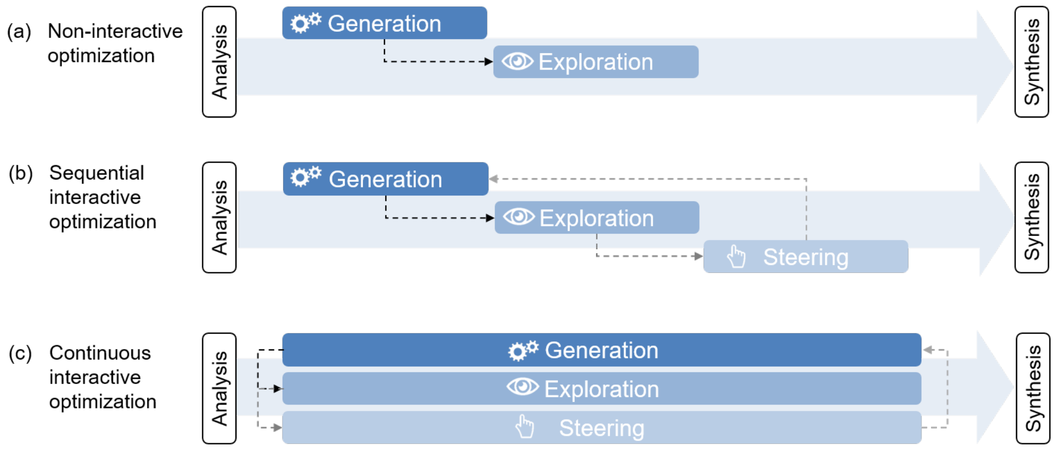


Figure 3.3 – Novel paradigm for interactive multiobjective optimization, where generation, exploration and steering are performed continuously instead of sequentially.

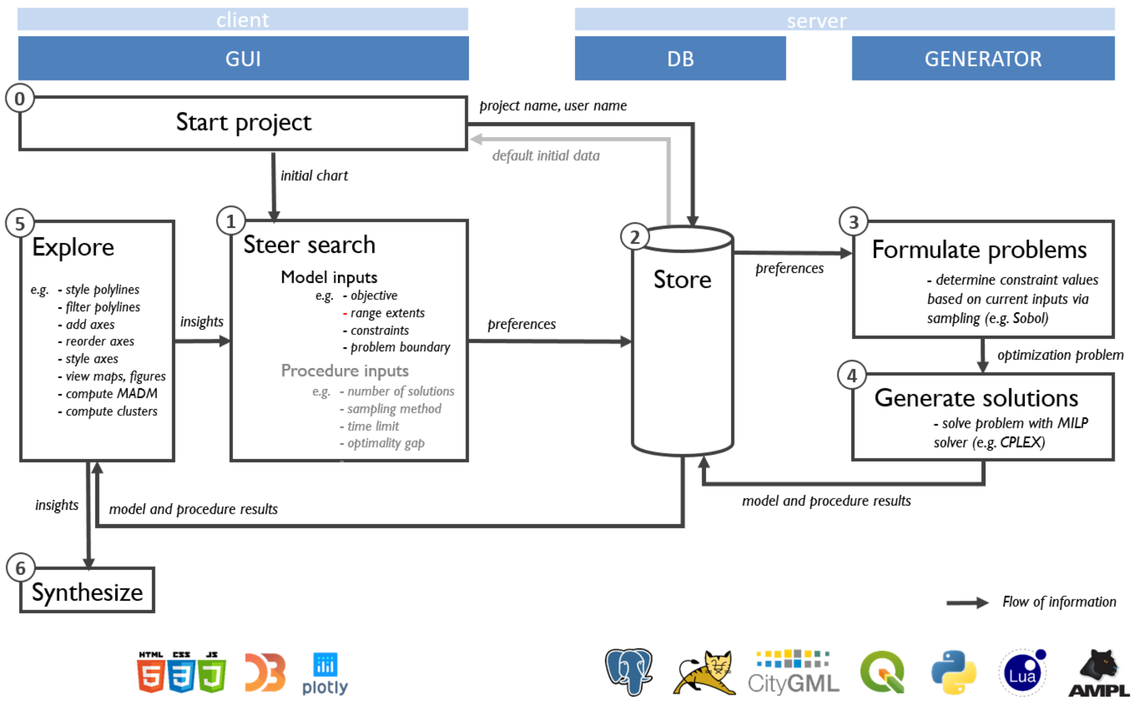


Figure 3.4 – Overview of components, workflow and main software involved in the interactive optimization methodology and case-study. Gray text indicates optional tasks.

3.2.2 Starting a project

When accessing the interface, the user can either start a new project, or reload an existing one. For a new project, by default an empty parallel coordinates chart with preselected criteria is displayed. An advantage of starting from an empty chart is that it attenuates the risk of anchoring bias, which may cause the user to fixate too soon on possibly irrelevant starting solutions, at the expense of exploring a wider variety of solutions (Meignan et al., 2015; Miettinen et al., 2010). Figure 3.5 shows the main components of the GUI, namely the parallel coordinates chart, and the tabs from which the user can perform and control the main SAGESSE actions.

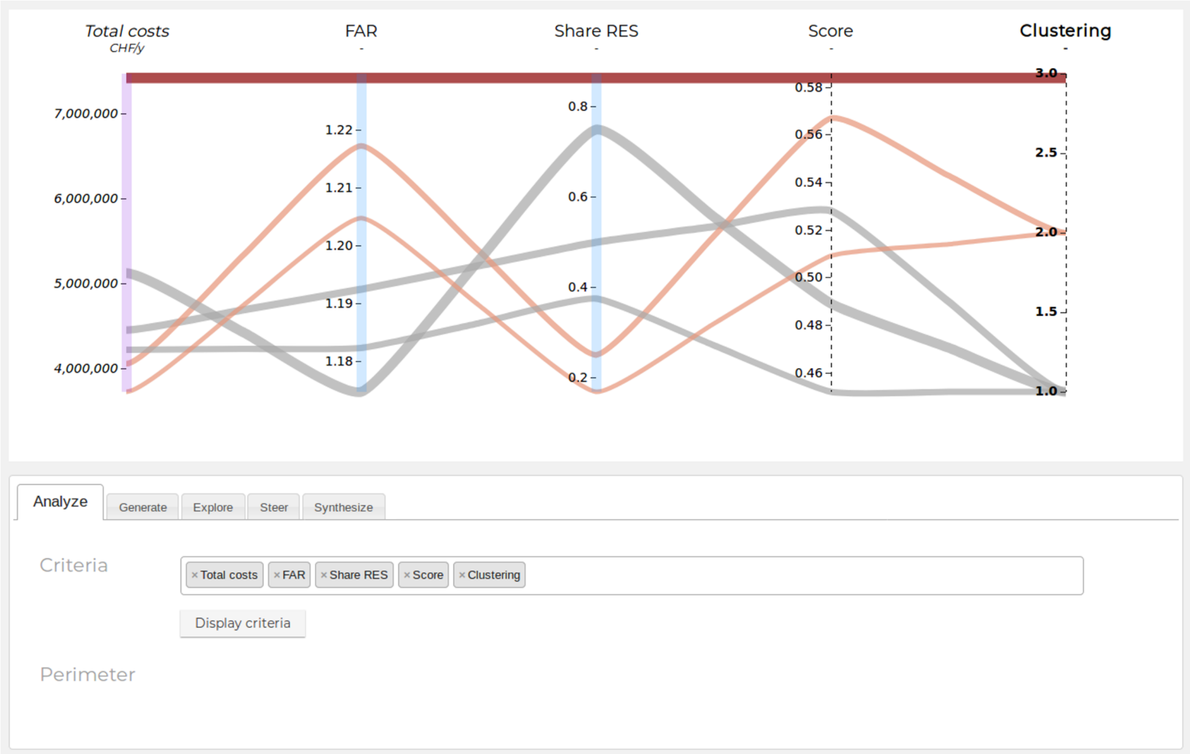


Figure 3.5 – Snapshot of the graphical user interface demonstrating several features of the SAGESSE methodology, including axis and polyline styling, multiattribute and cluster analysis results, and the axis selection menu. Line color indicates the belonging of a line to one of the three clusters (bold axis label), while line size is proportional to total costs (italic axis label).

3.2.3 Steering the search

The user can influence the optimization search in two ways: by providing inputs which influence either the optimization model, or the optimization procedure (Figure 3.4, Step 1). All user inputs are stored in the database, where the generator components can access them for further processing. These inputs, as well as various visual aids, constitute the available steering features, described hereafter and summarized in Table 3.1.

Optimization model inputs

The user specifies their preferences directly on the parallel coordinates chart which is used to display the solutions. This is done by brushing the axes to be optimized or constrained (Martin and Ward, 1995). There are three associated steering actions performed in Step 1, which will characterize the axes and the role they play in the the optimization procedure in Steps 3 and 4 (Figure 3.4).

- The first action consists in defining the main *objective* in the ε-constraint (epsilon-constraint) formulation described in Section 3.2.5. Exactly one objective is specified for any new problem to be formulated. This is done by brushing the axis with the "objective" brush (colored in purple). For this action, the numeric values of the brush boundaries do not matter.
- The second action consists in marking one or several axes as *single constraint* so that they achieve a specified value. A red brush is used for this action, and either the upper or lower bound of the brush defines the value to achieve, depending on the preferred direction of the

Table 3.1 – Steering features.

Feature	Variant	Purpose
Model inputs	– Objective – Sampling range – Single constraint – Preferred direction	Steer the search towards relevant areas of the solution space
Procedure inputs	– Sampling method – Number of solutions – Optimality gap limit – Solver time limit – Problem boundary	Control quality, scope and duration of calculations
Steering aids	– Authorized actions for model inputs (pointer shapes, axis style) – Recommendations for procedure inputs (tooltips) – Color-coded axes by former actions applied	Guide the user towards feasible and meaningful actions

criterion (see below).

- The third action allows to systematically vary the parametrized right-hand side of constraints within the boundaries of a brushed *range* (in blue). The numeric values for these parametrized constraints are automatically determined by the chosen sampling method (cf. Section 3.2.5), based on the requested number of solutions. While specifying single constraints denotes a "satisficing" (satisfy + suffice) behavior, which might arise if the user is certain that there is no tangible gain in achieving a value better then the specified one (Branke et al., 2008, p. 8), specifying ranges allows instead the optimization of multiple objectives (see Section 3.2.5).

Finally, for any criterion marked as either of the above actions, its preferred direction can be specified. For example, a cost criterion's preference will be "less", indicating that less of that criterion is preferred to more. A benefit criterion will be "more", as more is preferred to less. Practically, "less" results in *minimization* for criteria brushed as objectives, and in *upper* constraints for criteria brushed as ranges or constraints. Conversely, "more" results in *maximization* for objectives, and *lower* constraints for ranges or constraints. Typically, default preferences are known and already included during the analysis phase for each criterion, however they can be edited by the user during the search phase, e.g. to test extreme cases.

Optimization procedure inputs

The first type of input regarding the optimization procedure are the stopping criteria for the solver, i.e. a solving time limit, and an optimality gap limit. The optimality gap is a useful feature specific to deterministic global optimization, which allows to produce solutions "that differ from the optimum by no more than a prescribed amount" (Lawler and Wood, 1966). Thus, a user can decide *a priori* if they would be willing to accept a solution differing by no more than e.g. 5% from the theoretical optimum, in exchange for reduced computational time. Setting looser limits, i.e. lower time or larger optimality gap limits, leads to solutions being returned earlier by the solver, but being potentially further away from the global optimum. While the first is always desirable, the latter might be acceptable in case a close approximation of the optimum solution may suffice. However it is very important to not set these limits too loosely, as solutions too far from the optimum can lead to false interpretations. It is worth emphasizing also that because the calculations are continuously performed while the user explores existing solutions, a “waiting time” of up to two minutes seems acceptable. Indeed, given the user is likely occupied interpreting the already calculated alternatives across the many criteria available, they are therefore most likely not completely idle.

A second input is the sampling method to be employed within the specified ranges, and an associated number of solutions to be sampled (see Section 3.2.5). A third input consists in the desired scope or boundary of the problem. For example, in the case of urban planning, the geographic perimeter to be considered in the problem can be increased or reduced.

While in principle these inputs could also be made directly via the parallel coordinates, they are specified here with buttons, forms and drop down menus. Except for the problem boundary, it should be noted that these inputs are typically predefined by the analyst, and do not require particular understanding from the user. They are rather intended for more experienced users and modelers.

Steering assistance

Given the different types of content that can be displayed on the axes of the parallel coordinates chart, their typology and permitted steering actions must be clearly and intuitively conveyed to the user. The use of colored brushes, different axis styles and textual tooltips are used for this purpose. The axes can display two main types of information:

i. Methodology-specific information is displayed on axes drawn as vertical dashed lines (Figure 3.5) to visually distinguish them from context-specific ones. They contain metadata related to the optimization procedure (e.g. iteration number, achieved optimality gap by the solver, etc.), or calculated by the user in the exploration step (e.g. clustering results or aggregated score, see Section 3.2.7).
ii. Context-specific information generated by the optimization model is displayed on axes with a continuous line style (Figure 3.5). As such, they can represent an objective function, a constraint, a decision variable, a model parameter or a post-computed criterion (i.e. which is calculated after all decision variables have been determined). Functions expressed as a non-linear combination of decision variables can generally not be optimized with linear solvers, and, depending on the respective formulation, can also not be constrained. They are thus restricted to being post-computed. Axes containing linear functions, model parameters or decision variables can also be brushed (i) as single equality constraints to fix their values, (ii) as ranges in which the right-hand side of the constraints are systematically varied, or (iii) as objectives. To guide the user in the steering process, adapted mouse pointers inform them whether or not an action is allowed on any hovered axis. Furthermore, tooltips briefly explain any forbidden action, and, if possible, how to proceed to achieve an equivalent outcome (for example by specifying a range for a criterion, whose underlying objective function implies a non-linear combination of decision variables, but which can be transformed into a linear constraint).

Another feature to assist the user in steering consists in highlighting the axes which played an active role in the optimization problem (Figure 3.5). This information is specific to each solution, as the role of an axis is not unique and can change as the search progresses. Thus, when hovering over a polyline, the axes which acted as objective, range or constraint in the generation of that solution are temporarily colored with the respective colors (purple, blue and red). For example, this helps the user identify criteria which can potentially be further improved because they were so far only post-computed, and those which could be relaxed for the improvement of others.

3.2.4 Storing data

A relational database is used to store both the data provided by the user in the interface (e.g. project details, raw steering preferences), and the data produced by the solution generator engine (e.g. problem formulations, solution results and related metadata). The data model for interactive optimization which was developed for the present methodology is described in Schüler et al. (2018a)

3.2.5 Formulating problems

Once the user has specified the desired criteria to optimize (i.e. using objective and range brushes in Step 1), the goal is to solve the following generic multiobjective optimization problem, assuming without loss of generality all minimizing objectives (Collette and Siarry, 2004):

$$\begin{aligned} \min_{\boldsymbol{x}} \quad & \boldsymbol{f}(\boldsymbol{x}) \\ \text{subject to} \quad & \boldsymbol{g}(\boldsymbol{x}) \leq 0 \\ & \boldsymbol{h}(\boldsymbol{x}) = 0 \end{aligned} \tag{3.1}$$

where the vector $\boldsymbol{f}(\boldsymbol{x}) \in \mathbb{R}^k$ contains the k objective functions to minimize, $\boldsymbol{g}(\boldsymbol{x}) \in \mathbb{R}^q$ are the inequality constraints, $\boldsymbol{h}(\boldsymbol{x}) \in \mathbb{R}^r$ are the equality constraints, and $\boldsymbol{x} \in \mathbb{R}^d$ are the d decision variables in the feasible region $S \subset \mathbb{R}^d$, whose values are to be determined by the optimization procedure.

In order to benefit from widely available and efficient optimization algorithms such as the simplex or branch-and-bound algorithms (Lawler and Wood, 1966), a scalarization function is applied to transform the multiobjective optimization problem in Eq. (3.1) into N parametrized single-objective optimization problems which will each return a Pareto optimal solution to the original multiobjective problem. By varying the parameters of the scalarized function, different solutions from the Pareto front can be produced. Thus, to generate the points on a Pareto front what is needed is (i) an appropriate scalarization function, and (ii) a systematic approach to vary the parameters (Laumanns, Thiele, and Zitzler, 2006). The requirements for both of these aspects in the context of interactive optimization are discussed next.

Adopted scalarization function

Scalarization functions have three key requirements in the context of interactive methods (Branke et al., 2008): (i) capability of generating the entire Pareto front, (ii) reliance on intuitive input information which accurately reflect the user's preferences, and (iii) ability to quickly provide an overview of different areas on the Pareto front. Two of the most common and intuitive scalarization techniques are the weighted sum (WSM) and the ε-constraint methods (Mavrotas, 2009; Oberdieck and Pistikopoulos, 2016). While both are able to generate Pareto optimal solutions, the WSM only partially meets the above requirements. In the WSM, a new unique objective function is created, which consists of the weighted sum of all original k objective functions (Collette and Siarry, 2004,

p. 45):

$$\begin{aligned} \min_{\boldsymbol{x}} \quad & \sum_{i=1}^{k} w_{n,i} \cdot f_i(\boldsymbol{x}), \qquad w_{n,i} \geq 0, \\ \text{subject to} \quad & \boldsymbol{g}(\boldsymbol{x}) \leq 0 \\ & \boldsymbol{h}(\boldsymbol{x}) = 0 \end{aligned} \tag{3.2}$$

where $\sum_{i=1}^{k} w_{n,i} = 1$; $n = 1,...,N$, and N is the number of unique combinations of the parameters $w_{n,i}$ leading to Pareto optimal solutions. A first limitation of the WSM is that if the Pareto front is non-convex, the scalar function is not be capable to generate solutions in that area (Wierzbicki, 2010; Mavrotas, 2009; Branke et al., 2008). Second, the WSM is biased towards extreme solutions, instead of more balance between the objectives (Wierzbicki, 2010; Branke et al., 2008). Third, the specification of weights as inputs can have other counterintuitive and error-prone consequences on objectives, and thus be more frustrating to use for controlling the search (Branke et al., 2008; Wierzbicki, 2010; Tanner, 1991; Cohon, 1978; Larichev, Polyakov, and Nikiforov, 1987; Laumanns, Thiele, and Zitzler, 2006). For example, Wierzbicki (2010, p. 45) illustrates how in a three objective problem where each objective has an equal weight of 0.33, the attempt to strongly increase the first objective, slightly increase the second, and allow to reduce the third, will not be reflected accordingly in the change of weights. Indeed, in the proposed example, modifying the weights to 0.55, 0.35 and 0.1 respectively for each objective in fact only leads to an increase of the first objective, while both others are decreased. The larger the number of objectives, the greater such issues are expected to occur, and thus the more difficult it becomes for the user to determine weights which accurately reflect their preferences. Finally, the weighted sum also requires some form of normalization of incommensurable criteria towards comparable magnitudes, which can also influence the results and requires to specify upper and lower bounds *a priori* (Mavrotas, 2009).

In the ε-constraint method, introduced by Haimes, Lasdon, and Wismer (1971), instead of optimizing all k objectives simultaneously, only one is optimized, while the other objectives are subjected to parametrized inequality constraints:

$$\begin{aligned} \min_{\boldsymbol{x}} \quad & f_l(\boldsymbol{x}) \\ \text{subject to} \quad & f_j(\boldsymbol{x}) \leq \varepsilon_{n,j}, \qquad j = 1,...,k, \quad j \neq l, \\ & \boldsymbol{g}(\boldsymbol{x}) \leq 0, \\ & \boldsymbol{h}(\boldsymbol{x}) = 0 \end{aligned} \tag{3.3}$$

where $l \in 1,...,k$; $n = 1,...N$, and N is the total number of points calculated in the Pareto front, and where $\varepsilon_{n,j}$ are parameters representing the upper bounds for the auxiliary objectives $j \neq l$. In the original method, N_j unique upper bounds for each objective are determined within a range of interest $[\varepsilon_j^{min}, \varepsilon_j^{max}]$, by incrementing ε_j^{min} by a fixed value $\Delta\varepsilon_j = \frac{\varepsilon_j^{max} - \varepsilon_j^{min}}{N_j - 1}$. The minimum and maximum bounds can either rely on the expertise of the DM, or be computed by minimizing and maximizing each objective individually. The problem is solved for each unique combination of $\varepsilon_{n,j}$, i.e. for a total of N combinations, where $N = \prod_{j=1}^{k-1} N_j$ (Chankong and Haimes, 2008, p. 285) (Figure 3.6A). Conceptually, the ε-constraint method can be understood as the specification of a virtual grid in the objective space, and solving the single-objective optimization problem for each of the N grid points (Laumanns, Thiele, and Zitzler, 2006). The main advantages of the

ε-constraint method over the weighted-sum method are that: (i) it can handle both convex and non-convex Pareto fronts (avoiding the need to evaluate the convexity of the solution space), (ii) the specification of bounds is a more intuitive and less misleading concept than setting weights (Wierzbicki, 2010; Kok, 1986; Cohon, 1978), and (iii) the variation of constraints leads to a richer and less redundant set of solutions (Mavrotas, 2009; Branke et al., 2008). For these reasons, the ε-constraint is adopted in the present interactive optimization methodology.

However, the original ε-constraint method in Eq. (3.3) can be reformulated as a multiparametric optimization problem (Pistikopoulos, Georgiadis, and Dua, 2007), in which not only the upper bounds $\varepsilon_{n,j}$ of the auxiliary objectives are varied, but also any other model parameter θ_t in the vector $\boldsymbol{\theta} \in \mathbb{R}^m$. Thus, assuming without loss of generality all minimizing functions, the n^{th} problem being solved can be written as:

$$\begin{aligned}
\min_{\boldsymbol{x}} \quad & f_l(\boldsymbol{x},\boldsymbol{\theta}) \\
\text{subject to} \quad & f_j(\boldsymbol{x},\boldsymbol{\theta}) \leq \varepsilon_{n,j}, \qquad j = 1,...,k, \quad j \neq l, \\
& \theta_t = \varepsilon_{n,t}, \qquad t = 1,...,u, \quad u \leq m, \\
& \boldsymbol{g}(\boldsymbol{x},\boldsymbol{\theta}) \leq 0, \\
& \boldsymbol{h}(\boldsymbol{x},\boldsymbol{\theta}) = 0,
\end{aligned} \tag{3.4}$$

where $n = 1,...N$, and N is the total number of points calculated in the Pareto front. For simplicity, all parameters to be varied by a sampling scheme (regardless of whether they refer to a function f_j or to a model parameter θ_t) are referred to as $\varepsilon_{n,p}$, where $p = 1,...,P$, and where, by definition, $P = k - 1 + u$ is the total number of varied parameters. Thus, let E the matrix of all sampled parameters in Eq. (3.4), which contains in each row the sampled parameters of the n^{th} problem being sent from the client to the optimization procedure:

$$E_{N\times P} = \left(\varepsilon_{n,p}\right) = \begin{pmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & \cdots & \varepsilon_{1,P} \\ \varepsilon_{2,1} & \varepsilon_{2,2} & & \varepsilon_{2,P} \\ \vdots & & \ddots & \vdots \\ \varepsilon_{N,1} & \varepsilon_{N,2} & \cdots & \varepsilon_{N,P} \end{pmatrix}, \quad \varepsilon_p^{min} \leq \varepsilon_{n,p} \leq \varepsilon_p^{max} \tag{3.5}$$

Referring to the steering actions performed by the user and defined in Section 3.2.3, the brushed *objective* here corresponds to f_l in Eq. (3.4), while the lower and upper bounds of brushed *ranges* correspond to the lower and upper bounds of the range of interest $[\varepsilon_p^{min}, \varepsilon_p^{max}]$ in Eq. (3.5). It is worth noting here that for the particular case where $f_j(\boldsymbol{x},\boldsymbol{\theta}) = x_d$, the user can also control and vary individual decision variables directly. Finally, *single constraints* do not require sampling, and are thus handled separately: when brushed on an axis representing a function, a single parameter is fixed as equal to the upper value of the brush (or to the lower value of the brush for a maximizing function). Furthermore, as, from a modeling perspective, parameters do not possess any "preferred direction", in case a single constraint brush is employed to fix their value, the lower bound of the brush is considered by default.

Despite the advantages of the ε-constraint method, Chankong and Haimes (2008, p. 285) noted that it can be inefficient when perturbating the values of the $\varepsilon_{n,p}$ bounds in the incremental fashion described above. As such, and especially when many dimensions are involved, the generation of solutions using the ε-constraint method can be time-consuming and uneven across the objective space when interrupted prematurely, leading to a poor representation of the Pareto front (Collette and Siarry, 2004; Chankong and Haimes, 2008; Copado-Méndez et al., 2016). This lack of efficiency is particularly problematic in interactive methods, as the user should be presented with an overview of the Pareto optimal solutions as fast as possible in order to know which areas lead to preferred alternatives. The use of sampling techniques to facilitate and improve the determination of $\varepsilon_{n,p}$ in Eq. (3.4) is discussed next.

Adopted sampling method

Several studies have investigated ways to improve the determination of parameters in the ε-constraint method. For example, Chircop and Zammit-Mangion (2013) proposed an original algorithm to explore two dimensional problems more efficiently and evenly with the ε-constraint method, avoiding sparse Pareto fronts. However, their procedure is restricted to bi-objective problems. The use of various sampling techniques has also been studied as a means to efficiently explore a space with a minimum amount of points. Burhenne, Jacob, and Henze (2011) compared various sampling techniques and found that the Sobol sequence (Sobol, 1967) leads to a more efficient and robust exploration of parameter spaces, and is thus recommended when sample sizes must be limited due to time or computational limitations. A Sobol sequence is a quasi-random sampling technique designed to progressively generate points as uniformly as possible in a unit hypercube (Figure 3.6A) (Burhenne, Jacob, and Henze, 2011; Press and Teukolsky, 1989). Closely related to the present approach, Copado-Méndez et al. (2016) tested the use of pseudo- and quasi-random sequences to allow the ε-constraint method to handle many objectives more efficiently. They obtained better quality and faster representations of Pareto optimal solutions using a combination of Sobol sequences and objective reduction techniques, compared to the standard ε-constraint method and other random sequences. Franken (2009) also uses a Sobol sequence approach for the exploration of promising input parameters for particle swarm optimization in parallel coordinates. However, the adoption of quasi-random sequences for real-time benefits in interactive optimization has not been tried. This approach–rather than a regular systematic sampling typically adopted in the ε-constraint method –is particularly relevant when dealing with interactive methods, as the order with which the solutions are explored is critical when the user's time is limited. Furthermore, the Sobol sequence greatly removes a burden from the user, who must only specify loose ranges of approximate preference or interest, and the sequence automatically takes care of determining the constraints in the next most efficient location of the solution space. In SAGESSE, the quasi-random Sobol sampling method (Sobol, 1967) is therefore adopted and can be selected to vary the parameters in Eq. (3.5), ensuring a quick and efficient exploration of the entire space with a minimum amount of solutions (Figure 3.6B).

With the Sobol sampling approach, the user specifies a number of solutions N, and the corresponding parameters in E are computed as:

$$\varepsilon_{n,p} = \varepsilon_p^{min} + s_{n,p} \cdot (\varepsilon_p^{max} - \varepsilon_p^{min}), \qquad n = 1, ..., N, \quad p = 1, ..., P, \tag{3.6}$$

where $s_{n,p}$ is an element in the matrix $S_{N\times P}$, whose rows contain the Sobol sequence of N coordinates in a P-dimensional unit hypercube. Various computer-based Sobol sequence generators have been developed and implemented to compute the elements of $S_{N\times P}$. Here, a Python implementation based on Bratley and Fox (1988) was used, allowing the generation of sequences including up to 40 dimensions (naught101, 2018). Other generators could increase this number, e.g. allowing sequences for up to 1111 dimensions (Joe and Kuo, 2003). As illustration, the numeric values sampled with the Sobol approach for $N = 5$ points and $P = 3$ parameters in ranges $[0, 1]$ are provided in E^{sob}, Eq. (3.7). This choice of range further implies that in this example, the coordinates of the parameters are in fact identical to those of the Sobol sequence in a unit hypercube:

$$E^{sob}_{5\times3} = S_{5\times3} = \begin{pmatrix} 0.5 & 0.5 & 0.5 \\ 0.75 & 0.25 & 0.75 \\ 0.75 & 0.25 & 0.25 \\ 0.375 & 0.375 & 0.625 \\ 0.875 & 0.875 & 0.125 \end{pmatrix} \tag{3.7}$$

Alternatively, a standard systematic sampling method can also be used (Gilbert, 1987), which can in some cases be preferred to the Sobol sampling method. With systematic sampling, the space is systematically explored by dividing the sampled dimensions into regular intervals. An important drawback from this sampling method is that it can lead to misleading or biased insights if the sampled solution space contains “unsuspected periodicities” (Gilbert, 1987). In addition, it is less convenient for real time optimization because of its slower progression throughout the solution space (Figure 3.6A). Nevertheless, this sampling technique can provide more control to the user than the Sobol approach. For example, it can be used to perform a systematic sensitivity analysis on the parameters in Eq. (3.4), by systematically combining specific values on different axes. Unlike for the Sobol sequence, in this approach, the total number of sampled points is given implicitly by $N = \prod_{p=1}^{P} N_p$, where N_p is the number of requested points in the range of interest $[\varepsilon_p^{min}, \varepsilon_p^{max}]$ of each dimension.

Therefore, each dimension thus contains N_p unique values to sample, computed as:

$$\varepsilon_{n',p} = \varepsilon_p^{min} + (n'-1)\cdot\Delta\varepsilon_p, \qquad n' = 1,...,N_p \tag{3.8}$$

where $\Delta\varepsilon_p = \frac{\varepsilon_p^{max}-\varepsilon_p^{min}}{N_p-1}$ is the increment between each $\varepsilon_{n\prime,p}$. The corresponding matrix E^{sys} resulting from systematic sampling is then populated by combining all parameter values in the following order:

$$E^{sys}_{N\times P} = \begin{pmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & \dots & \varepsilon_{1,P} \\ \varepsilon_{1,1} & \varepsilon_{1,2} & & \varepsilon_{2,P} \\ \vdots & & \ddots & \vdots \\ \varepsilon_{1,1} & \varepsilon_{1,2} & \dots & \varepsilon_{N_P,P} \\ \varepsilon_{1,1} & \varepsilon_{2,2} & & \varepsilon_{1,P} \\ \vdots & & \ddots & \vdots \\ \varepsilon_{N_1,1} & \varepsilon_{N_2,2} & \dots & \varepsilon_{N_P,P} \end{pmatrix} \tag{3.9}$$

As an example, for three dimensions sampled with systematic sampling between $[0,1]$ and for

$N_1 = 3$, $N_2 = 2$, $N_3 = 2$, the resulting matrix of varied parameters is:

$$E^{sys}_{12\times 3} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 1 \\ 0.5 & 0 & 0 \\ 0.5 & 0 & 1 \\ 0.5 & 1 & 0 \\ 0.5 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix} \tag{3.10}$$

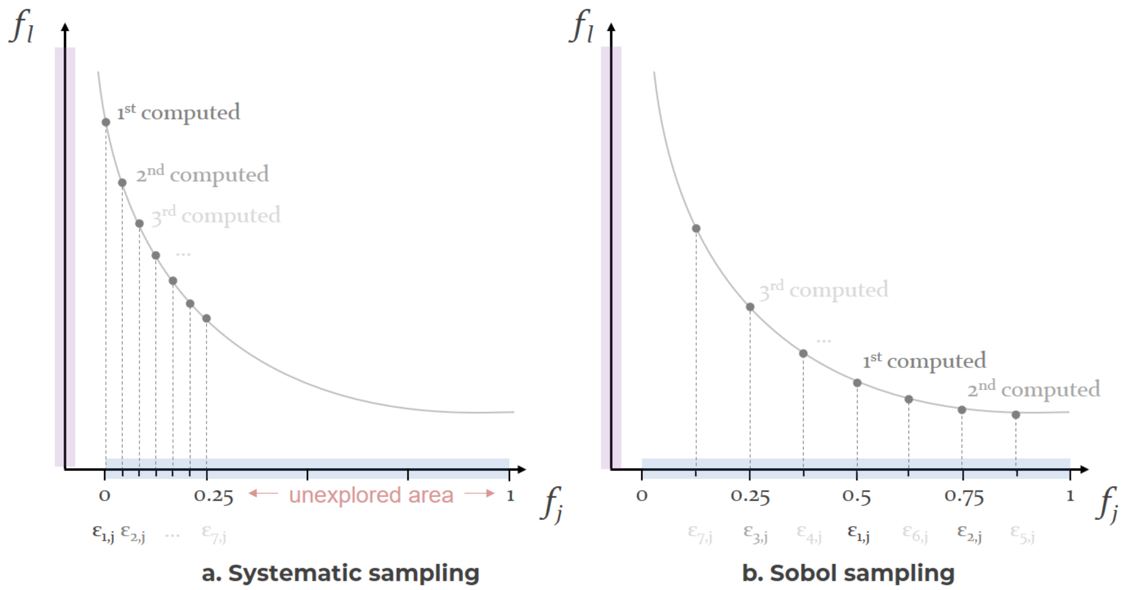


Figure 3.6 – Schematic comparison of (a) systematic and (b) Sobol sampling for specifying constraints in an ε-constraint problem minimizing two objectives: state after 7 computed samples of a total of 25 requested points. Purple: main ε-constraint objective f_l. Blue: arbitrary range of interest in the auxiliary objective f_j, in which the upper bounds $\varepsilon_{r,j}$ are automatically allocated by the sampling method (note: the ticks indicate the relative position of the constraints for a normalized range, and the subscripts r indicate the order in which each upper bound is used by the solver).

3.2.6 Generating solutions

In this step, the single-objective optimization problems formulated based on Eq. (3.4) are solved. In particular, the solver receives from the client the main objective to optimize, as well as the values for all specified parameters contained in $E_{N\times P}$. As long as the user has not specified new objectives on the parallel coordinates chart, the generation process continues to add solutions in the current ranges, taking as inputs the rows of $E_{N\times P}$ one after another. As soon as a change in objectives occurs, the solver interrupts the current sampling sequence and starts again with the newly provided objective and $E_{N\times P}$.

3.2.7 Exploring solutions

The purpose of exploration is for the user to learn about tradeoffs and synergies between the solutions, and develop their confidence in what qualifies a good solution. The interface should offer a positive and intuitive experience, respecting the information-seeking mantra "overview, filter, details on demand" (Shneiderman, 1996). Parallel coordinates provide a basis for this mantra (Heinrich and Weiskopf, 2013), allowing the user to develop a feeling for achievable values in competing objectives, and understand the reasons preventing the achievement of goals. The available functionalities supporting exploration are summarized in Table 3.2 and described below, organized according to their main purpose (i.e. overview, filter or details).

Overview of relationships between criteria

The parallel coordinates reveal tradeoffs (or negative correlations) between two axes as crossing lines, and synergies (or positive correlations) non-crossing lines (Inselberg, 1997; Li, Zhen, and Yao, 2017). Because the chart can only show such patterns for pairs of adjacent axes, two approaches are available to explore more relationships. First, the implementation of the chart (which relies on the data driven documents (D3) library (Bostock, Ogievetsky, and Heer, 2011; Chang, 2012)) allows to dynamically drag-and-drop axes in various positions, making it possible to quickly investigate specific pairs on demand. Second, different visual encodings for the polylines can be used to emphasize various aspects of the data (Cleveland and McGill, 1985). In addition to their vertical position along each axis, properties such as color, width, line style, transparency, animation etc. can be mapped to polylines to reflect the values of a criterion. Here, color and width are used to reveal the relationships between the criterion being mapped with respect to all other axes. This allows for example to highlight high (respectively low) performing solutions, as well as clusters of solutions on any given axis. Different coloring schemes include linear bi- or multi-color gradients (each color shade indicates increasing values), Z-score gradient (indicating the deviation from the mean value) and categorical (assigning a unique color to each value). The line width property can be assigned to an other criterion, so that high polylines with high values are thicker than those with low values. Another way to improve readability and identify patterns and clusters is by using curves instead of lines. The user can adjust the intensity of the curvature of polylines in order to balance the readability of correlations (most readable with straight lines), and of overlapping lines and clusters (most readable with curves) (Heinrich and Weiskopf, 2013).

Filtering solutions and criteria

The user can filter the polylines to display only those of interest by "brushing" the desired axes (Bandaru, Ng, and Deb, 2017b; Heinrich and Weiskopf, 2013). The ability to display only the solutions which satisfy desired values on the different axes is a common response to the problem of cluttering, which causes parallel coordinates to become unreadable when too many lines are present (Li, Zhen, and Yao, 2017; Johansson and Forsell, 2016). Various brushing options are available (Heinrich and Weiskopf, 2013), including a normal one-dimensional brush (defining upper and lower bounds on an axis), multiple one-dimensional brushes (to select several distinct portions on an axis), an angular brush (to filter solutions according to their slope (i.e. correlation) between two axes, or two-dimensional brushes which allows the selection of solutions based on their path between two axes. Additional information can be computed for the brushed subset of polylines, such as clustering or multiattribute decision analysis. Related to brushing is the action of hovering a polyline with the pointer, which highlights it across the chart, and displays additional information (e.g. its exact numeric values for the different visible axes, information not currently displayed on the axes, or information regarding how the polyline was generated, cf. Section 3.2.3). Hovering is also a way to access information in linked views, such as a graphical representation of the solution.

Table 3.2 – Adopted exploration features related to the parallel coordinates interface, classified by type (O: overview, F: filter, D: details on demand).

Feature	Variant	Type	Purpose	Reference
Polyline color	Single color, Linear gradient, Z-score, Categorical colors	O	Identify patterns and clusters across axes	(Heinrich and Weiskopf, 2013; Shneiderman, 1996)
Polyline width	Customizable scale	O	Identify patterns and clusters across axes	-
Polyline curve	Customizable curve intensity	O	Identify patterns and clusters across axes Avoid ambiguities	(Palmas et al., 2014; Franken, 2009; Heinrich and Weiskopf, 2013)
Axis choice and ordering	Drag-and-drop, Drop-down menu	O, F	Identify patterns and clusters across axes, Avoid redundancy	(Zhen et al., 2017; Jaszkiewicz and Słowiński, 1999)
Clustering	k-medoids	O, F	Focus attention on few distinct and representative solutions, group similar solutions together	(Kaufman and Rousseeuw, 2009; Aguirre and Taboada, 2011; Mokhtar et al., 2017; Xiao, Bennett, and Armstrong, 2007)
Brushing	1D, 2D, angular, etc.	F	Avoid cluttering, Provide additional information related to brushed polylines	(Packham et al., 2005; Mokhtar et al., 2017; Shneiderman, 1996; Heinrich and Weiskopf, 2013)
Hovering	-	F/D	Avoid cluttering, Provide additional information related to hovered polyline	-
Multiattribute decision analysis	TOPSIS	F/D	Provide aggregated score and ranking to facilitate interpretation of MODA results	(Hwang and Yoon, 1981; García-Cascales and Lamata, 2012)
Linked views	3D scatter plots, 2D scatter plot matrices Maps	D	Overcome and complement visual limitations of parallel coordinates, Avoid visual overload	(Xiao, Bennett, and Armstrong, 2007; Buja et al., 1991)

Another way to filter the displayed information concerns the visible axes representing the criteria. While parallel coordinates scale well to large numbers of criteria (Inselberg, 2009), in practice, working simultaneously with up to "seven plus or minus two" axes is advised to account for the user's cognitive ability (Miller, 1956). French (1984) argue that in the case of multicriteria decision analysis, this number may already be too large for simultaneous consideration. Because the relative importance of criteria in the decision process is not necessarily known in advance, and might change as new knowledge is discovered, the user must be able to access and dismiss axes in real-time. For this purpose, a drop-down menu allows to type or scroll for other criteria, and easily dismiss currently visible ones. This allows to compose new charts on-the-fly which reflect the most relevant information to the user at a given point. In the experience of the authors, the act of including criteria incrementally facilitates the consideration of even over seven axes, because the complexity gradually builds up in a structured way.

Filtering representative solutions with clustering

The use of clustering techniques is a common approach to help make the selection of solution from a large Pareto optimal set more manageable (Aguirre and Taboada, 2011; Chaudhari, Dharaskar, and Thakare, 2013; Zio and Bazzo, 2012). Clustering aims to group objects with similar characteristics into distinct partitions, or clusters. Practically, an algorithm seeks configurations for which "objects of the same cluster should be close or related to each other, whereas objects of different clusters should be far apart or very different" (Kaufman and Rousseeuw, 2009). A popular k-medoids technique called partitioning around medoids (PAM) is adopted here (Kaufman and Rousseeuw, 2009, p. 68). Unlike the related k-means technique which computes k virtual cluster centroids, k-medoids directly determines the most representative solutions from the existing data set (Park and Jun, 2009). While this increases computational effort, it reduces its sensitivity to outliers. Furthermore, the additional computational effort is justified in the case of interactive optimization for decision support, as it allows to focus the attention of the user on *existing* representative solutions, instead of virtual points which may not actually be feasible. Another main limitation of both k-means and k-medoids is the need to input a number of clusters a priori (Aguirre and Taboada, 2011). While various quality indices could be applied to assess the quality of the clusters (Goy et al., 2017), the direct feedback from the graphical display in parallel coordinates and 3D scatter plots lets the user easily explore the effect of various inputs on the final clusters (Kaufman and Rousseeuw, 2009, p. 37). The inputs consist in both the number of clusters k (specified by the user in the GUI) as well as the initial seed medoids which are chosen randomly by the algorithm from the solution set each time it is executed. In addition, the way with which the data is normalized can influence the resulting clusters identified by the clustering technique (Kaufman and Rousseeuw, 2009). Another input is therefore the choice of normalization approach, which are elaborated in the next subsection and illustrated in Figure 3.7.

Filtering solutions with multiattribute decision analysis (TOPSIS)

When many solutions are compared across many dimensions, it can become overwhelming to distinguish which stand out overall. Psychological studies have emphasized the limited ability of human decision makers in balancing multiple conflicting criteria, even between a limited number of alternatives (French, 1984; Jaszkiewicz and Słowiński, 1999; Larichev, Polyakov, and Nikiforov, 1987). Here an aggregative multiattribute decision analysis (MADA) method is proposed to facilitate this task, by revealing the best rank or score of each alternative relative to the others (Cajot et al., 2017b). Each solution is attributed a score that is displayed as an additional axis in the parallel coordinates, and that is used as additional decision criterion.

As pointed out in the introduction (Hwang and Masud, 1979), multiobjective decision analysis

(MODA) methods are designed for the *generation* of alternatives, while the strength of MADA lies in the *evaluation and comparison* of predetermined alternatives. Many methods could be adopted, and there is a wide body of literature comparing the similarities, pros and cons of these methods (Zanakis et al., 1998; Cajot et al., 2017b). The often implicit assumption with most MADA methods is that the criteria can compensate each other. While the combined strength of interactive multiobjective optimization and parallel coordinates precisely is to avoid the need to aggregate the different incommensurable criteria, providing the user with a simplified aggregated metric can nevertheless provide useful and reassuring support to make sense of the data. The resulting score is not intended to replace the DM's decision, but rather to focus their attention on a limited number of alternatives, and stimulate questions and learning (e.g. discovering what characterizes a top- or low-ranked alternative). As reviewed by Cajot et al. (2017b), the application of MADA as a way to support decisions on precalculated non-dominated sets generated with MODA is fairly common (e.g. (Ribau, Sousa, and Silva, 2015; Aydin, Mays, and Schmitt, 2014; Fonseca et al., 2016; Carli et al., 2017)). However, these applications are typically performed a posteriori. Here, the feedback from the MADA score provides direct insights which the user can use to steer the search with MODA.

To avoid burdening the user with further methodological aspects, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method is adopted for its most intuitive and understandable principle, limited need for inputs and ability to handle many criteria and solutions (Cajot et al., 2017b; Zanakis et al., 1998). The method ranks each alternative according to its proximity to a positive ideal solution (PIS)—which would present the best value in every criterion—and respectively according to its distance from a negative ideal solution (NIS)—which would present all worst values (Hwang and Yoon, 1981). The final score provided by TOPSIS is a relative closeness metric between 0 and 1, where higher scores reflect higher proximity to the positive ideal solution.

The basic procedure of the TOPSIS method, first formally described by Hwang and Yoon (1981), consists of the following steps:

1. *Establish decision matrix*

As presented in Chapter 2, z_{ij} indicates the numerical measure of performance of alternative A_i for criterion C_j, where there are m alternatives and n criteria. All z_{ij} are organized in the following decision matrix:

$$\begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & C_2 & \dots & C_j & \dots & C_n \end{array} \\ \begin{pmatrix} z_{11} & z_{12} & \dots & z_{1j} & \dots & z_{1n} \\ z_{21} & z_{22} & \dots & z_{2j} & \dots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{i1} & z_{i2} & \dots & z_{ij} & \dots & z_{in} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & \dots & z_{3j} & \dots & z_{mn} \end{pmatrix} \end{array} \tag{3.11}$$

2. *Normalize decision matrix*

In this step, the decision matrix is normalized into dimensionless attributes to allow comparison. In the original TOPSIS method, the following normalization method is used:

$$n_{ij} = \frac{z_{ij}}{\sqrt{\sum_{i=1}^{m} z_{ij}^2}} \tag{3.12}$$

3. *Establish weighted normalized decision matrix*

Different methods exist to elicit a vector of weights describing the relative importance of each criterion, such as the AHP method, SWING, SMART (Wang et al., 2009). Alternatively, equal weights are also commonly adopted by default. Weights are generally specified so that $\sum_{j=1}^{n} w_j = 1$. The weighted normalized decision matrix is then established as follows:

$$v_{ij} = w_j \cdot n_{ij}, \quad j = 1,2,...,n \tag{3.13}$$

4. *Determine positive and negative ideal solutions*

$$A^* = \{v_1^*,...,v_n^*\} = \{(\max_i(v_{ij}), \ \ j \in J), \quad (\min_i(v_{ij}), \ \ j \in J') \quad | \quad i = 1,2,...,m\} \tag{3.14}$$

$$A^- = \{v_1^-,...,v_n^-\} = \{(\min_i(v_{ij}), \ \ j \in J), \ (\max_i(v_{ij}), \quad j \in J') \quad | \quad i = 1,2,...,m\} \tag{3.15}$$

where A^* is the positive ideal solution (PIS), A^- is the negative ideal solution (NIS), J is associated with the benefit criteria, and J' with the cost criteria.

5. *Calculate distance to ideals*

The Euclidean distance from each alternative to the positive and negative ideal alternatives are computed respectively as follows:

$$d_i^* = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \quad i = 1,2,...m \tag{3.16}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, \quad i = 1,2,...m \tag{3.17}$$

6. *Determine score*

Finally, the score of each alternative, representing the relative closeness of A_i with respect to the positive ideal alternative A^*, is:

$$c_i^* = \frac{d_i^-}{d_i^* + d_i^-}, \quad 0 < c_i^* < 1, \quad i = 1,2,...,m \tag{3.18}$$

An alternative A_i is thus closer to the ideal A^* as the indicator c_i^* approaches to 1. Conversely, A_i is closer to the negative ideal A^- as c_i^* approaches to 0.

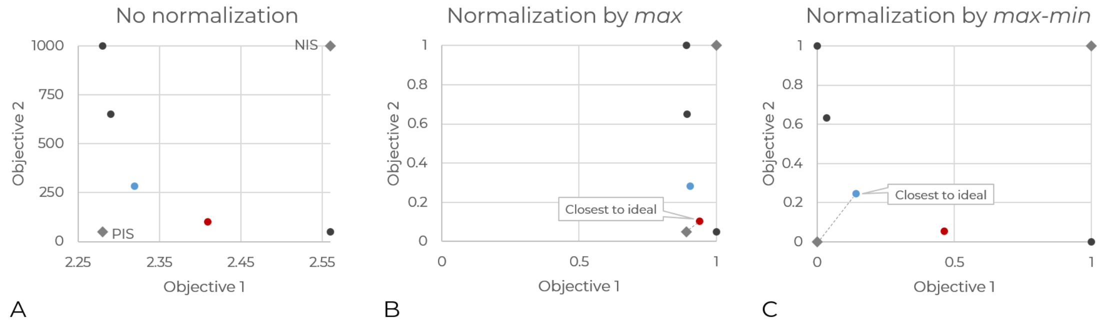


Figure 3.7 – Numerical example illustrating the effect of normalization method on the TOPSIS ranking. (A) shows the unnormalized data, (B) the same data normalized by the "max" method, and (C) with the "max-min" method. Diamonds indicate the positive ideal (PIS) and negative ideal (NIS) solutions.

Two methodological aspects of the TOPSIS method are discussed in more detail here, due to their implications in the interactive procedure, namely the normalization of data, and the choice of ideal solutions.

Choice of normalization method

As described in the second step of TOPSIS, values must be normalized to allow comparability between criteria (Kaufman and Rousseeuw, 2009). Here, two different normalization methods are adopted to improve the outcomes of the original TOPSIS method, the "max" and the "max-min" variants (Chakraborty and Yeh, 2009); for similar reasons, these variants can also be selected when applying cluster analysis techniques, as discussed in the previous subsection. First, García-Cascales and Lamata (2012), suggested the use of the "max" variant to normalize data:

$$n_{ij} = \frac{z_{ij}}{\max_i(z_{ij})} \tag{3.19}$$

They argue that compared to the original normalization method used by Hwang and Yoon (1981), this method reduces the risks of rank reversal, an undesirable side-effect which causes some MCDA methods to change the ranking of solutions when new alternatives are added (García-Cascales and Lamata, 2012; Zanakis et al., 1998).

However, in situations where the spread of values is not consistent across criteria, this normalization tends to neglect the importance of criteria with more compact values (Rousseau and Martel, 1994). In case the criterion is sensitive to such small changes, these should be accounted for in the TOPSIS score. Thus, to avoid this bias, the "max-min" variant should be preferred, as it distributes all values between 0 and 1, providing not only comparable magnitudes between criteria, but also comparable spread (Chakraborty and Yeh, 2009). With this variant, the normalized values are calculated as:

$$n_{ij} = \frac{z_{ij} - \min_i(z_{ij})}{\max_i(z_{ij}) - \min_i(z_{ij})} \tag{3.20}$$

At the expense of being more sensitive to rank reversal (Chakraborty and Yeh, 2009), this method more accurately accounts for criteria with relatively smaller spreads. Figure 3.7 illustrates with a simple numerical example the effects of both normalization methods on the resulting closeness of solutions to the positive and negative ideal solutions, when objectives have different scales. In Figure 3.7B, the normalization with the "max" variant leads to essentially determining the solution which is closest according to the second objective, while the importance of the first objective is nearly insignificant, as visible by the vertically "collapsed" set of points, and the choice of a solution performing very well in the second objective (red point). On the other hand, in Figure 3.7C, both objectives are completely spread between 0 and 1, and thus have a similar influence in the calculation of the TOPSIS score. Consequently, a solution which also performs well in the first objective is ranked first by TOPSIS (blue point).

Ultimately, there is no single best method for normalizing data. This shows the importance of letting the DM choose a normalization method which reflects their preferences, for only they are capable of assessing whether or not an infinitesimal change in one objective is meaningful or not. Despite the profound consequences of the choice of normalization method, Branke et al. (2008, p. 160) noted that "user-defined scaling is actually a usually ignored form of user preference".

Choice of ideal solutions

Regarding the choice of ideal solutions, while the original TOPSIS methods computes them *relatively* to the studied data, García-Cascales and Lamata (2012) propose the adoption of *absolute* positive and negative ideal points, either defined by the user or by context-specific rules. Here, the relative approach is preferred, in order to avoid asking the user for additional information, especially because of the possibly large number of criteria. They may however choose to apply the method on all computed solutions, or just a subset, for example for comparing only solutions selected in the comparer dashboard (cf. Section 3.2.8). If the user wishes to benefit from more reliable and consistent MADA results not subject to rank-reversal, they can manually provide reasonable upper and lower bounds for each criterion, and use those absolute values instead. As noted by Wierzbicki (2010, p. 51), there are no fundamental reasons to restrict such analyses to the ranked alternatives, and using more information (e.g. absolute values if known, or historical data), or less (e.g. limiting the definition of ideals only through non-dominated solutions) can affect the strictness of the ratings. They can also give higher weights to criteria to better reflect their subjective preferences, though again to reduce the need for inputs, equal weights are assumed by default. As illustrated in Figure 6.4, the scores provided by the TOPSIS method easily reveal the solutions which perform best, i.e. which have both high values in criteria to maximize, and low values in the criteria to minimize.

Details on demand: linking views to parallel coordinates

In some cases, the content and format of parallel coordinates is not sufficient or adapted to convey certain types of information. Xiao, Bennett, and Armstrong (2007) highlight in particular the need to complement parallel coordinates visualizations with maps, while Stump et al. (2009) suggest displaying physical geometries of generated designs–not just the design variables and performance metrics. Furthermore, Cohon (1978) noted that the communication of qualitative concepts such as aesthetics may be difficult for analysts to handle, although desirable for decision makers. Closely related is the importance to also communicate the decision variables–when requested–because in some cases the objectives and criteria alone may not provide all the necessary information to decide (Gardiner and Vanderpooten, 1997; Shenfield, Fleming, and Alkarouri, 2007).

To address these gaps, two features are implemented. The first allows to visualize all (or subsets of) solutions in interactive 2D scatter plot matrices and 3D scatter plots (Plotly-Technologies-Inc., 2015). While these are limited to a limited number of dimensions, they offer a more direct and familiar interpretation of distances than in parallel coordinates. The second allows to access additional information regarding individual solutions. For this purpose, polylines are made clickable to allow the user to access other types of information associated to a solution. When clicked, a visual dashboard opens below the chart, which could display any additional information such as images, charts, maps, exact numerical values, etc. Both views are linked, so that when the cursor hovers over the information in the dashboard, the corresponding polyline is highlighted. Like the axes, the dashboard offers reorderable containers to allow side-by-side comparisons between graphical representations.

In the context of urban planning for example (cf. Chapter 6), clicking a polyline triggers the generation of geographic maps, which complement the parallel coordinates chart with spatial and morphological information, providing also a more detailed insight into the decision variables of a solution (location, size, and type of buildings, energy technologies, etc.).

3.2.8 Synthesizing the search

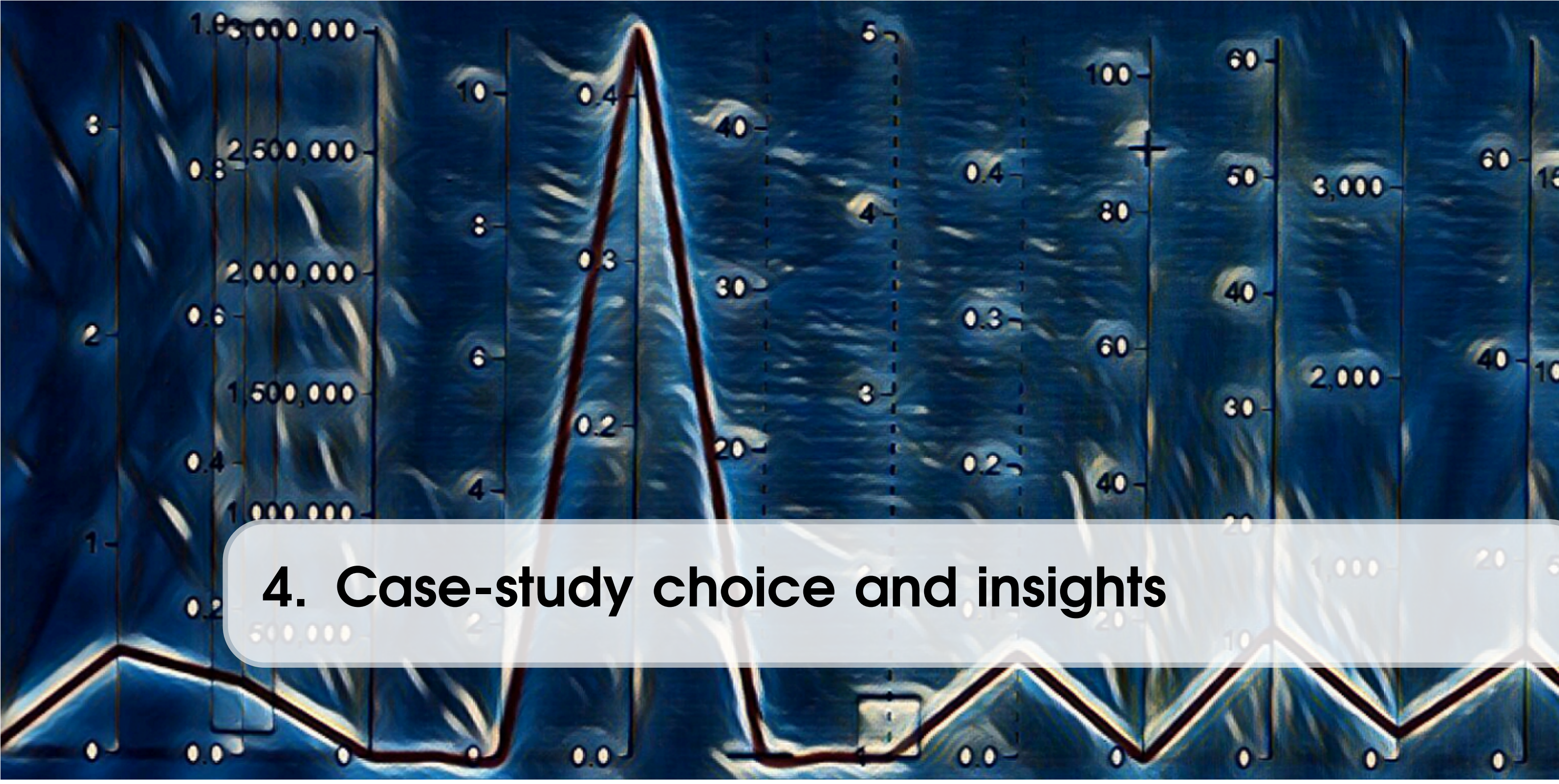
The ability to effectively convey key analytical information from the methodology to complement the decision maker's intuitive and emotional thought process is essential to influence the decision process. Studies performed by Trutnevyte, Stauffacher, and Scholz (2011) showed for example that combining analytical and intuitive approaches in elaborating municipal energy visions led stakeholders to revise their initial preferences and values and take better quality decisions. However, the choice of parallel coordinates may not be the most effective way to communicate the analytical insights obtained from the search, in particular to stakeholders or decision makers which did not actively take part in the search. Indeed, Wolf, Simpson, and Zhang (2009) noted how novice users might feel overwhelmed or less likely to exploit a dense amount of solutions in parallel coordinates. Piemonti, Macuga, and Babbar-Sebens (2017) further emphasized the added-value of summarizing the most preferred alternatives found in interactive optimization methods to make the selection process easier, while Gardiner and Vanderpooten (1997) suggested the importance of synthesizing the characteristics of obtained solutions to facilitate the communication to others.

A "comparer dashboard" is thus developed to address this need, synthesizing with key information the main insights gained during the search process (Figure 6.6). Three types of information are displayed in the dashboard. First, the total number of explored solutions is displayed on top of the comparer as a reminder of the extent of the search performed so far. This mainly serves the purpose of increasing the confidence and conviction of the user in the relevance of the final alternatives, or to encourage them to pursue the search. The interpretation from the user remains purely subjective, because often even a large number of explored solutions (e.g. thousands) will anyway remain marginal compared to the immensity of the solution space. Nevertheless, studies have revealed that users of IO typically perform few iterations, and methods should be designed to encourage them to explore more, rather than converge too soon (Gardiner and Vanderpooten, 1997; Miettinen et al., 2010; Buchanan, 1994). Second, in addition to the numerical identifier of the alternative, a graphical thumbnail is displayed–if available–to symbolize the alternative and easily identify it. the numerical identifier of the alternative. Third, the values of the selected criteria are displayed in a tabular format. Depending on the target audience and decision maker, the values can be displayed in full numerical values, colorized to emphasize best and worst values (e.g. green and red font color), or they can be aggregated into more qualitative scales, using injunctive symbols such as emoticons, red-amber-green dots or star-based ratings (Ayres, Raseman, and Shih, 2013).

3.3 Discussion

A novel interactive optimization methodology was presented, which enables users to simultaneously generate and explore solution spaces of large problems in real-time. It aimed at addressing the four main gaps in current interactive optimization methods, namely the ability to handle many objectives and alternatives, to explore the latter in an efficient way, to communicate the results effectively, and remain overall simple and accessible to users unfamiliar with optimization. The contributions are summarized hereafter:

- **Accessible.** Parallel coordinates offer an effective framework for interactive optimization, as they provide a single entry point both for exploring a wide range of criteria and alternatives, while also offering an intuitive and natural way to specify preferences. By reducing the cognitive effort required from the user, the approach allows interactive optimization to benefit a wider audience. Indeed, the learning curve is essentially limited to understanding parallel coordinates, and not the technical aspects and jargon of optimization.
- **Quick and efficient.** The combined use of exact mathematical programming and quasi-random sampling offers an efficient approach to quickly explore large, multi-dimensional spaces. The real-time process allows the user to adapt the explored areas at any time, while building on the so-far acquired solutions.
- **Improved parallel coordinates.** While the main limitations of parallel coordinates such as cluttering and restriction to pairwise comparison of axes are well known and commonly addressed by means of brushing, line coloring and manual axes reordering, the present work extends traditional parallel coordinates in four ways. First, the traditional paradigm of parallel coordinates for exploring *existing* data is enhanced by the ability to *dynamically* populate the chart with desirable solutions. Second, a searchable axis-selection menu is appended to the chart to dynamically customize the visible axes. This allows to work with hundreds of criteria, by dynamically toggling the visibility of axes as initial questions are answered and new ones emerge. Third, cluster analysis can be performed interactively in order to focus the attention of the user on the most distinct solutions. Fourth, linked views allow to explore the entire data set as 3D scatter plots, while individual solutions can be explored beyond the purely quantitative nature of data in parallel coordinates. In this chapter, cartographic maps were proposed, but the generation of other types of visualization (images, flowcharts, time-series...) could be linked to polylines in a similar way.
- **Multiattribute and multiobjective decision analysis.** The complementary strengths of MODA and MADA are harnessed to provide the user with a value-focused approach in generating good alternatives, while also providing them with assistance in ranking and selecting the best performing ones.



4. Case-study choice and insights

> SOCRATES: *Do you think, then, that someone would be any less good a painter if he painted a model of what the most beautiful human being would be like, and rendered everything in the picture perfectly well, but could not demonstrate that such a man could actually exist?*
> GLAUCON: *No, by Zeus, I do not.*
> SOCRATES: W*hat about our own case, then? Weren't we trying, as we put it, to produce a model in our discussion of a good city?*
>
> — Plato, *Republic*

This chapter describes the two urban planning case-studies from Geneva, to which the SAGESSE methodology presented in the last chapter will be applied. The choice for these case-studies was determined for their ability to illustrate the challenges identified in Chapter 1, as well as for their complementary planning questions, one dealing with urban development (i.e. greenfield), and the other with urban regeneration (i.e. brownfield). The iterative workflow which enabled the characterization of these case-studies is described. This process led to the development of both a multiparametric mixed integer linear programming model and the SAGESSE methodology, which together form the planning support system URB^{io}. This workflow involved in particular a series of workshops, which main outcomes and conclusions are presented.

4.1 Choice of case-studies and methodology

Two case-studies were selected in Geneva for their ability to illustrate the various challenges identified in Chapter 1: the presence of multiple conflicting values and criteria in the planning process, spanning over long horizons, and involving multiple scales and actors. They were deliberately chosen to cover the two main urban planning situations mentioned in Chapter 1: the project of Les Cherpines is an example of greenfield planning, while the project of Palettes is an example of brownfield planning.

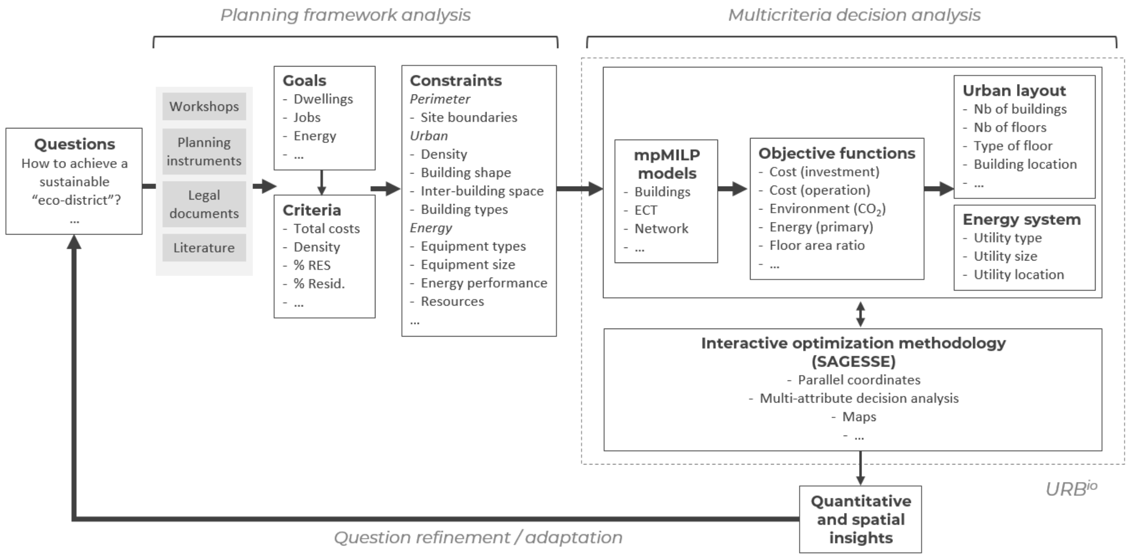


Figure 4.1 – Workflow describing the steps to analyze the planning framework, and capture its main features in an optimization model. Gray boxes indicate the sources of information considered. Adapted from (Cajot et al., 2016).

In both cases, the workflow in Figure 4.1 was adopted and repeated several times over the course of four years. This included a total of four workshops (two for each case-study) and several informal meetings with the respective local planning teams. This allowed to analyze the planning framework and issues from a practitioner's perspective, while the model development and applications allowed to refine the questions and provide answers.

The planning framework analysis aimed in particular to identify (i) the driving questions of the project, (ii) the planning goals and corresponding criteria and (iii) the legal or practical constraints involved (Figure 4.1). The information was collected from a review of existing planning instruments, legal documents, literature and validated during the workshops. A detailed list of the reviewed documents can be found in Appendix C, Table C.1.

This analysis led (i) to a multiparametric mixed-integer linear programming (mpMILP) model, implemented by Schüler et al. (2018b), and (ii) to the interactive optimization methodology SAGESSE, presented in Chapter 3. The application of the developed mpMILP model with SAGESSE constitutes the planning support system URB^{io} (Cajot et al., 2017a), which will be used to explore the solution spaces of each case-study in Chapters 5 and 6. A detailed description of the developed model, i.e. the mathematical formulations of the identified criteria and constraints, as well as the input parameters, is found in Schüler et al. (2018b) for the greenfield aspects, and in Schüler and Cajot (2018) for the brownfield aspects.

From a modeling perspective, one of the main differences in approaching the case-studies was the data requirements (Figure 4.2). In the case of greenfield projects, the "base-case" or *status quo* scenario contains no information aside from the administrative project or parcel boundaries in which the neighborhood is to be built. Thus, a simplified grid is adopted, for which specific uses (building, park, left empty) are allocated to each cell by the optimization procedure. The grid size and level of detail was influenced both by computational motivations (Schüler et al., 2018b) and in accordance with common floor occupation values found in practice (Ruzicka-Rossier, 2005). In summary, a total of 233 parcels of 1000 m^2 are used, in which buildings or parks can be allocated. In the case of brownfield projects, the model should handle a large amount of existing data, in

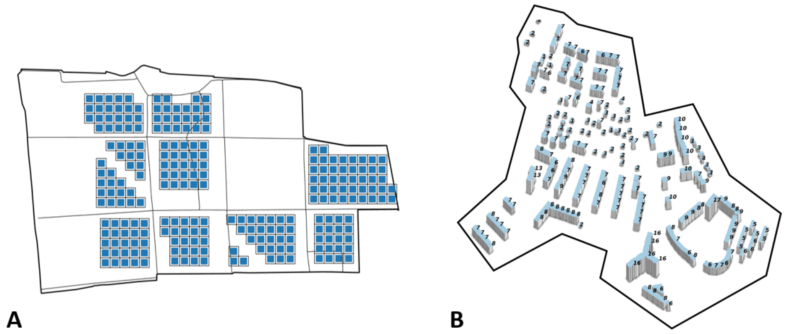


Figure 4.2 – Comparison of "base-case" maps for (A) greenfield and (B) brownfield projects.

particular the buildings (size, location, occupation type) and installed energy technologies. To facilitate the integration and management of this data, the CityGML standard was adopted and extended to efficiently handle large amounts of scenarios, as required by the underlying interactive optimization methodology (Schüler et al., 2018a).

4.1.1 Goals of the workshops

For each case-study, two workshops were held with the local urban and energy planning teams in the canton of Geneva. Each workshop lasted half a day. The participants included urban planners from the cantonal urban planning office and from the involved communes, energy planners from the cantonal energy office, as well as representatives from the cantonal energy utility. Seven participants engaged in the greenfield workshops, and three in the brownfield workshops.

The goals of these workshops were twofold, the first contextual, and the second methodological:

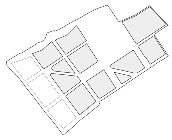
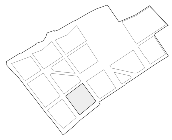
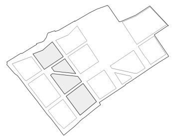
1. to elicit the predominant issues encountered by the planning teams in each project, as well as the corresponding criteria to implement in the optimization model (Figure 4.1),
2. to investigate the *applicability* of the approach in the planning process, the *interpretability* of the outputs from the mpMILP model, and the *usability* of the interface.

During the first workshops, the participants were asked to elicit the key issues and conflicting criteria encountered in their project. This was performed through semi-structured interviews and a "post-it session", followed by a synthesis and prioritization of the resulting criteria by relevance and feasibility. To facilitate discussions, criteria were structured according to a five-domains canvas: social, environment, economy, urban form and energy. Following the typology of sustainability indicators from Bourdic, Salat, and Nowacki (2012), the "urban form" domain was set apart from the three traditional domains of sustainable development to facilitate analysis and discussions. Similarly, due to the particular focus on energy in this work, and because of its often transversal nature, energy was also attributed an independent domain. Furthermore, in the first brownfield workshop, a live polling session was conducted to elicit responses regarding the usability and content requirements for the planning tool. Due to the limited attendance, the results cannot be considered statistically significant, but nevertheless the activity contributed to raise several important aspects presented in Section 4.3.3.

During the second workshop, the model and interface implementations were presented, and demonstrations of the methodology and results were shown. The feedback collected here allowed to further refine the content of the optimization model and decision support methodology.

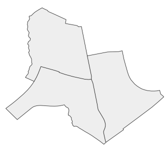
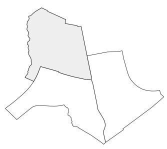
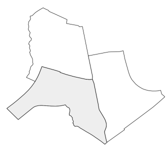
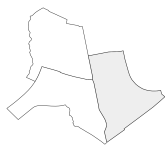
The remainder of this chapter summarizes the insights gathered from these workshops. Section 4.2 addresses the first goal, providing a contextual description of each case-study and summarizing the

Table 4.1 – General characteristics of the greenfield case-study, Les Cherpines, and two subsectors. Source (unless specified otherwise): (Confignon and Plan-les-Ouates, 2013)

	Cherpines	$\text{Cherpines}_{\text{Ba}}$	$\text{Cherpines}_{\text{Babc}}$
			
Surface [ha]	67[a]	2.9[b]	8.6[b]
Buildings[c]	129	19	51
Dwellings	3000	n/a	n/a
Jobs	2500	n/a	n/a

[a] Refers to the total area within the project perimeter, including 9 hectares of existing sports area.
[b] Refers to the gray plot area, measured on (SITG, 2018).
[c] Estimation based on non-binding guiding plan (OU, 2017).

Table 4.2 – General characteristics of the brownfield case-study, “Palettes”, and its three subsectors. Source (unless specified otherwise): (SITG, 2018)

	“Palettes”	Les Semailles	Les Palettes	Le Bachet
				
Surface [ha]	62[a]	19.7[b]	21.2[b]	20.8[b]
Buildings	312	104	106	102
Dwellings	4841	734	2350	1757
Jobs	n/a	n/a	n/a	n/a

[a] Refers to the total area within the project perimeter, mesured on (SITG, 2018).
[b] Refers to the gray area, mesured on (SITG, 2018).

key issues and criteria. Section 4.3 addresses the second goal, synthesizing the feedback on the methodological aspects of URB^{io}.

4.2 Key questions and developed criteria

4.2.1 Greenfield case-study: Les Cherpines

Les Cherpines is a greenfield development project in the periphery of Geneva, which aims to transform a former rural area into a mixed-use “eco-district”. The context of the project was described in Chapter 1, and only the key issues, or stakes are recalled here. The new district aims to achieve sufficient built density to accommodate expected population growths. A mix of uses is expected, with approximately 60% of residential area, 15% industrial and artisanal area, 10%

jobs and services area, 10% schools and cultural activities area, and 5% area dedicated to sports (Confignon and Plan-les-Ouates, 2013). Regarding energy, it strives to achieve the 2000 Watt society targets (Novatlantis, Swissenergy, and SIA, 2011), covering a minimum of 75% of the energy demand with local renewable energy sources, and reducing overall demand. Foreseen local energy sources include low-temperature waste heat from nearby industrial activities, geothermal energy and solar PV, in combination with the construction of low-energy to passive buildings (Confignon and Plan-les-Ouates, 2013). The general characteristics of the project are presented in Table 4.1, as well as those of two arbitrary subsectors (urban block "Ba" and the group of blocks "Ba", "Bb" and "Bc"), which will be investigated in the following application chapters.

Three key questions that were raised during the workshops and discussed in the planning documents are:

- **How can urban planners arbitrate renewable energy targets with traditional urban planning targets such as built density?** Density is one of the most sensible and critical aspects in the Cherpines project, and more generally in the canton of Geneva, due to limited land available for urbanization (see Chapter 1). This often leads to tensions between the local residents and higher governmental levels (Cajot et al., 2017c). Two years after the publication of the neighborhood master plan, the Swiss confederation required the canton to increase density in all urban projects (Geneva, 2015c), which the canton translated into a 20-30% density increase in Les Cherpines, or 900 additional dwellings. Adjusting the original master plan accordingly took nearly two years and included participative sessions with local actors. Thus, to provide insights on the underlying tradeoffs between density and renewable energy targets, two main criteria were adopted. The modeled indicator for built density, or floor area ratio (FAR), is based on the cantonal density index, which is the ratio of total floor area (*surface brute de plancher*, SBP) to net constructable area (*surface nette à bâtir*, SNB, Figure 4.3). It was adopted in Geneva to reflect the fact that some neighborhoods contain relatively more public equipment and public space, such as parks, streets, playgrounds or schools. Therefore, in the density index (*indice de densité*, ID), the corresponding public space (*surface d'équipement publics*, SEP, and *surface de circulation*, SC) is not considered, to allow a fairer comparison between areas which benefit more to the general public (DALE, 2014). However, as the exact interpretation of what constitutes public space is contextual and locally defined by planners (DALE, 2014), the adopted model assumes the net buildable area is contained in the 233 grid cells (Section 4.1), which loosely excludes the area dedicated to mobility and to predefined public equipment. For this reason, the calculated FAR may differ from values of density index found in existing master plans, and would require a calibration factor to allow direct comparison. Regarding renewable energy sources, the criteria "share of renewable energy sources" (share RES) was adopted. This criterion indicates the total energy originating from air, soil, solar electric, local residual heat from industrial activities, as well as a fraction (i.e. 47.1%) of the national electricity network, considered renewable mainly due to hydraulic power, divided by the total energy demand of buildings, and including transport losses and electricity exports (Schüler et al., 2018b).
- **Which is the relevant perimeter of analysis?** The determination of the adequate scope of analysis was a challenging and recurring question raised during the workshops, especially in relation to the topic of energy. For example, in Les Cherpines, the long term goal of having an "energy-positive" neighborhood might not be achievable by considering only resources and activities within the original administrative boundaries. Or, it may be achievable but only by means of economically, technically or politically challenging measures. For example, the assumption that all buildings shall be built following the most efficient norms may be difficult to enforce, or lead to unbearable costs for the actors involved. Local, deep

geothermal energy has been considered, but entails to date many uncertainties regarding technical feasibility, social acceptability and costs. Measures beyond the original boundaries have been suggested, such as the use of waste heat from the industrial zone located south of the district, or the expansion and connection to existing heating networks nearby. A model-based optimization approach was foreseen as a means to provide quantifiable insights for assessing the relevance of each perimeter considered. This issue motivated the choice of the model's spatial resolution (from floor to neighborhood), as well as the consideration of energy sources (national electricity grid, waste heat) and landmarks also beyond the perimeter of Les Cherpines.

- **What defines the liveability of the neighborhood?** A detailed answer to this broad question lies beyond the scope of this thesis. However, several studies which have attempted to define and capture the many facets of "liveability" through systems of indicators—and in turn influenced the development of URB^{io}—can be presented.

  Lowe et al. (2015) performed a literature review of indicators related to liveability, and found that safety, transport, housing, and employment were the four most common criteria used to describe liveable cities. Another study considers all criteria except those related to natural resources and the environment as describing liveability, including e.g. high quality spaces, housing diversity, employment opportunities, accessibility, equity in services and good governance (Newman, 2006). Bourdic, Salat, and Nowacki (2012) developed an indicator system describing urban sustainability—a concept often assimilated to urban liveability (Lowe et al., 2015)—and propose metrics organized by intensity, distribution, proximity, diversity, and form. For example, they associate well-being with metrics representing intensity of noise pollution or proximity of leisure facilities, and advocate in particular diversity (of land-uses, buildings, transportation modes, populations, incomes, etc.) as "an essential aspect of urban sustainability". Rey (2012) proposed a catalog of 42 indicators tailored to brownfield planning. He notes that well-being and quality of life require the largest number of criteria, compared to other domains. He distinguishes between indoor well-being (e.g. thermal comfort, noise pollution, visual comfort, electromagnetic radiation, dwelling flexibility) and outdoor well-being (number of parks, vegetation, playgrounds, benches, etc.). He also provides several prescriptive targets and thresholds for each criterion. The approach of Wiek and Binder (2005) more closely relates to the present work. They propose a "problem-oriented derivation of indicators", through which local experts or involved stakeholders select indicators based on specific problems linked to the sustainable development of their city. Furthermore, accounting for scientific and socio-economic uncertainties, they propose a method to define targets for each indicator as "ranges", rather than strict thresholds.

  In contrast to the studies above which aim at defining an exhaustive set of criteria, a *process-oriented* approach is proposed here. The approach aims to stimulate the progressive identification of criteria which appear most relevant to describe the issues encountered in the considered case-studies. In parallel to this process, their implementation in an mpMILP model continuously enriches the catalog of available criteria in URB^{io}. While several indicators described in the brief review above were adopted by following this process (e.g. distances to shops or transport stops, diversity of functions and urban form), only two of the more innovative indicators are described here. Discussions and mathematical formulations for the other implemented criteria can be found in Schüler et al. (2018b) and Schüler and Cajot (2018).

  Landmark view factor. In Les Cherpines, the master plan specified the importance of promoting open views on the surrounding landscape, including the Jura mountains to the north-west. A novel landmark view factor (LVF) was consequently developed (Schüler et al., 2018b), indicating the share of floors with a view on a specified landmark.

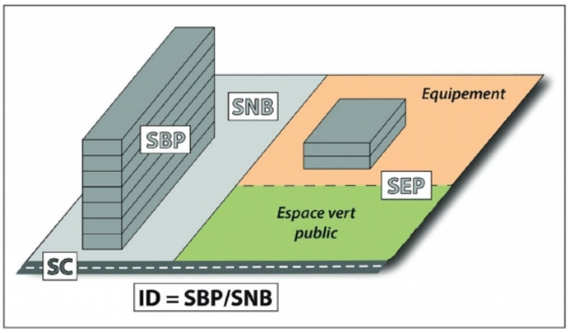


Figure 4.3 – Description of the density index (or FAR) as used in the canton of Geneva. Source: (DALE, 2014).

Liveable parks. Also important was the availability of green spaces for environmental and social reasons. Extending the basic measure of share of green areas, other quality requirements for "liveable parks" where modeled based on the seminal work of Jacobs (1961). According to her, four key characteristics contribute to making lively, secure parks:

1. Enclosure: parks should be visually and spatially delimited by surrounding buildings, avoiding excessive isolation due to traffic, natural obstacles or being located at an "edge" of a neighborhood.
2. Diversity: Mixed-uses in buildings in the direct surroundings should be planned, to promote a continuous occupation of the park throughout the day.
3. Sunlight: Ensure sufficient sun exposure within the park.
4. Parsimony: A certain rarity in the number of parks can foster attachment and avoids overly "dispersing and dissipating" the human presence.

While there are no strict rules to how these requirements actually correlate to more liveable parks, their parametrization in the model allows to explore the consequences of diverse combinations of e.g. number of minimum surrounding buildings, and distance to the park.

4.2.2 Brownfield case-study: Palettes

The "Palettes" project is an urban regeneration—or "brownfield"—project in the commune of Lancy, located less than 1 kilometer east from Les Cherpines, towards the urban center of Geneva. The nature of this planning project is not as clearly defined as with Les Cherpines, and originates from the retrofit of a large boiler located in a multi-family building in the neighborhood of Les Palettes, which raised more general questions such as how to adapt or renovate the extended area around this boiler and the possibilities of developing the district heating network with renewable energy sources. In this case, the relevent perimeter to be analyzed was discussed, and in order to consider also relationships with the broader context of Les Palettes, two adjacent neighborhoods were also considered, namely Les Semailles and Le Bachet. A note on terminology: the term "Palettes" (without determinant) refers here to the area including all three neighborhoods, Les Semailles—predominantly low-density single-family houses—as well as Les Palettes (with determinant) and Le Bachet, both higher density and mostly residential neighborhoods.

While most criteria developed in the greenfield project could also apply for a project in an existing neighborhood (e.g. density, share of renewable energy sources, etc.), the focus here was set on issues, which were specific to the brownfield context. Consequently, the driving questions and corresponding criteria are the following:

- **How to reduce the carbon emissions of an existing district?** The basis from the greenfield model already allows to answer this question partly, i.e. by letting the optimization procedure determine the optimal portfolio of central or decentral energy technologies and resources. However, unlike for Les Cherpines, where the energy demand for all buildings could be established based on legal standards for new constructions, here the base-case demand had to be determined otherwise. This was done both by relying on annual heat demand measurements from the cantonal database (SITG, 2018), or determined based on a multiple linear regression model applied to the building stock in Geneva (Schüler et al., 2015). The main measures available to tackle the question are either the replacement of existing energy conversion systems—oil boilers are particularly targeted by the canton—or refurbishment of buildings towards more efficient standards, including those specified by the intercantonal "MoPEC" prescription (EnDK, 2015), or the Swiss standard MINERGIE-P (MINERGIE, 2018). Refurbishment costs are estimated based on national statistics (Meier, 2015). In addition, indicators for primary energy and greenhouse gas emissions were included to assess the overall efficiency and carbon emissions associated to both the base-case and the calculated alternatives.

- **What is the potential for densification?** The topic of density had to be adapted for the brownfield context in two ways. First, as buildings are already in place, densification was mainly foreseen as constructing new floors on top of them. Following the construction law (LCI, 1988), such a measure is only permitted for residential floors. Second, the presence of heritage buildings limits the opportunities for increasing density, and those buildings were marked accordingly. Related to this, the question of "neighborhood identity" is also addressed in the communal master plan (Lancy, 2008). Several landmarks have been designated as fostering the identity of the neighborhood, while also facilitating orientation. As such, their visibility should be preserved and highlighted. This was implemented in the model by extending the original landmark view factor—originally developed for maximizing the view to *distant* objects—to account also for multiple landmarks located *within* the urban area (e.g. the church).

4.2.3 Resulting criteria implemented

Figure 4.4 shows an overview of the criteria which were progressively implemented after multiple iterations of the workflow in Figure 4.1.

The size of this list has grown progressively as new questions appeared in the workshops and by generating and exploring solutions with URB^{io}. The overview in Figure 4.4 contains nearly 300 criteria, collected and implemented by the end of the last workshop. A certain proliferation in this list is in part due to the granularity of technologies, and of actors required to capture the complexities of the planning problems. For example, to allow a finer analysis of electricity imports and exports, 6 criteria are used: 4 concern the imports and exports of two different actors—the energy provider and the building owners—and the two remaining are the total imports and exports for the considered perimeter.

As discussed in Chapter 2, most multicriteria decision analysis methods require a careful selection and structure in the adopted criteria set. In particular, the criteria set should be complete, operational, decomposable, non-redundant and minimal (Keeney and Raiffa, 1976). Regarding completeness of the criteria set, the first applications of the methodology with urban planning practitioners proved its potential in stimulating discussions and identifying missing criteria. In particular, the need for new criteria occured for every raised question which could not be answered by the available criteria. This led for example to the inclusion of the criterion "Costs per floor area" to reflect the scale efficiencies of larger densities, or of "Standard deviation of building heights" to assess the diversity of building heights without needing to visualize a map.

Figure 4.4 – Map of criteria identified during the planning framework analysis, classified by domain.

Furthermore, while undeniably non-redundancy in the criteria set should be respected by the decision maker when applying multi-attribute decision analysis (i.e. TOPSIS), some nuance is necessary for the multiobjective and exploratory part of the methodology. Indeed, the main purpose here is to present information to the decision maker in a non-aggregated form, as efficiently and completely as possible. Considering this, SAGESSE is in fact well suited to handle a large number of (possibly redundant) criteria, allowing to visualize the desired information on demand. Even if there exists some redundancy between certain criteria (e.g. as in between CO_2 and primary energy), the user may wish nevertheless to see *how* they correlate. The drop-down menu and reorderable parallel coordinates allow in particular to keep this process manageable.

4.3 Methodological insights from the workshops

4.3.1 Interpretability

In order to take more informed decisions in the early stages of planning, one must overcome the "planning-design gap" (deVries, Tabak, and Achten, 2005), to allow a quick check of the spatial feasibility of plans and their performance relative to different criteria. Because the calculations related to a greenfield project are performed on non-existing objects (buildings, technologies, infrastructure...), their representation and interpretation can be subject to misunderstandings.

During the workshops, the scope and limits of the proposed results to inform the planning process were discussed. The term “interpretability” was used to express the extent to which the quantified and spatial outputs could be directly used or adopted in master plans or strategic decisions. This question is closely linked to the question of “applicability”, i.e. in which phases is the optimization tool most suited (Section 4.3.2).

The main cause of the interpretability problem was identified as follows, and essentially relating to the greenfield case: there is a key difference between traditional architecture and planning approaches—which rely on intuitive negotiation processes—and the proposed solutions which are precise and clearly attached to a definite grid. If the relevance of the scientific analysis and quantified information is well understood, the contradiction between both approaches remains to be resolved.

The general conclusion from the workshops is that although the results from the tool have spatial and physical representations (location of buildings, parks, technologies), these are only approximative and non-dogmatic. This is also supported by Bruno, Henderson, and Kim (2011), whose optimization results of urban morphologies are deliberately abstracted in order to focus more on the relationships between density, distances and land uses, than on the morphology itself. The abstraction of results is done by resorting to basic geometrical shapes such as circles or cylinders, and use of color to express quantities. Indeed, what should mainly be exploited to support decisions are the quantified relationships between criteria (Bayliss, 1973; Brill, 1979), as well as the general type of solutions identified by the optimization process (e.g. urban configurations with or without district heating, density hotspots, etc.).

Furthermore, the fact that these solutions only partially reflect the final plan should not be regarded as a reason to dismiss the use of optimization methods. In this context, Keen (1977) have raised the argument that...

> *...the approximate attainment of an optimal plan may be more desirable than the exact attainment of an inferior one.* (Keen, 1977, p. 18)

The implication of this argument is that although the optimization results may not always be directly operational, they contribute to expanding the boundaries of traditional planning approaches, which typically rely on “incremental” and alternative-focused generation approaches (Lindblom, 1959; Lawrence, 2000; Balling et al., 1999).

Different levels of interpretation

Consequently, as the optimization results are non-dogmatic, it follows that they can be interpreted under varying levels of abstraction (Figure 4.5). The tradeoff can be summarized as follows: with a more literal interpretation (a building in a cell represents an actual building and position), the various calculated criteria will more precisely reflect the actual relationships in a given urban configuration (e.g. investment costs, view quality, et.). However, their direct applicability in early stages of planning is reduced, because their preciseness conflicts with the necessary flexibility required at this stage. The necessary abstraction can be done gradually, interpreting only more general conclusions, but at the cost of relevance.

As an example, if a cell is attributed the type “park”, this doesn’t strictly imply that a park should be built in that exact location (Figure 4.5 and Table 4.3). It is up to the planner to make use of this information in the best way possible, and to become mindful about possible implications of deviating from the proposed “optimal” solution (e.g. are there consequences if the park is moved from a cell within the same block? Or to another block?). For simple cases, these consequences

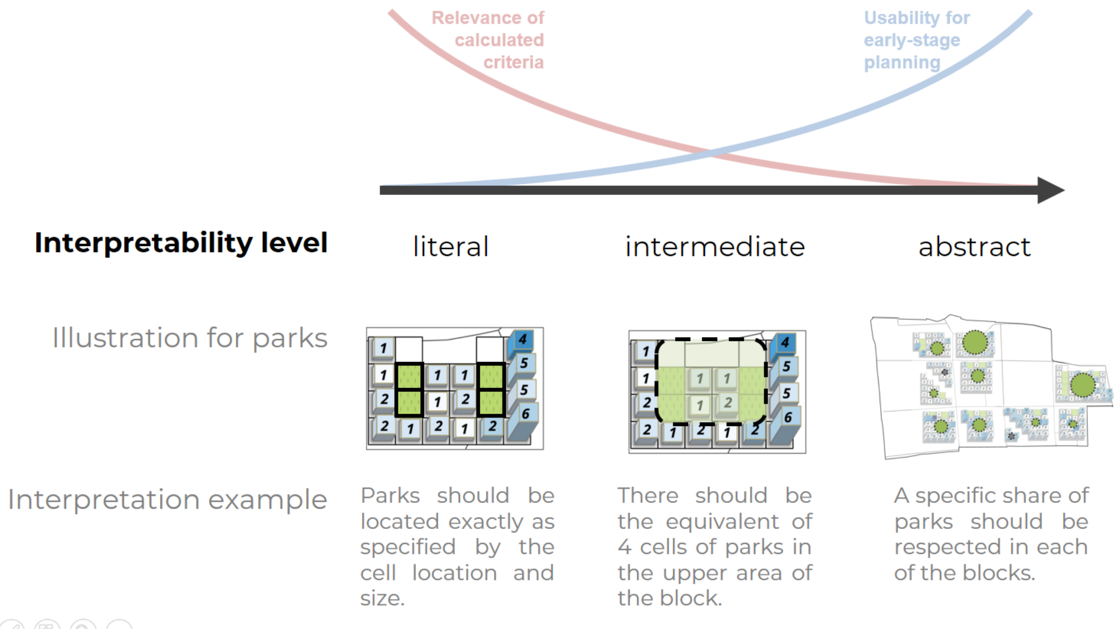


Figure 4.5 – Tradeoffs associated with different levels of interpretability of spatial results, illustrated with the topic of parks.

can be directly evaluated by means of sensitivity analysis, which is relatively straightforward to perform and to visualize with SAGESSE (cf. Chapter 6). For more impacting changes which cascade or propagate through the entire solution, the use of interactive reoptimization methods could be considered to support the planner (Meignan, 2014). Meignan et al. (2015) describe the need for these methods as follows:

> *(...) an optimization model may contain some simplifications or inaccuracies that require some adjustments by the user during the decision-making process. To correct these inaccuracies, the user can directly modify a candidate solution provided by the optimization procedure. However, manually modifying a solution has major drawbacks if it is not assisted by an optimization procedure. First, it may be difficult for the user to apprehend all constraints and objectives of the optimization problem when a solution is manually edited. In addition, due to the complexity of considered optimization problems, it is generally difficult or impossible to reflect the modification to the whole solution.* (Meignan et al., 2015, p. 15)

In other words, interactive reoptimization facilitates the task of making manual adjustments to the optimized results, while minimizing the deviation from the original performance.

However, the planner may not always require such a detailed level of interpretation. Indeed, the results could be interpreted in a more abstract way, indicating for example the share of green surfaces in each block (Figure 4.5). By iterating through the methodology with new constraints and objectives, it is possible to test the sensitivity of different criteria of interest and draw the relevant conclusions to be included e.g. as targets in master plans.

Another example concerns density (Table 4.3). At the most abstract level, URB^{io} allows to test extreme solutions, e.g. identify which maximum density could be achieved under various constraints. The level of information can be reduced also to allocate density values in different blocks, which implicitly might determine the preferred centrality of the neighborhood. The exact form of buildings

Table 4.3 – Interpretability examples for parks and density.

	Literal interpretation	Intermediate interpretation	Abstract interpretation
Parks	Parks should be located exactly as specified by the cell location and size.	There should be the equivalent of 4 cells of parks in the upper area of the block.	A certain share of parks should be respected in each of the blocks.
Density	Height, type and place of buildings are to be respected.	Density values can be allocated per block. Relative position and heights can inspire architecture.	The centrality of the district can be loosely located. The feasibility of extreme densities are explored.

and location in a parcel is then left to designers and architects.

Over time and with further applications, it is expected that this new "language" will become more precise, and easier to interpret. To avoid the risk of setting too much importance on the spatial representations, the predominant use of non-spatial representations of data such as parallel coordinates is recommended. This allows to focus first on the study of tradeoffs and synergies, and only second on their possible physical representation. Furthermore, the application of URB^{io} to urban redevelopment projects, as is discussed next, also reduces the importance of spatial aspects: as most buildings are already built, the focus is on achieving e.g. CO_2 reduction targets, rather than on spatially locating buildings with unknown forms.

4.3.2 Applicability

As described in Chapter 1, urban planning is a complex field involving multiple actors and departments, and spanning across scales and long temporal horizons. In order to support planners, it becomes important therefore to study in detail the planning processes and instruments involved to understand which types of information are required and when. Furthermore, while the tool initially was developed to support early stages of planning and addressing the "planning-design gap" (deVries, Tabak, and Achten, 2005), it became also relevant to test the "limits" of the tool's applicability, i.e. whether optimization models could also be harnessed to answer questions from the design and operation phases.

Based on the demonstration of the tool and presentation of typical results, the scope of the results relative to the different planning instruments was discussed with planners.

Given the *interpretability* issues discussed above, in particular the abstraction requirements, the results proved most relevant and applicable to the earlier stages of the planning process. Figure 4.6 illustrates the main entry points which could benefit from optimization throughout the planning process.

In particular, between the vision and strategic phases, the optimization model can be exploited to support upstream reflections, and the generation of "sketch plans" (rough sketches and concrete images of what the neighborhood could look like) (Keirstead and Shah, 2013). This takes place in parallel studies ("mandat d'études parallèles", MEP), a procedure which is similar to a restricted urban planning competition, in which a limited number of private planning offices develop plans in agreement with the public planning department.

Between the strategic and design phase, the canton relies on the involvement of an interdisciplinary

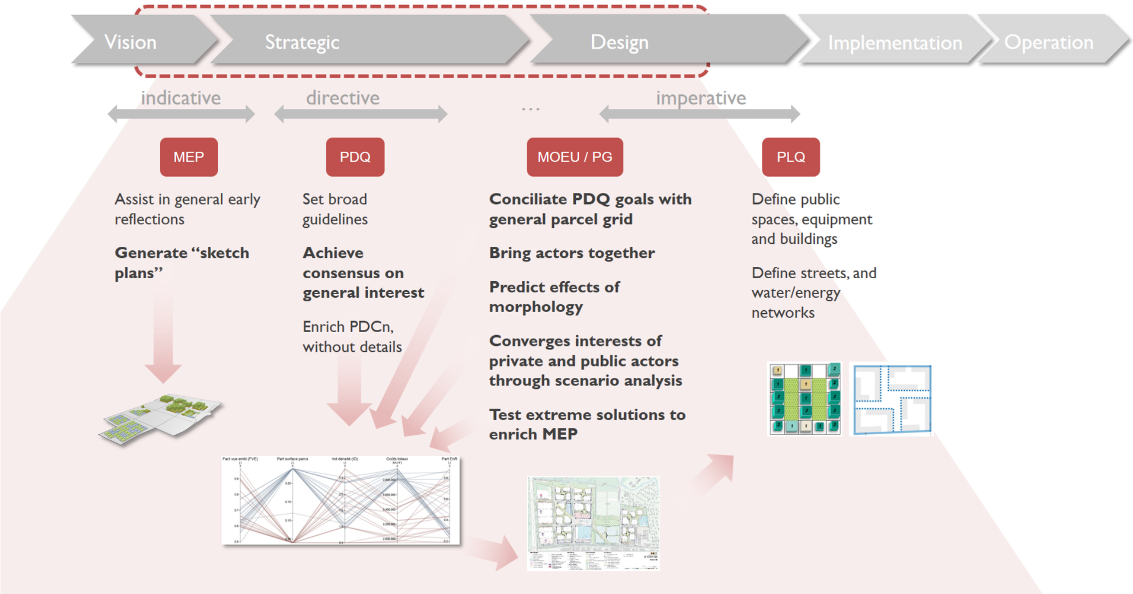


Figure 4.6 – Depiction of application areas of URB^{io} along the planning process.

group of planners and technical experts in a so-called "mandat de maîtrise d'œuvre urbaine" (MOEU). The MOEU results in a guiding plan ("plan guide", PG) which fixes certain spatial and organizational aspects to be used in the subsequent localized neighborhood plans ("plan localisé de quartier", PLQ). Optimization could be used during the elaboration of the guiding plan to deepen the analysis of the MEP's sketches, and investigate consequences and interdependencies of political targets (on density, RES, costs, parks. . .). It could also help scan more broadly the range of alternatives, and explore extreme solutions (e.g. low-rise vs high-rise configurations).

At the MEP stage, the speed of generation of sketch maps could be valuable, as well as generating several distinctive configurations. For the PDQ and MOEU, the quantitative evaluation of criteria from different sectors can help reach consensus and evaluate sensitivities of tradeoffs between objectives. Based on a scientific approach and visual display of information, it can also help gather stakeholders, support interdisciplinary discussions and foster consensus.

The applicability to more detailed and physical plans was also discussed in the second greenfield workshop. The actual elaboration of the guiding plan (spatial organization, management of mobility flows, etc.) lies outside of the scope of URB^{io}. However, exploiting optimization results for a finer analysis at the PLQ scale has been tentatively explored. Figure 4.7 shows the known constraints already decided, as well as the remaining decisional margins. These could be further explored systematically with optimization, while providing insights which are still only partially spatially relevant, e.g. average heights of buildings and location, size and location of open spaces, day lighting, etc. Further developments of the model would be required to capture also the more precise consequences of building location (e.g. build-to and set-back lines), and are at this point out of scope of the model.

4.3.3 Usability

During each workshop, participants were shown a demonstration of the tool, illustrating the current state of the workflow, and indicating the actions to perform in the parallel coordinates interface to generate and explore solutions to the stated problems. Of particular interest was the planners'

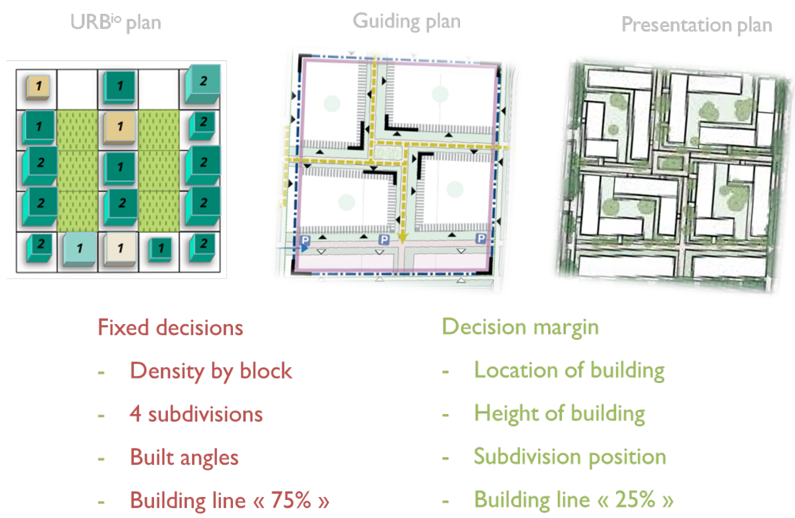


Figure 4.7 – Comparison of contents from URB^{io} results, plan guide and associated (non-imperative) presentation plan. Red indicates all decisions settled at the plan guide, green the margins for decisions to still be taken at the PLQ phase

perceived "usability" of the tool.

The concept of usability is often associated to the definition from the ISO Standard 9241, which defines it as the "*extent to which a product can be used by the specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use.*" These three aspects—effectiveness, efficiency and satisfaction—were loosely evaluated by performing a live poll during the first brownfield workshop.

The formulated poll questions (Figures 4.8 and 4.9) were prepared in advance and projected on a screen, and the participants had a few minutes to think about each question before replying with an electronic "clicker" device. All questions had multiple choices to be selected from. The results of the poll were then directly projected and discussed collectively. The questions and results of this poll can be found in Appendix C.

While the poll could be repeated on a larger sample, its interactive format nevertheless proved useful in triggering concrete discussions on the questions asked. The main indicative conclusions based on the poll results and subsequent discussions are summarized hereafter. The original slides describing the questions (in French) and containing the detailed responses are available in Appendix C.

Interface-related questions

- When asked about the added-value of visualizing results in spatial **maps**, participants had diverging opinions: 67% replied little importance, while 33% replied very important. On the one hand, the non-spatial and quatitative nature of parallel coordinates may suffice, while avoiding ambiguities related to the "interpretability" of the spatial results. However, they can be beneficial to understand the results by providing a more concrete representation.
- Regarding the improvements of the **parallel coordinates**, there was strong agreement on the importance of being able to explore in parallel coordinates data from different spatial levels, i.e. to toggle between highly aggregated information (i.e. whole neighborhood scale), to more detailed information at the plot or building scale. Furthermore, the majority of participants found a very important added-value in applying multiattribute decision analysis to facilitate the ranking of solutions, while one found it of little importance. They were

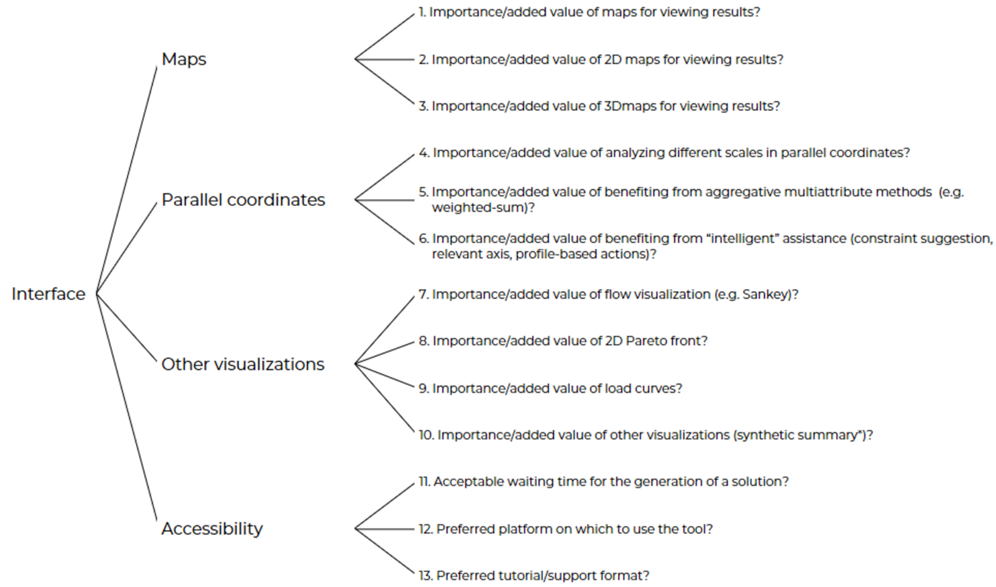


Figure 4.8 – List of questions related to the interface asked during the live poll session in the first brownfield workshop.

also mostly interested in the idea of benefiting from "intelligent" assistance for steering and exploring, such as the automatic suggestion of constraints to relax, the display of least redundant axes, or the suggestion of actions or solutions previously selected by users with similar profiles or backgrounds.

- There were diverging opinions also regarding **other forms of visualization** (Pareto fronts, Sankey diagrams and load curves). However, when asked to suggest any other desirable visualizations, one participant suggested the importance of providing a synthetic and simplified overview of the preferred alternatives. They described it as a "multicriteria table" with simplified scales for each attribute (e.g. colored dots or +/- symbols), arguing that they would require such a format to easily and quickly convey the information to other actors (e.g. politicians) which did not take part in the solution generation process. The suggestion was then rated by the other participants, which mostly agreed to its importance.
- **Accessibility** questions indicated that participants have fairly high expectations in terms of computation time for individual solutions, (i.e. less than 10 seconds), that computers remain the most likely platform on which to use such a tool, and that training should be provided in video or hands-on training sessions, rather than in written manuals or via tooltips.

Model-related questions

- The various **issues** relative to the Palettes case-study were ranked by importance by each participant. Costs (24%), CO_2 (20%) and densification (20%) appeared slightly prioritary in the project, followed by heritage (17%) and disturbances such as noise or air pollution (19%).
- Regarding **scale and model resolution**, the participants argued that depending on the actor, the estimation of energy demand is relevant both at an aggregated level of detail (for groups of buildings) than at building to sub-building scale (estimation of demand by surface type, by dwelling unit, etc.). All participants noted the importance of addressing retrofit with sufficient resolution to distinguish between individual retrofit measures (e.g. facade, roof, window, energy conversion system...), to allow to maximize the economic efficiency of any intervention.

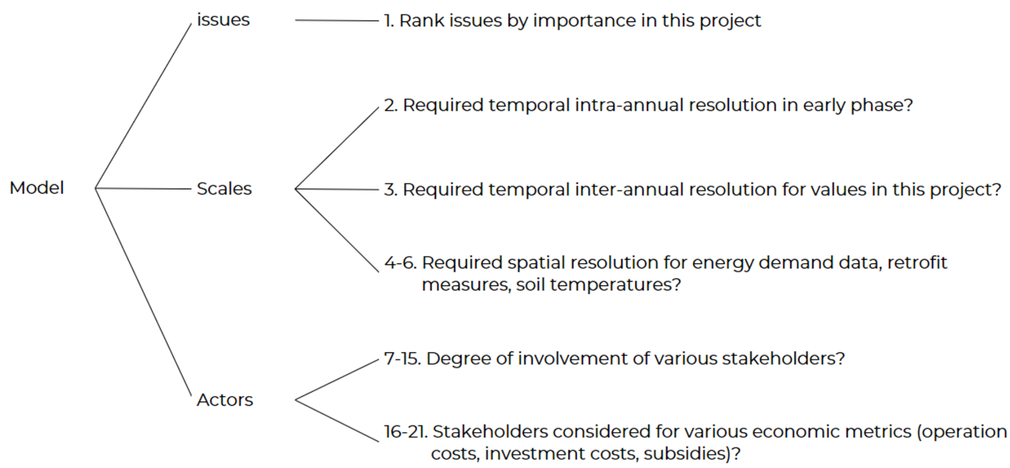


Figure 4.9 – List of questions related to the model asked during the live poll session in the first brownfield workshop.

- Regarding the importance of **actors**, building owners were considered relatively involved in the project, whereas tenants were rather declared little to not involved. When asked if any actor was missing from the poll, participants mentioned to importance of involving municipals and politicians, to foster general acceptance of the project towards the general public.

4.4 Discussion

The main contribution in this chapter is the iterative workflow described in Figure 4.1, which proved useful to establish a lasting and constructive collaboration with practitioners. The ability to obtain regular feedback on the problem statements, the modeled criteria as well as on the usability of the interface allowed to progressively enrich and adapt the development process.

The consideration of two case-studies with different issues and data requirements demonstrated the adaptable and modular nature of the workflow and of the resulting tool. Many of the identified criteria in the first case-study could be exploited in the second case-study. Consequently, the adaptation of the model to the brownfield context could be performed in approximately 3 months, including an adaptation of the underlying data model, which represents a fraction of the time required for the first prototype used in the greenfield case, which spanned from 2015 to 2017.

Key insights from the workshops

During the workshops, in particular with the live poll, several relevant improvement points for the planning tool were raised and partly integrated. Interface-wise, the suggestions contributed for example in the choice of integrating the more familiar scatter plots for visualizing Pareto fronts, and the synthetic summary of preferred alternatives. Model-wise, a distinction between actors was made, allowing to differentiate the costs allocated to the involved stakeholders. Currently, the local energy utility and building owners are considered, but in principle others could be included such as the canton, the commune or tenants. Accordingly, new questions could be studied with the methodology, including for example the landlord-tenant dilemma, in which economic conflicts undermine the achievement of satisfying retrofit solutions (Ástmarsson, Jensen, and Maslesa, 2013). In addition, the adoption of the CityGML data standard allowed to efficiently make use of existing data from the canton (Agugiaro, 2016; Schüler et al., 2018a). This implies that the adaptation of the model to other case-studies also relying on this standard would be greatly simplified. New criteria were included to reflect specificities of both case-studies, for example building type and park allocation in empty grid cells, or visibility of surrounding landmarks for the greenfield case, and refurbishment, building heightening and heritage restrictions for the brownfield case.

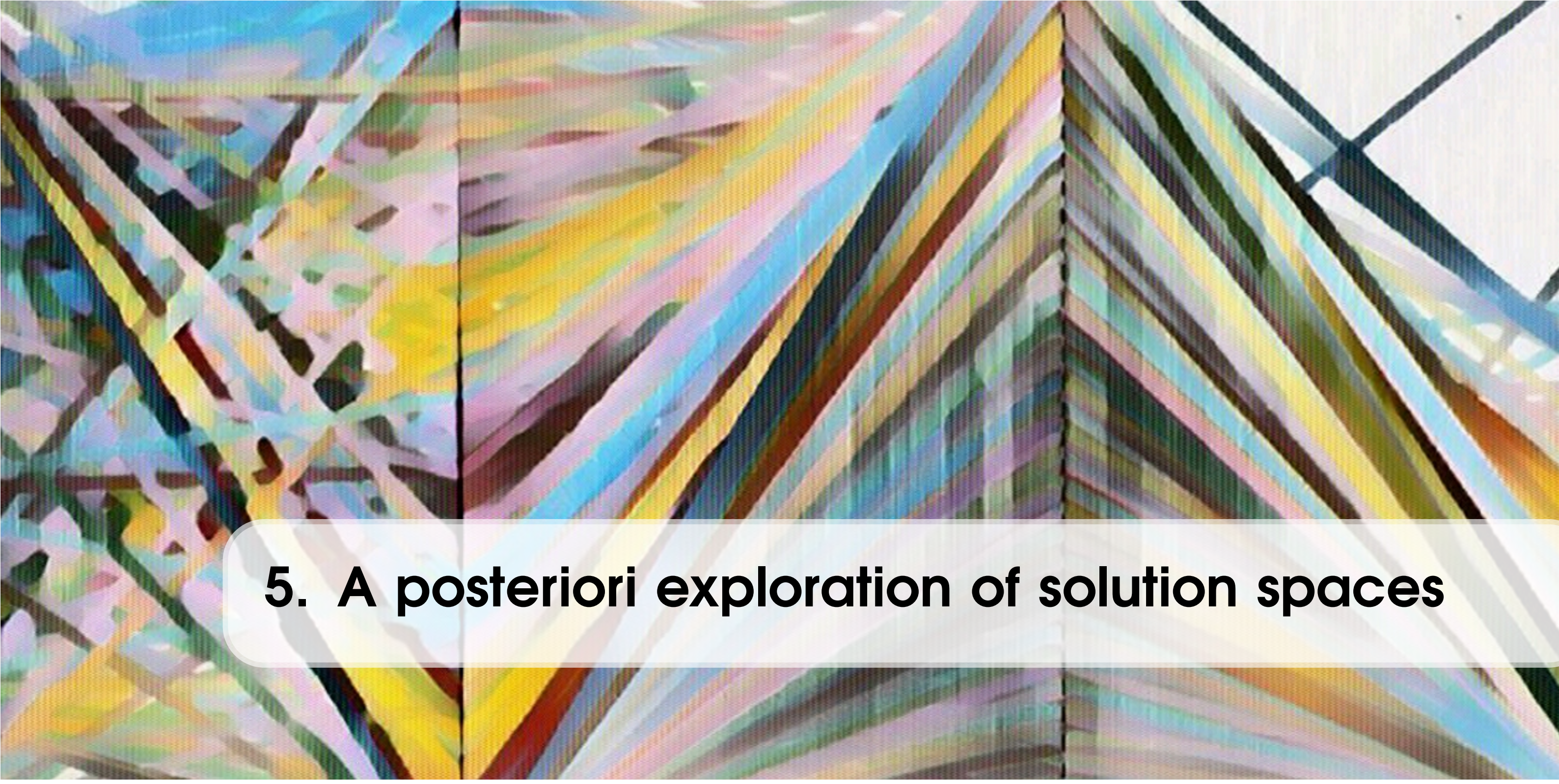
The questions of interpretability and applicability were raised, and the main issues were identified. In spite of several difficulties in interpreting optimization results in greenfield projects, the potential and added-value of optimization to generate plans in the early stages of planning has been shown.

Open issues

However, many identified aspects still remain to be explored in future work. The use of artificial intelligence for learning from user behaviors is particularly promising, and could have positive repercussions on usability and speed. The positive feedback on this topic denotes a certain openness and recognition of the need for more computer support in the field of urban planning. According to Russo et al. (2018), one of the leading causes for low adoption of planning support software is the low usability of tools. Therefore this question would be worth investigating based on a larger sample of planners, to verify whether the use of more automation would encourage the use of the tool, or instead whether it would reduce its use, due e.g. to lower trust in the final solution.

The relevance of maps in the context of this methodology remains a debatable topic. While their interpretation is fairly straightforward in the brownfield context, further research should explore ways to depict and to interpret the spatial insights provided, and how to make use of them.

In this chapter, the main applications along the planning process were also outlined, but further practical applications, e.g. in the context of planning competitions, or to support the elaboration of localized plans, would allow to support these assumptions.



5. A posteriori exploration of solution spaces

It is easy to fall into the trap of contemplating a city's uses one at a time, by categories. Indeed, just this – analysis of cities, use by use – has become a customary planning tactic.

— Jane Jacobs (1961)

The main purpose of this chapter is to illustrate the generation and exploratory features of the SAGESSE methodology. Therefore, the methodology is applied to generate a representative approximation of the Pareto front for a problem with three objectives, to allow choosing a preferred solution "a posteriori". First, the main inputs of a multiobjective optimization problem are determined, namely the lower and upper boundaries of the objectives, and the number of points to be sampled for a good approximation of the Pareto front. Second, the problem is solved for both the greenfield and the brownfield case-studies introduced in the previous chapter. Two different sampling methods are compared for the generation of the Pareto front, and the generated solutions are explored and characterized by visualizations in parallel coordinates and 3D scatter plots. Third, multiattribute decision analysis is applied to facilitate the analysis of multiple dimensions and to identify preferred solutions. Fourth, different approaches to improve the quality of the generated Pareto front are discussed. The chapter is concluded with a brief discussion on the importance of data visualization for multiobjective optimization, and on the relevance of interactive optimization for addressing large problems.

5.1 Delimiting the solution space

In Chapter 3, three types of multiobjective optimization approaches were presented, distinguishing the phase of the search process in which the decision maker (DM) specifies their preferences: a priori, a posteriori or interactively. Among the three, a posteriori methods have the advantage of providing the DM with a complete overview—or at least a sufficient representation—of the Pareto optimal alternatives. At the expense of being potentially time-consuming and computer-intensive, it can be beneficial in cases where the DM either (i) can afford waiting until the generation of the full Pareto set is complete, and/or (ii) has limited availability, and interaction with them is difficult (Mavrotas, 2009; Branke et al., 2008). As will be shown, this approach is rather unadapted for urban and energy system planning problems, due to both the size of the problem, and the number of criteria involved. Nevertheless, a limited example based on only three criteria can serve to better illustrate some of the basic methodological aspects of the SAGESSE methodology and their relevance when dealing with large data-sets.

The choice of criteria optimized in the following examples—total costs, density and share of renewable energy sources—is based on the first question identified in the greenfield case-study: *"How can urban planners arbitrate renewable energy targets with traditional urban planning targets such as built density?"* While three criteria alone cannot reflect the full complexity of the problems at hand, they nevertheless reflect a fairly generic and recurring issue of urban planning, in which planners must balance economic, social and environmental facets of sustainable urban development (Teriman, Yigitcanlar, and Mayere, 2009). Furthermore, limiting the example to three criteria also allows to visualize the solution space not only in parallel coordinates, but also in 3D scatter plots, which can help build a "mental image" of the data in the decision maker's mind (Branke et al., 2008, p. 216), and may be more intuitive to use for low dimensions (Netzel et al., 2017).

The solutions presented in this chapter were generated with URB^{io} (Cajot et al., 2017a), which relies on the mpMILP model presented in Schüler et al. (2018b). The N problems being solved, based on the generic formulation in Chapter 3, Eq. (3.4), can be expressed as:

$$
\begin{aligned}
\min_{\boldsymbol{x}} \quad & f_{TC}(\boldsymbol{x},\boldsymbol{\theta}) \\
\text{subject to} \quad & f_{FAR}(\boldsymbol{x},\boldsymbol{\theta}) \leq \varepsilon_{n,FAR}, \qquad \varepsilon_{FAR}^{min} \leq \varepsilon_{n,FAR} \leq \varepsilon_{FAR}^{max}, \\
& f_{RES}(\boldsymbol{x},\boldsymbol{\theta}) \leq \varepsilon_{n,RES}, \qquad \varepsilon_{RES}^{min} \leq \varepsilon_{n,RES} \leq \varepsilon_{RES}^{max}, \\
& \boldsymbol{g}(\boldsymbol{x},\boldsymbol{\theta}) \leq 0, \\
& \boldsymbol{h}(\boldsymbol{x},\boldsymbol{\theta}) = 0,
\end{aligned}
\tag{5.1}
$$

where $f_{TC}(\boldsymbol{x},\boldsymbol{\theta})$ is the objective function expressing the total costs (TC), including investment and operational costs related to the energy system, $f_{FAR}(\boldsymbol{x},\boldsymbol{\theta})$ is the function expressing the built density as floor area ratio, and $f_{RES}(\boldsymbol{x},\boldsymbol{\theta})$ is the share of renewable energy sources, and $n = 1,...,N$. The resulting Pareto front will thus consist in N Pareto optimal points. In the case of systematic sampling, N is the product of the number of requested grid points N_p on each dimension p, i.e. in this case $N = N_{FAR} \cdot N_{RES}$. For Sobol sampling, the same number of points are sampled on each dimension and $N = N_{FAR} = N_{RES}$.

To obtain a complete overview of the solution space by solving Eq. (5.1), it is necessary (i) to specify the upper and lower bounds of $\varepsilon_{n,FAR}$ and $\varepsilon_{n,RES}$, and (ii) to choose a total number of points to calculate. The determination of these inputs are presented and discussed in the following sections.

5.1.1 Defining the upper and lower bounds

A precise estimation of the upper and lower bounds of each objective is necessary to avoid leading to infeasible solutions during the search process and wasting time and computational effort. If these bounds are known (e.g. by the user's experience), they can be directly specified. If not, either reasonable (and sufficiently large) bounds should be estimated, or alternatively, they can be calculated by first minimizing and maximizing $f_{FAR}(\boldsymbol{x},\boldsymbol{\theta})$ and $f_{RES}(\boldsymbol{x},\boldsymbol{\theta})$ individually as single-objective optimization problems (Chankong and Haimes, 2008). Here, the latter approach was performed, and the resulting upper and lower bounds for density and share of renewable energy are provided in Table 5.1 for each sector considered.

Regarding the bounds of the density objective, the upper bounds for the Cherpines sectors indicate that if all parcels are occupied by buildings as high as legally authorized for that zone (up to 27 meters, or 6 floors assuming the last floor is for residential purposes (LCI, 1988)), the maximum computed floor area ratio is 3.5, i.e. 3.5 m^2 of floor area per m^2 of constructable land (Table 5.1). This value is a function of the different building footprints assigned to each building type on selected during the optimization process (Schüler et al., 2018b). The lower bounds were set at 0.18. While a feasible alternative could, in principle, include no buildings, and thus a FAR of 0, this option was not considered, as non-realistic, and furthermore to avoid any edge effects in the model formulations for near-zero values. The minimal FAR value was chosen to ensure that at least two parcels are occupied by a building.

For the Palettes case-study, in which buildings are already constructed, the minimization of FAR was necessary to obtain the *status quo* density. This value thus reflects the state of the current building stock as available in the cantonal data base, which was used as the main source of data for the modeling of the buildings (SITG, 2018). The overall density of the case-study area was 1.17, with different allocations in each subsector (Table 5.1). The least dense neighborhood is Les Semailles with a density of 0.59, reflecting its predominance of single-family houses. The neighborhood of Les Palettes is the most dense (2.27), due to the presence of several large multi-family buildings. Le Bachet has an intermediate density of 0.97. The maximization of FAR led to scenarios in which the number of stories was increased on all acceptable buildings, namely those whose height is below the legally authorized height, and which do not have any heritage conservation restrictions. This reveals different potentials for densification in each subsector: the single-family house neighborhood of Les Semailles indicates a maximum increase of 24%, Le Bachet of 6%, and Les Palettes of less than 2%. For the entire project, a final density of 1.26 would represent an increase of 8% from the status quo.

Table 5.1 – Calculation of the upper and lower bounds of the auxiliary objectives in Eq. (5.1).

	ε_{FAR}^{min}	ε_{FAR}^{max}	ε_{RES}^{min}	ε_{RES}^{max}
Cherpines	0.18	3.50	0	100
Cherpines-Ba	0.18	3.50	0	100
Cherpines-Babc	0.18	3.50	0	100
Palettes	1.17	1.26	0	97.7
Les Semailles	0.59	0.73	0	100
Les Palettes	2.27	2.31	0	96.2
Le Bachet	0.97	1.03	0	97.2

Regarding lower bounds for the shares of RES, 0 was adopted in all cases, reflecting energy systems being completely fueled by fossil resources. For the upper bounds, the share of RES could not be directly maximized because of the non-linear combination of decision variables in the expression of this objective. Instead, the function was reformulated as a linear constraint, which was systematically varied between 95-100%, while optimizing FAR. This procedure leads to the bi-objective Pareto fronts in Figure 5.1. Not only do these charts inform about the maximum achievable share of RES for each subsector, but they also provides the maximum density for which it is achievable. In addition, it also reveals the maximum share of RES which is achievable for the highest density of each subsector.

Thus, Figure 5.1A shows that 100% share of RES is achievable in Les Cherpines for densities up to 3.14, while the maximum density of 3.5 can, at most, take into account 97.7% of RES (note: only the results for the entire district are shown, because all subsectors behave identically). Likewise, for the Palettes case-study, the bends in Figure 5.1B show the tipping points in RES values, from which the density must be reduced for more RES to be adopted. The right-most points indicate the maximum theoretical shares of RES which can be obtained in each subsector, and its corresponding density. Only the low density single-family house subsector of Les Semailles can achieve 100%, while other subsectors must rely at least on 2-4% of non-renewable sources.

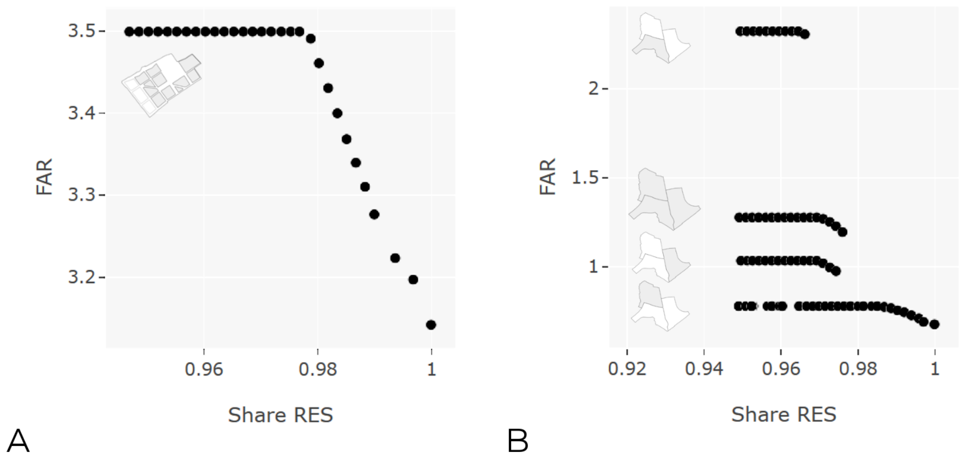


Figure 5.1 – Pareto fronts for the bi-objective optimization of the share of renewable energy sources (RES) and floor area ratio (FAR) for (A) the Cherpines project, and (B) the different sectors in Palettes.

5.1.2 Defining the number of points in the Pareto front

Determining an appropriate number of points which leads to a useful approximation of the Pareto front depends on the shape of the Pareto front itself, and the sensitivity to the perturbated parameters in the scalarization function, which are not necessarily knowable a priori (Ruzika and Wiecek, 2005; Branke et al., 2008). Here, sample sizes of 400 points were found to be sufficient for the purposes of this chapter. As visible in Figure 5.2, the general shape of the Pareto front is already well approximated with 200 points. For illustration purposes, the systematic sampling of the Palettes project was sampled with 900 points (Figure 5.3). They were determined by empirically evaluating the regularity of the Pareto front shape for different numbers of sampling points.

5.2 Characterizing the solution space

5.2.1 Comparison of sampling methods

After determining the upper and lower bounds of the objectives (Table 5.1), as well as a suitable number of points to sample in the parameter space, the problem in Eq. (5.1) was solved multiple times for each subsector and comparing both sampling approaches. When generating the solution space for the entire Palettes project area, a finer grid of $N = 900$ solutions was adopted with the systematic sampling approach (i.e. 30 grid points per range), while $N = 400$ points were chosen in the Sobol sampling case (Figure 5.3). For the three subsectors in Palettes (Figure 5.4), $N = 400$

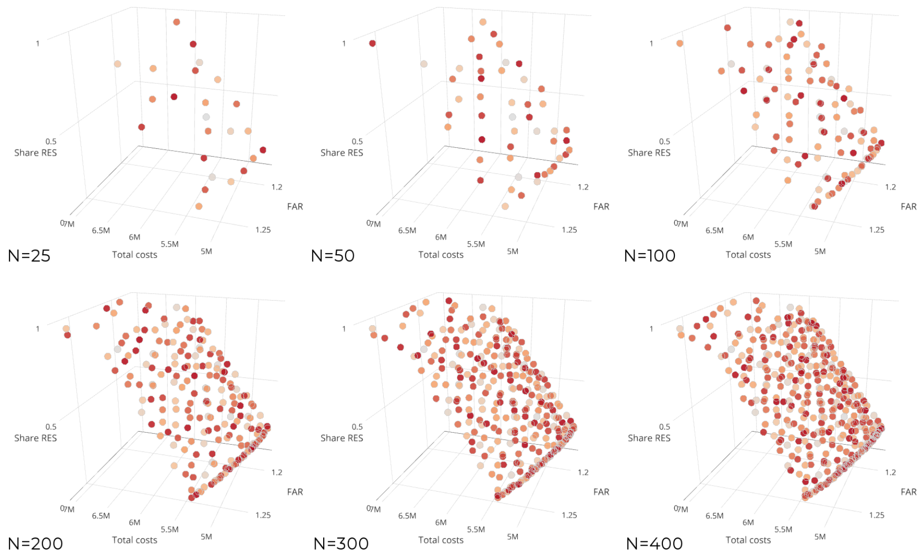


Figure 5.2 – Comparison of the three-dimensional Pareto front approximation of the Palettes project, for varying sample sizes N between 25 and 400, and for costs, density and share of renewable energy sources as objectives.

solutions were requested for each individual subsector (i.e. 20 grid points per range in the systematic cases). The number of solutions requested for the Cherpines project was $N = 441$ (i.e. 21 grid points per range in the systematic sampling cases).

Figure 5.3 shows the final computed solution space for the Palettes project in parallel coordinates and 3D scatter plots. Similarly, Figure 5.4 shows the respective scatter plots for each of the project's subsectors (their visualization in parallel coordinates is found in the Appendix, Figure C.8).

The color of the points in the 3D scatter plots (respectively of polylines in the parallel coordinates) indicates the order with which they were calculated (from light to dark red). While arguably the order matters little in a posteriori approaches, because it is assumed that the DM is willing to wait however long the generation process lasts, it is critical in interactive methods. To illustrate this point, Figure 5.6 shows the solution space for Le Bachet after only 25% of the 400 requested solutions (Figure 5.6A). The Sobol sampling approach provides a good approximation and overview of the entire solution space (Figure 5.6B), while the systematic approach only provides a detailed but limited subset in the lower part of the RES dimension. Thus in interactive optimization, with the Sobol approach, the user could more rapidly spot particularities in the solution space (i.e. the sharp increase of costs for solutions with over 90% of renewable energy sources, observable in Figures 5.3 and 5.4), and decide for example to explore more in depth the area around that tipping point, or instead to restrict the search to areas before the sharp increase occurs. This more detailed analysis and interpretation of the shape, and how it influences decision making, is discussed next.

5.2.2 Interpreting the shape of the solution space

The calculation of up to 900 Pareto optimal solutions provides a good approximation of the Pareto optimal set of alternatives which characterize the problem according to three objectives. The visualization of such information is a first step in supporting the DM's decisions. The generated Pareto points indeed constitute a form of "catalog" from which the DM can pick a most satisfying solution. Balling et al. (1999) had called this a posteriori approach "design by shopping", arguing that planners would make better decisions and have a more precise understanding of their preferences if they had the opportunity to examine efficient plans. The reliance on parallel

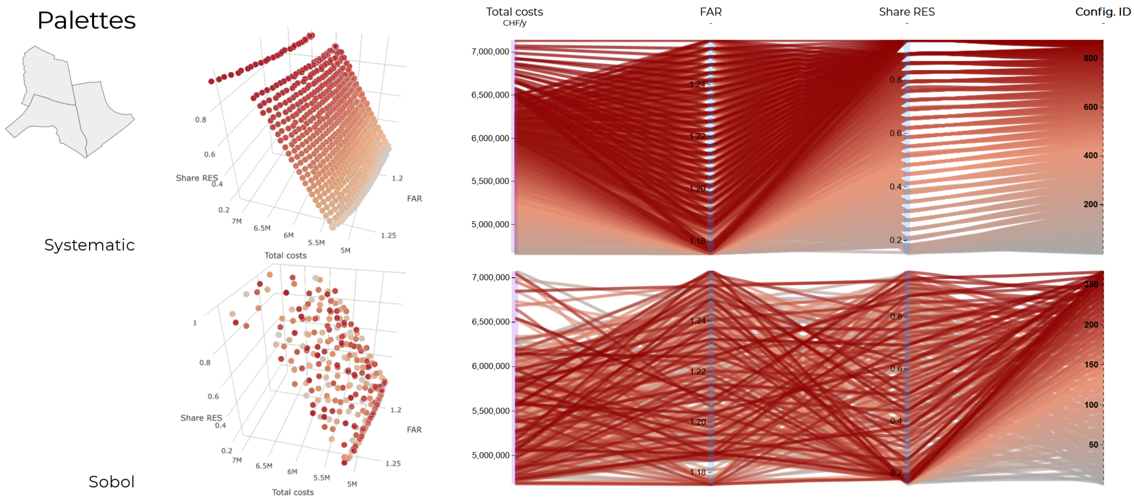


Figure 5.3 – Comparison of systematic ($N = 900$) and Sobol ($N = 400$) sampling techniques for exploring the FAR and RES dimensions while minimizing total costs in the Palettes project. The color of the points/polylines indicates the configuration ID, i.e. the order in which they were generated, from light to dark. The color of the axes denote whether they were a main objective (purple) or sampled as a range (blue).

coordinates improves this approach by letting the DM easily filter individual axes to identify a solutions which best meets their preferences, and explore additional criteria more in detail. In this process, their preferences may be influenced by the shape of the solution space and its exploration. Here for example, what stands out from Figures 5.4 and 5.5 is the sharp increase in costs beyond a certain threshold of RES. One user might already benefit from such an insight, e.g. to discard those with the least interesting tradeoff between RES and costs. Another might need to explore more in depth the reasons for this tipping point.

For this purpose, nine additional axes relating to the underlying energy technologies (ET) and resources involved in the different scenarios are displayed (Figure 5.7). The chosen axes (their names are italicized hereafter) relative to the renewable energy sources consist of the number of decentralized PV systems (*Dec. PV systems*) and their total electricity production (*Elec. dec. PV*), as well as the energy from imported biomass sources (*Wood import*). Furthermore, these are compared with the neighborhood's consumption of oil (*Oil import*) and gas (*Gas import*), used either by decentralized boilers, or by a centralized gas-fueled combined heat and power (CHP) system. In case a centralized CHP plant is installed, then buildings can install decentralized heat exchangers (*Dec. HEX*), whose total capacity (*Cap. dec. HEX*) is also displayed. Both the imports (*Elec. import*) and exports (*Elec. export*) of electricity are also displayed. Note that all of these criteria were post-computed based on the decision variables identified to satisfy the three objectives. The following analysis focuses on the solution space of the Palettes project generated with systematic sampling, where $N = 900$ (Figure 5.3).

The exploration of more than two or three dimensions can benefit here from three main features discussed in Chapter 3: polyline coloring, axis reordering, and brushing. It is worth underlining the advantage of the interactive nature of parallel coordinates, which facilitates the task of identifying patterns or particularities in the data through movement (Shneiderman, 1996). The results presented here are thus merely a static summary of the key findings form the interactive exploration process. Figure 5.8 shows how the animation of sequential portions of the solution space can reveal trends when varying a criterion of interest (only five levels of RES share are shown in the depiction, while the actual animation allows to covers every increment defined by the systematic sampling approach, see Chapter 3).

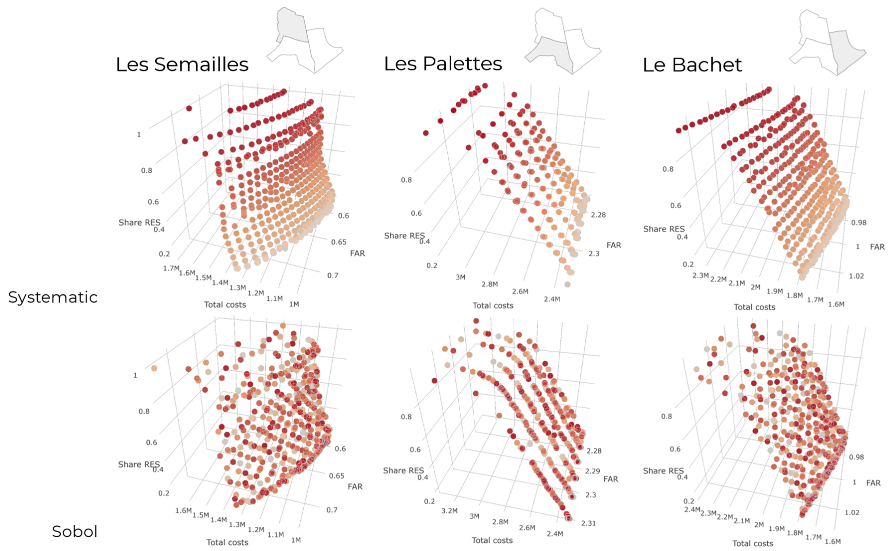


Figure 5.4 – Comparison of systematic and Sobol sampling techniques for exploring the FAR and RES dimensions while minimizing total costs in each subsector of Palettes, with $N = 400$. The color of the points indicates the order in which they were generated, from light to dark.

The present goal being to understand the reasons for the cost increase above a certain RES threshold, the user can brush the corresponding *Total costs* axis incrementally to "spot" any particularities and tipping points. The main insight in this case is the apparition of decentralized PV systems to cover the electricity demand (cf. the back-most panel in Figure 5.8). Although a deeper analysis would be required to ensure this is, in fact, the leading cause of costs increase, it provides at least a clear distinction with alternatives with lower shares of RES, and the necessity of PV to reach the set goals.

Figure 5.7 presents six levels of RES shares for the Palettes project. For each level, the "portfolios" of the corresponding energy systems, i.e. the types and capacities of selected ETs, are visible. Exploring from low to high shares of RES, the following observations can be made. For low shares of RES (15% or lower), the energy system is predominantly driven by a centralized gas-fueled CHP plant, indicated by the gas imports and number of installed decentralized heat exchangers, i.e. about 150-200. The remaining buildings are likely heated by centralized oil boilers, as denoted by the high values on the corresponding oil imports axis. For alternatives aiming at least 30% of RES in their energy system, a transition from oil and gas begins, as visible by the increase of wood imports, and overall lower values in oil and gas imports. Above 45% of RES, electricity export is no longer possible, due to its non-renewable origin. Indeed, for 75% of RES, the lack of electricity formerly produced via local CHP must be replaced by imports from the national electricity grid, which contains roughly 50% of renewable energy (Schüler et al., 2018b). However, on the path towards 100% RES, that fraction is insufficient, and consequently, after peaking for alternatives around 85%, electricity imports decline again, and are replaced as far as possible by PV panels.

5.3 Identifying the preferred RES share

After being presented with the visualization of the Pareto front, finding the preferred tradeoff between more than two objectives remains a cognitively challenging task (French, 1984; Jaszkiewicz and Słowiński, 1999). The use of aggregative MADA can in this case provide some insights into "tipping points" between the most attractive solutions.

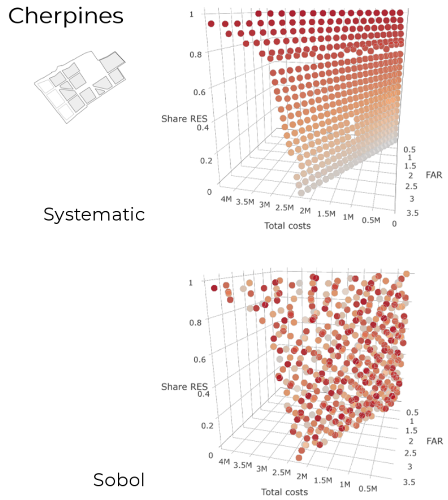


Figure 5.5 – Comparison of systematic and Sobol sampling techniques for exploring the FAR and RES dimensions while minimizing total costs in the Cherpines project ($N = 441$). The color of the points indicates the order in which they were generated, from light to dark.

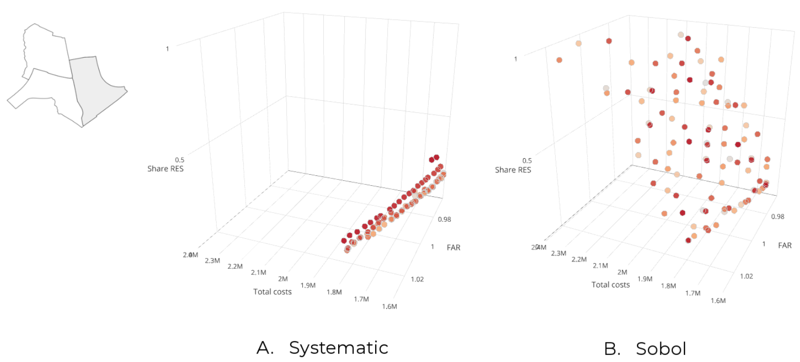


Figure 5.6 – Comparison of (A) systematic and (B) Sobol sampling techniques after calculating 100 out of 400 requested Pareto optimal solutions for the subsector Le Bachet, in Palettes. The color of the points indicates the order in which they were generated, from light to dark.

The TOPSIS method (see Chapter 3) was applied to the Pareto optimal solutions of all Palettes sectors, and displayed in parallel coordinates (Figure 5.9). Polylines are colored according to the resulting TOPSIS score, and dark red lines indicate the solutions with higher scores, i.e. those which are closest to the virtual ideal point. An immediate observation revealed by the color is that the most preferable solutions are not necessarily the ones with higher shares of RES, nor are they the cheapest. For example, in the case of the entire Palettes project, the more balanced solutions are those which lie between 60-90% RES shares, have total costs of less than 6.5 MCHF, and densities above 1.22. In the case of Semailles—the predominantly single-house area—higher shares are advisable according to the TOPSIS score, i.e. between 70-90%. This is also the subsector for which the highest TOPSIS scores are achieved (i.e. 0.70), which means feasible solutions exist which are overall closer to the ideal solution. Such solutions could be interpreted as leading to less regret (in case of single DM), or more consensus (in case of a group of DMs).

Figure 5.10 shows a closeup of the RES "profiles" colored by TOPSIS score. This visualization allows to aggregate in a single dimension the tradeoffs between three or more criteria. By exploring such profiles, the DM can intuitively grasp which areas of any given criterion are more likely to

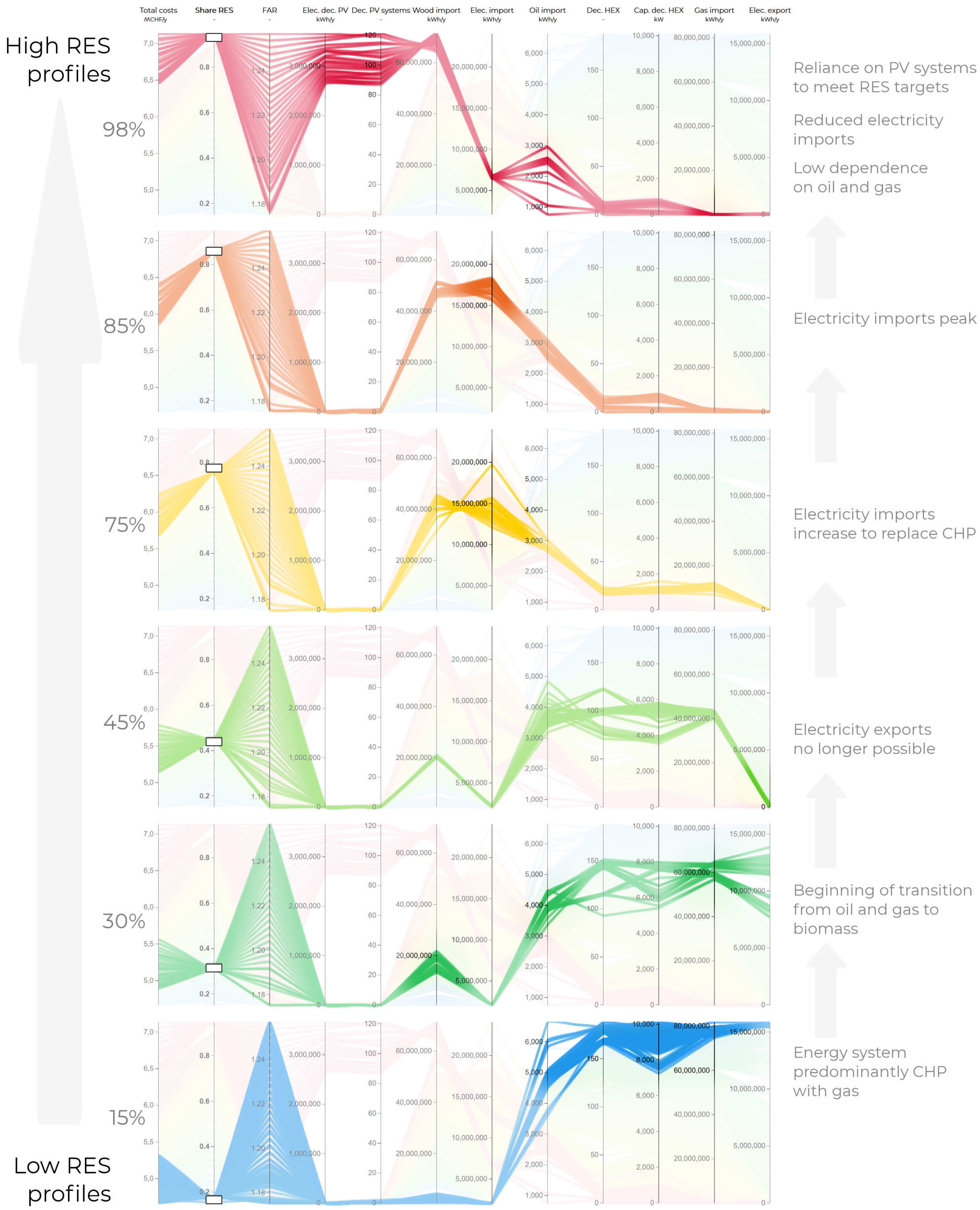


Figure 5.7 – Depiction of energy system "portfolios" for increasing shares of RES, computed by optimization of costs, density and share of renewable energy for the Palettes project. Color of the lines indicate varying shares of RES. Colors are mildly emphasized (darker) to highlight the portions of the chart which are commented.

satisfy also other criteria in a balanced way.

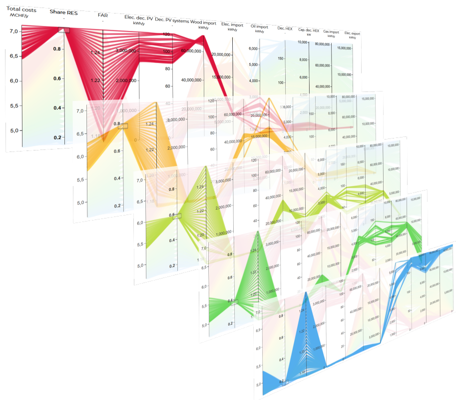


Figure 5.8 – Schematic illustration of the animation feature in parallel coordinates, typically performed by brushing an axis. Here, five snapshots of the Palettes project's solution space are shown, for increasing shares of RES from front to back.

5.3.1 Learning the preferred weights between criteria

So far, the TOPSIS method was applied with equal weights, meaning all criteria were considered equally important when computing the distance to the ideal point. However, the resulting scores may not necessarily reflect the actual preferences of the DM. In this case, the DM can specify how much more important a criteria is relatively to the others, and obtain a score reflecting these preferences. Two main approaches exist regarding weight elicitation: direct explication, in which weights are obtained a priori from the DM, and indirect explication, in which weights are obtained a posteriori from the preferred alternatives (Kao, 2010). In some cases, it can be valuable to inform the DM how much more they value one criterion over the other. As noted by Cohon (1978):

> *If the weights themselves are considered important results, then some degree of control over their value is a significant attribute of the solution method. For instance, it may be worthwhile to communicate to decision makers that this solution implies that objective Z_1 is equally as important as objective Z_2; this solution results when objective Z_1 is twice as important; etc.* (Cohon, 1978, p. 157)

In Figure 5.11, the indirect approach is adopted to answer the question: "*What are the weights for which the solution with the maximum share of RES ranks first*"? For this purpose, TOPSIS was thus performed for various weight combinations $(w_{TC}, w_{FAR}, w_{RES})$ as follows: costs and density where kept with a weight of $w_{TC} = w_{FAR} = 1$ (before normalization), while the weight of RES share w_{RES} was increased incrementally. For each combination in Figure 5.11, an asterisk indicates the share of RES which corresponds to the highest TOPSIS score. Naturally, as the weight of the RES criterion increases, solutions with higher shares of RES obtain better scores. As shown, the weight of RES share must be 7 times higher than those of the other criteria for the highest RES share to be ranked first with TOPSIS, i.e. the corresponding weight combination is $(w_{TC}, w_{FAR}, w_{RES}) = (1, 1, 7)$ (before normalization). In other words, this can be interpreted as follows: if a DM were to select the solution with the highest share of RES, their preferences for that criterion would be considered 7 times greater than for the two others. Note that including variations of the weights of the two first criteria as well might lead to other combinations for which this solutions ranks first, however the use of methods to automatically determine such combinations was not investigated in this work (Kao, 2010; Wang et al., 2009).

Similarly, this approach was repeated for determining the weighting combination which leads to

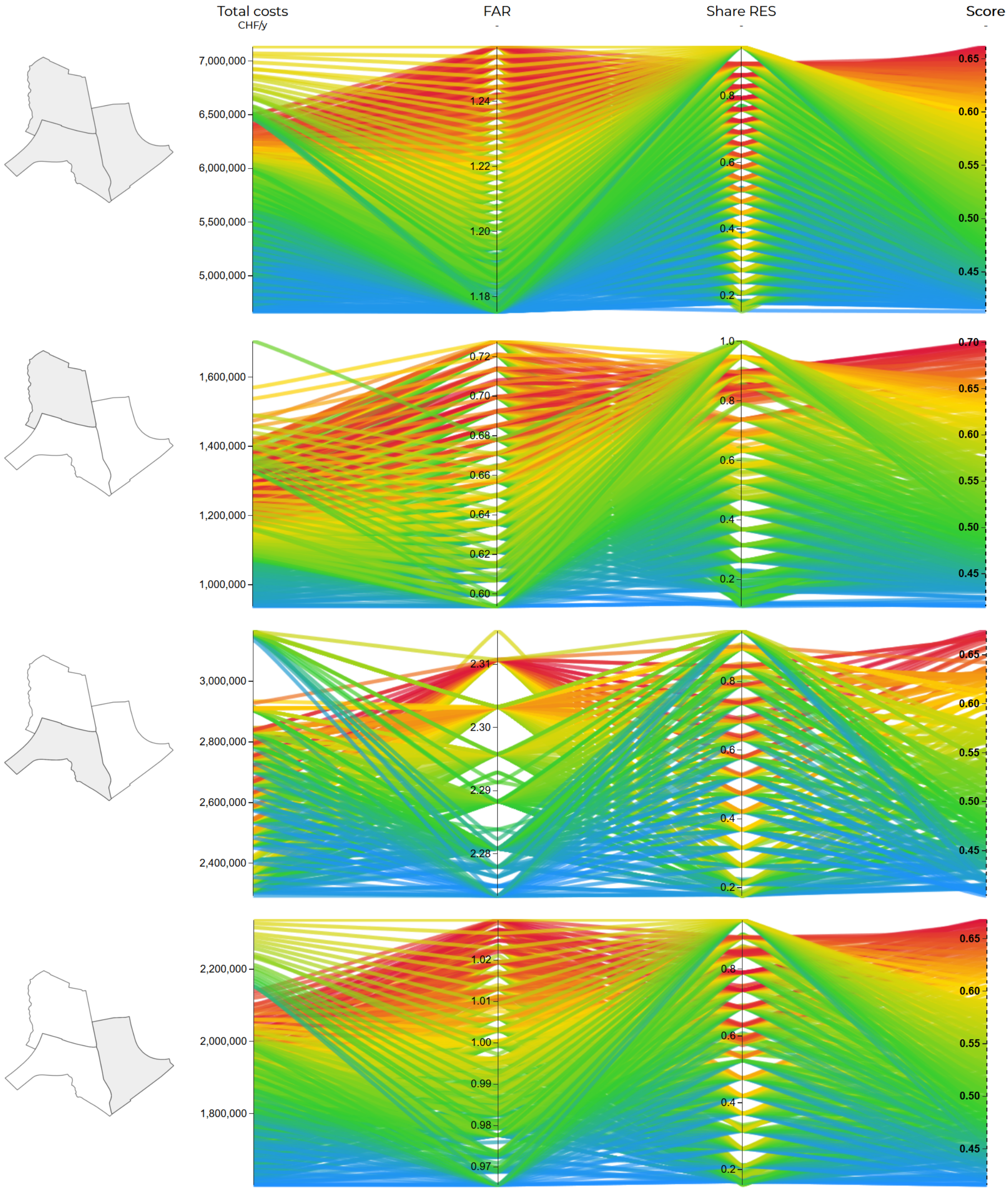


Figure 5.9 – TOPSIS score applied with equal weights on all criteria for the different subsectors (indicated by the map thumbnails on the left) in Palettes (systematic sampling case). Lines are colored according to the last axis (TOPSIS score).

selecting the cheapest solution. Figure 5.12 indicates that the corresponding weight combination is $(w_{TC}, w_{FAR}, w_{RES}) = (1, 1, 16)$ (before normalization).

Finally, the combination of weights for which the highest density is chosen is coincidently $(w_{TC}, w_{FAR}, w_{RES}) = (1, 1, 1)$ (before normalization). This can be observed in Figure 5.9, in the top parallel coordinates chart.

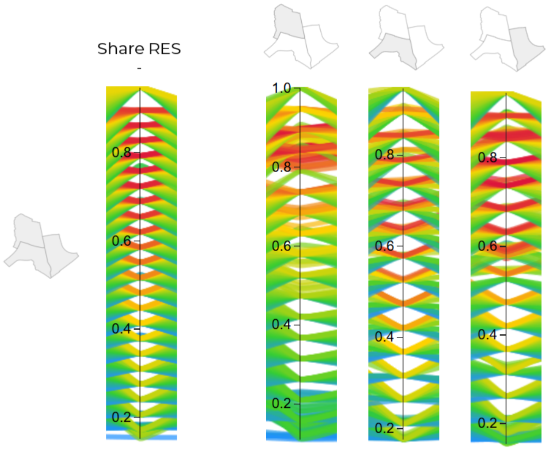


Figure 5.10 – The share of renewable energy sources (RES) axis for each sector in Palettes is shown, colored by TOPSIS score, which was computed for total costs, density (FAR) and share of RES. Red areas denote higher TOPSIS scores, i.e. solutions closer to the ideal point, and blue denotes lower scores.

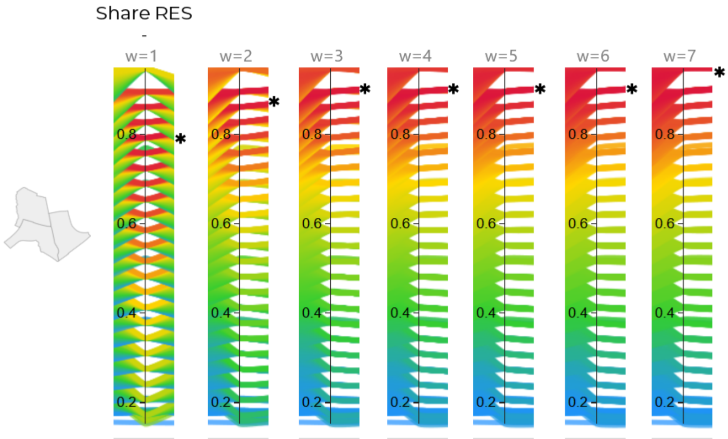


Figure 5.11 – RES objective colored by TOPSIS score for varying weights of RES, and constant weights of 1 for the total costs and FAR objectives. Asterisks ($*$) locate the best performing TOPSIS solution for each combination of weights. Results correspond to the Palettes project. Red areas denote higher TOPSIS scores, and blue lower scores.

5.3.2 Applying known weights to the TOPSIS method

To illustrate a case in which weights are defined *a priori* in order to find a preferred solution, the weighting of issues elicited by the planning team during the live poll in the first brownfield workshop is adapted to reflect the weights of the present criteria. The weights were obtained using anonymous remote controls (“clickers”) with the software TurningPoint [1], and the participants were asked to rank 5 issues (energy and building costs, CO_2, density, heritage, and nuisances) according to how critical they were perceived in the planning project. If an issue was selected first, it received 10 points, if selected second, 9 points and so on for all 5 criteria. The ranking of the five issues is found in Table 5.2. In the present case, only the three first issues are used as proxies for the three considered criteria, respectively, total energy related costs, floor area ratio and share of renewable energy). Their weights are therefore normalized to add up to 1, i.e. the original weights from the live poll $(w_{TC}, w_{FAR}, w_{RES}) = (0.242, 0.2, 0.2)$ become $(0.377, 0.312, 0.312)$.

[1] https://www.turningtechnologies.com/turningpoint/

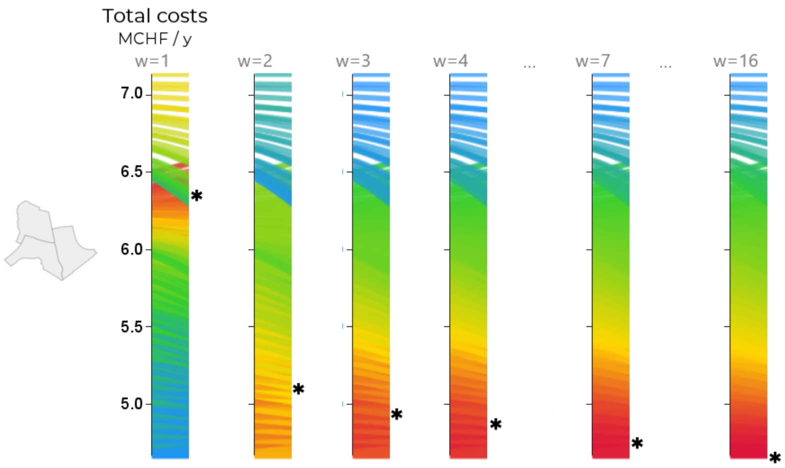


Figure 5.12 – Total costs objective colored by TOPSIS score for varying weights of RES, and constant weights of 1 for the FAR and RES share objectives. Asterisks (∗) locate the best performing TOPSIS solution. Results correspond to the Palettes project. Red areas denote higher TOPSIS scores.

Table 5.2 – Ranking of issues during the first brownfield workshop. Original data taken from Appendix, Figure C.4.

	Percent [%]	Weighted count
Costs[a]	24.17	29
Densification	20	24
CO_2	20	24
Nuisance	19.17	23
Heritage	16.67	20
Total	100	120

[a] Including costs for energy and construction.

Figure 5.13 shows the resulting solution for equal weighting, and the one obtained from the participants' custom weighting. The larger weight on the cost criterion leads to a solution which is 230'000 CHF/y lower than the top ranked solution with equal weights. This reduction in costs is possibly due to the lower density (1.25) and share of RES (72%). Additionally, the corresponding maps show that due to reduced costs, less buildings in the northern single-family house neighborhood are refurbished, as might happen for example if the commune's subsidies are directed to some other sector.

It should be noted that because the ranked issues during the workshop are only proxies for the criteria in the present application, they do not necessarily reflect the actual preferences of the planners and thus the results are only indicative. Furthermore, while other advanced weighting elicitation methods such as AHP, SWING or SMART could be adopted (Wang et al., 2009), and the ratings collected from a larger group of planners—including for example citizens—the present example already illustrates how TOPSIS can be used to identify solutions which reflect one or several DMs' preferences.

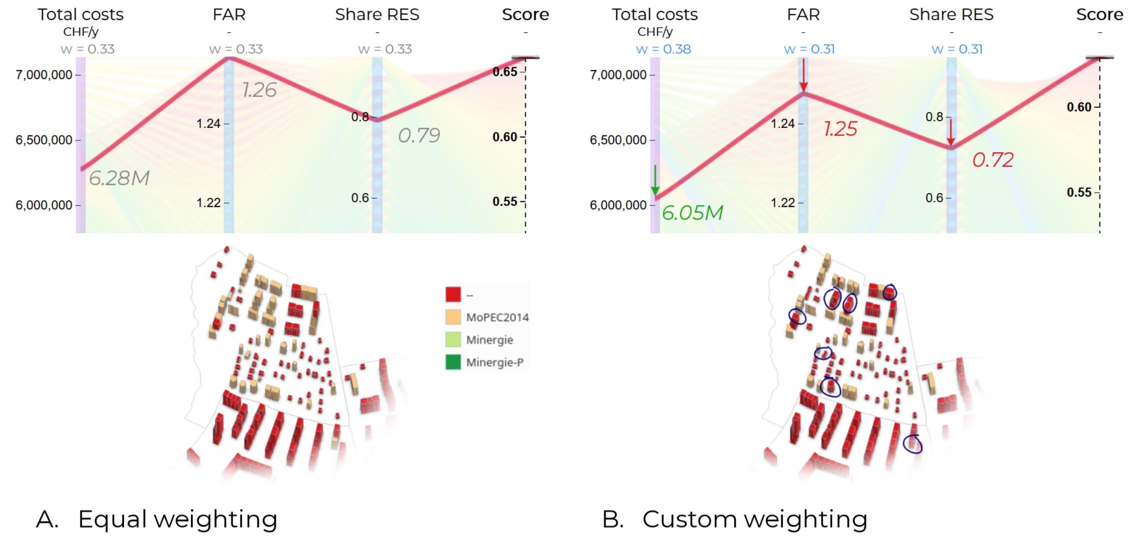


Figure 5.13 – Comparison of TOPSIS ranking in parallel coordinates for (A) equal weighting and (B) custom weighting of all three criteria. Maps correspond to the top ranked solution for both cases, and show the different refurbishment levels of buildings in the northern subsector (no differences in refurbishment were noticeable in the two other subsectors and are thus not shown). Arrows in chart emphasize improvement (green) or degradation (red) of the objectives. Differences in refurbishment are highlighted in map (B).

5.4 Refining the search: towards interactive optimization

The main purpose of a posteriori methods is to provide a *sufficient* approximation of the Pareto front (Branke et al., 2008; Mavrotas, 2009). The number of solutions required for it to be considered sufficient is however somewhat subjective, and depends on the shape of the Pareto front.

One important aspect is that the approximated Pareto front contains evenly distributed points on the Pareto front (Messac, Ismail-Yahaya, and Mattson, 2003). In the examples shown in this chapter, and particularly visible in Figure 5.3, the bend in the upper area of the Pareto front causes an irregular spacing in that area. Even with a relatively high number of sampled points (i.e. respectively 900 and 400 for the systematic and Sobol cases in Figure 5.3), the area eventually remains poorly explored.

Several responses allow to improve the regularity of the Pareto front in such cases. Three variants are discussed here in regard to a posteriori and interactive approaches (Figure 5.14). A first approach, shown in Figure 5.14B, involves the normal constraint (NC) or normalized normal-constraint (NNC) method, which consist in specifying constraints which are normal to a “utopia line” connecting the anchor points at each end of the Pareto front (for a bi-objective case) (Messac, Ismail-Yahaya, and Mattson, 2003; Sharma and Rangaiah, 2014). While this method is proven to generate more evenly spaced Pareto fronts and would thus be valuable for a posteriori approaches, the formulation of constraints is less intuitive then in the ε-constraint, where the upper and lower bounds correspond directly to the area of interest to the user.

A second approach suggested here is to formulate the multi-parametric problem Eq. (5.1) in such a way that the dimension relative to which the Pareto front changes the fastest is subject to the parametrized constraint, while the other is optimized (Figure 5.14C). This requires either to know a priori roughly how the objectives behave, or to adapt the problem formulation interactively once this knowledge is discovered, as foreseen in SAGESSE. In the present case, this would require setting the share of RES as main objective, and ranges on the two others (i.e. total costs and floor area ratio). However, because this particular function (i.e. Share RES) is expressed as a nonlinear

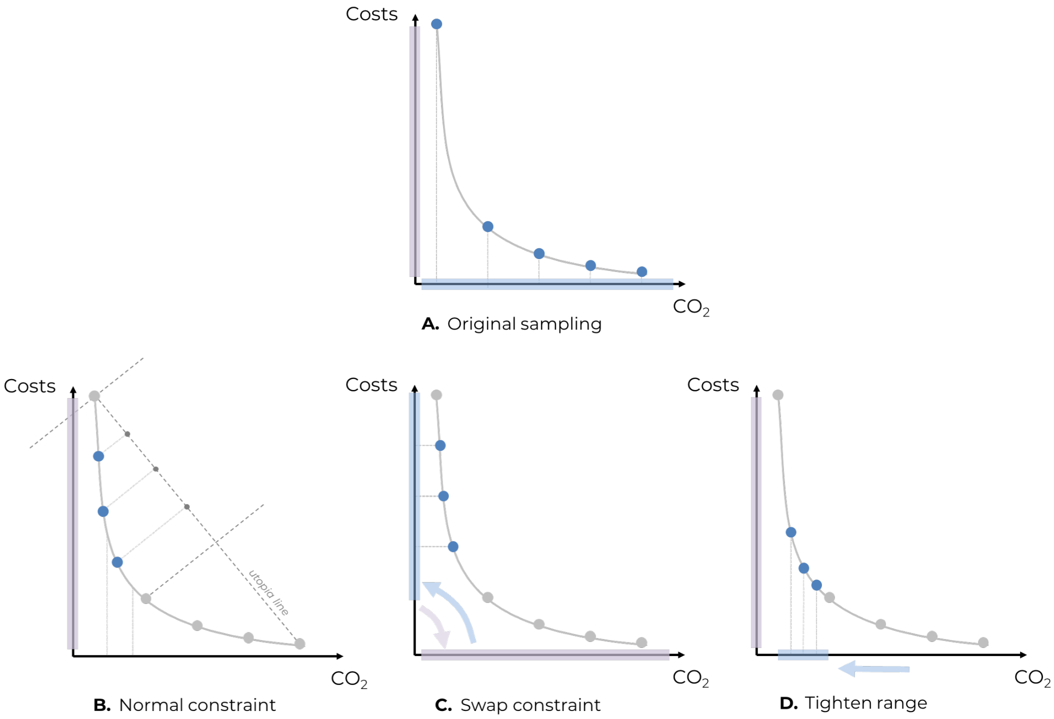


Figure 5.14 – Schematic depiction of three possible responses to an uneven distribution of points on the Pareto front (for two minimizing objectives). Purple denotes the main objective, and blue the sampled range. Illustration B is adapted from Messac, Ismail-Yahaya, and Mattson (2003).

combination of variables, this approach is not applicable here (Schüler et al., 2018b).

A third approach consists in simply adjusting the size of the explored range to fit the sparse area: while the pitfalls of the original sampling approach remain, at least the efforts of the search are focused in the area of interest, and the user can thus manually "patch" any such blind spots (Figure 5.14D). This is applied to the original data calculated with the systematic sampling approach in Figure 5.3, by requesting 100 new points with the Sobol sequence, and tightening the original range for the RES share to $[\varepsilon_{RES}^{min}, \varepsilon_{RES}^{max}] = [0.896, 0.977]$, where the lower bound corresponds to value where the sparse area begins in the original data, and the upper bound is chosen based on the maximum value of RES share computed in Table 5.1. For the FAR objective, the same range is used as in the original problem, namely $[\varepsilon_{FAR}^{min}, \varepsilon_{FAR}^{max}] = [1.17, 1.26]$. The resulting solution space is shown in Figure 5.15, where the darker points were added in this second step.

5.5 Discussion

5.5.1 Systematic vs Sobol sampling

In the light of the applications in this chapter, the main advantages and limitations of the adopted sampling methods are summarized. While the choice matters only little in the case of a posteriori approaches, the discussion considers also implications in interactive applications.

Advantages of Sobol sampling

The Sobol sequence approach provides incontestably the quicker overview of the entire searched area. This was shown in Figure 5.6. As the size of the Pareto front and the number of objectives

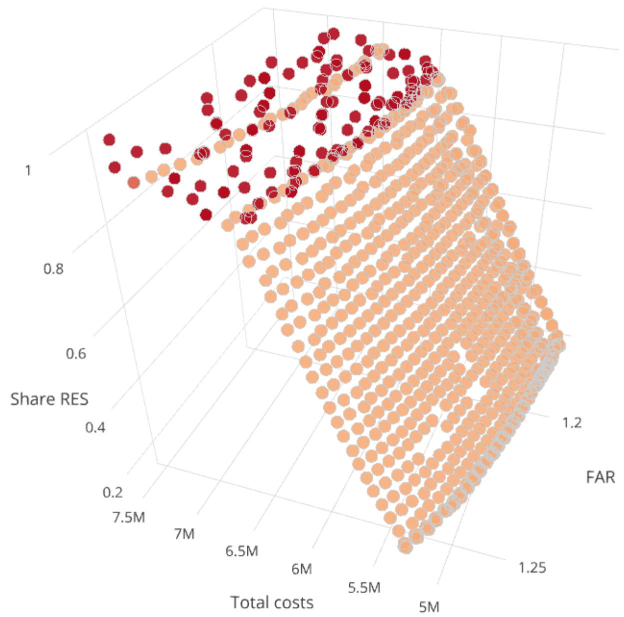


Figure 5.15 – Interactive "patching" of gaps in the Pareto front by tightening the sampled range on the RES share axis. 100 additional points (dark red) sampled with the Sobol sequence are added to the 900 original systematically sampled points (light red) from Figure 5.3 for a better approximation of the Pareto front.

grow, this advantage becomes always more critical. Another key advantage from the user's point of view is that this approach does not require much thought in the number of solutions requested. Indeed, the sequence is designed to always sample the next most meaningful point in the parameter space. Thus, one could imagine setting an infinite—or nearly infinite—limit to the number of solutions, and only stopping the search when the DM considers the approximation sufficient. Until stopped, the sequence continues to fill in the ever diminishing gaps. In the case of systematic sampling, one must carefully anticipate the number of requested solutions. Figure 5.6A clearly illustrates how the more points are requested per axis, the longer it takes to start exploring another "step" in the next dimension. Press and Teukolsky (1989) describe this advantage of quasi-random sequences as the ability to "*sample until* the desired point is found, moving smoothly to finer scales with increasing samples", as opposed to sampling a space according to a predefined number of points.

Advantages of systematic sampling

The systematic approach is more appropriate than the Sobol sequence regarding control and systematic analysis. Indeed, the user can control precisely how densely each individual dimension should be sampled. This means that if the user wants to analyze in depth the characteristics of three different densities, for a continuous variation of RES share, then the systematic approach should be chosen. To achieve something similar with the Sobol sequence, the user would either have to wait for many points to be computed before reaching a same density of points in the areas of interest, or they would need to formulate three distinct sets of problems, where the densities are fixed with single constraints, and only the RES share dimension is sampled with the Sobol sequence. While this may be cumbersome, the lack of regularity in the intervals between each point may also be undesirable, and could prevent a systematic analysis of evenly spaced points.

Disadvantage of both methods

Stump et al. (2009) argues that contrary to systematic, quasi-random or other stratified approaches, random sampling presents the following advantage:

> *"While more advanced sampling strategies can be employed (e.g., Latin hypercubes, uniform designs), we have found that random sampling is more advantageous when exploring the trade space visually since any structure that occurs in the sample data is an artifact of the model M (potentially valuable information to a decision maker), rather than being induced by the sampling process."* (Stump et al., 2009, p. 3)

While the systematic sampling suffers the most from this risk of inducing visually biased structures in the Pareto front (Gilbert, 1987), the Sobol sequence is not entirely risk-free, given it is quasi-random. Press and Teukolsky (1989) showed how the first 128 points are positioned rather uniformly in the unit hypercube, and how the following points systematically fill the remaining gaps following some fairly regular pattern. Such patterns are slightly emphasized in Figure 5.2 due to the coloring of most recent points. Due to the marginal effect of these patterns when the entire Sobol sequence is considered globally, its advantage of guaranteeing to explore the entire space the fastest (Burhenne, Jacob, and Henze, 2011; Press and Teukolsky, 1989) arguably outweighs the risk mentioned by Stump et al. (2009), and is therefore preferable to true random sampling in interactive methods.

Advantages of a combination of systematic and Sobol sampling

As was shown in Figure 5.15, a combination of both sampling methods can be achieved. In this case, Sobol sampling was adopted to rapidly fill in the gap left by the systematic exploration of the Pareto front. The opposite combination would also be relevant in some cases: the Sobol sequence could first be run to loosely "materialize" the outline and shape of the Pareto front, allowing the user to then run a systematic sampling on one or multiple "slices" of the front.

5.5.2 Data visualization for Post-Pareto analysis

Generating the Pareto optimal set is only the first step of multiobjective optimization: selecting one solution, and understanding the underyling tradeoffs between objectives, constitutes the second step, which is often avoided or overlooked in multiobjective optimization studies (Aguirre and Taboada, 2011; Balling et al., 1999).

The type of data visualization adopted plays a central role in how the user's questions may be answered (Branke et al., 2008; Miettinen, 2014). In this chapter, a combination of parallel coordinates and 3D charts allowed to make some interpretations about the characteristics of the entire Pareto front, and of individual solutions. The added-value of interacting with parallel coordinates to animate the data was illustrated when attempting to obtain insights from multiple axes simultaneously (Figure 5.7). It should be stressed that in print, parallel coordinates are necessarily a reduction of the actual exploratory insights which they are capable of in their interactive form.

Given the large data set explored in this chapter, it became clear that at some point, individual solutions may matter less than their aggregation. This was for example the case in results discussed in Figures 5.7–5.12. This point is particularly relevant in the context of the "interpretability" issue in Chapter 4: the ultimate purpose of interactive optimization for urban planning is indeed not to identify *a* definite solution to a problem, but rather to gain knowledge regarding the *general relationships and tradeoffs* between criteria. This knowledge should allow planners to identify interesting *ranges* of solutions on which to focus more deeply in their strategic and physical plans, and ranges to avoid. The importance of specifying loose ranges rather than strict thresholds was already advocated by Wiek and Binder (2005) in the context of sustainable development target identification, to better accommodate the required flexibility in decision making. This notion of "abstracting" the optimization results from discrete lines to loose ranges can be visualized by "blurring" the frontiers between polylines in the parallel coordinates, and conserving only the general features contained both in color and space. Figure 5.16 shows an abstracted version of the first chart in Figure 5.9: the lines aggregated into coarse pixels are sufficient to locate the interesting corridors of solutions (red pixels), and those which are less relevant (blue pixels). A quick glance at such a figure indicates that in the present case, the planners should strive for an alternative with densities beyond 1.23, share of renewable energy sources between 60-80%, while a budget of 6 MCHF/y would allow to achieve the corresponding targets.

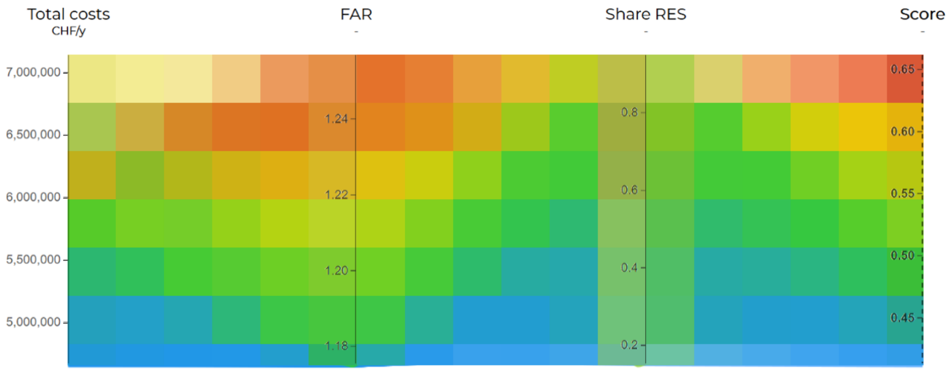


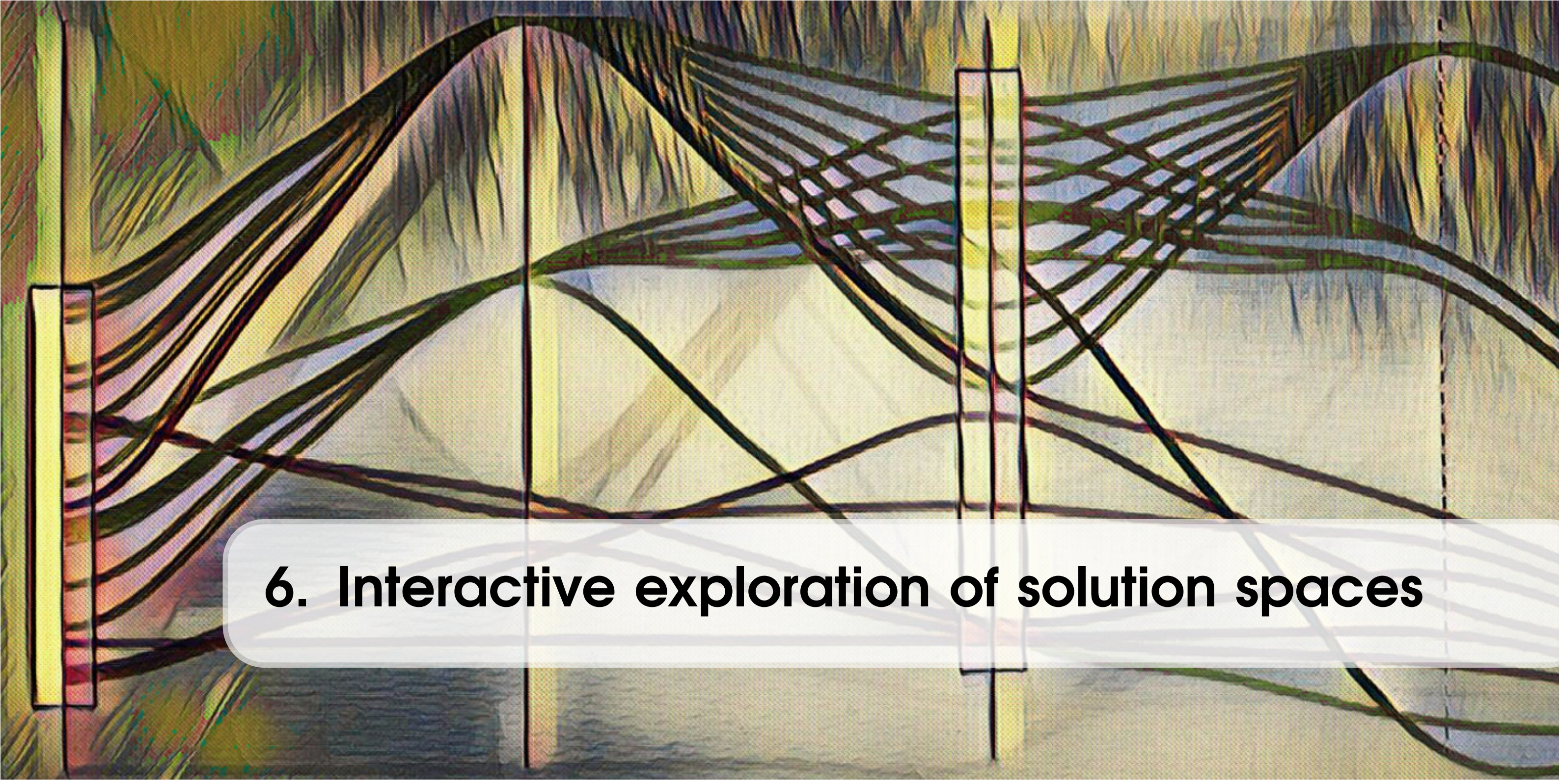
Figure 5.16 – Abstraction of the original data set from Figure 5.3, revealing corridors of "interesting" solutions (in red) and of less relevant solutions (in blue). Colors represent TOPSIS scores applied with equal weights on all three criteria.

When handling large amounts of alternatives, the focus on individual lines seems less relevant than considering the more general patterns which the parallel coordinates reveal, sometimes, in unexpected ways. While the trained eye is fairly accustomed in recognizing slopes, clusters or optima in two or three dimensional scatter plots, such observations are not always as explicit, or directly obvious for more dimensions visualized in parallel coordinates (Akle, Minel, and Yannou, 2016; Netzel et al., 2017). However, this does not mean the information cannot be accessed. Recent studies on the use of parallel coordinates investigated for example the benefits of providing novice users with training (Wolf, Simpson, and Zhang, 2009), how to interpret the shape of optimal data sets in comparison to traditional scatter plots (Li, Zhen, and Yao, 2017), the benefits of clustering solutions for leaner visualizations (Palmas et al., 2014) or how users focus their attention on different components of parallel coordinates (Netzel et al., 2017). As parallel coordinates become increasingly widespread in scientific literature (Inselberg, 2009) and in mainstream media, and with the availability of a variety of easily accessible interactive data visualization tools, it is likely that the "fluency" in interpreting such charts will improve, allowing in the future richer and innovative intepretations of complex data sets, both by academics and practitioners.

5.5.3 Shortcomings of a posteriori methods for large problems

One of the main benefits of a posteriori methods is to provide the DM with a representative overview of all feasible Pareto optimal solutions, promoting confidence in the selection of a preferred solution (Mavrotas, 2009). Arguably, time spent exploring the generated Pareto optimal plans is worthwhile, given the considerable "legwork" performed by the computer to filter out any inefficient alternative (Balling et al., 1999). However, the practical relevance of the results presented in this chapter must be put into perspective. First, only three dimensions were sampled. To gain an overview as detailed as the examples provided, computational costs are known to grow exponentially with increasing number of objectives (Copado-Méndez et al., 2016; Laumanns, Thiele, and Zitzler, 2006; Cohon, 1978). Second, the problem size itself also increases the computational demand. On average, each of the 900 solutions calculated for the Palettes sector (Figure 5.3) took approximately 93 seconds to converge. For 30 sample points on both constrained objectives, the entire process lasted nearly 24 hours. Adding simply one objective would bring the size of the sampled grid to 27'000 points. Assuming a similar average calculation time, the Pareto front would require almost a month to compute. For the greenfield case, this limitation is even more important, with an average solve duration of approximately 19 minutes per solution of the Cherpines sector (Figure 5.5), or about 6 days to generate all 400 Pareto points.

As demonstrated in this chapter, the use of the quasi-random Sobol sampling technique is a first measure which guarantees an efficient exploration of the entire space (Copado-Méndez et al., 2016). While other approaches could be combined to further improve the computational efficiency (e.g. parallel computing or machine learning), the next chapter will illustrate with concrete applications how interactive optimization can be used to make the exploration of the entire multi-dimensional solution space achievable in a reasonable amount of time, while improving the learning experience for the user. Balling et al. (1999) formerly emphasized the benefits of having an optimization approach help the DM focus on efficient solutions; here the proposed interactive optimization approach "mirrors" this advantage, by having also in return the DM help the computer focus on generating only the most relevant solutions. The resulting human-computer interaction system thus allows to adequately handle even large, multi-dimensional problems such as those found in urban planning.



6. Interactive exploration of solution spaces

SOCRATES: *Then next, it seems, we should try to discover and show what is badly done in cities nowadays that prevents them from being managed our way, and what the smallest change would be that would enable a city to arrive at our sort of constitution – preferably one change; otherwise, two; otherwise, the fewest in number and the least extensive in effect.*

— Plato, *Republic*

The aim of this chapter is to illustrate with concrete examples how the SAGESSE methodology can be used to answer planning questions in an iterative way. The methodology is therefore applied to the two case-studies of Palettes and Les Cherpines, describing in particular the steering features used for generating Pareto optimal solutions in multiple dimensions. The questions tackled in these applications are based on the issues identified in Chapter 4.

The brownfield case has been published in Cajot et al. (submitted), while the greenfield case is adapted from the application published in Cajot et al. (2017a).

6.1 Brownfield application

The results in this section are structured following the SAGESSE acronym, i.e. *systematic analysis, generation, exploration, steering and synthesis experience*. First, the *analysis* is described. Typically the analysis phase is performed globally and jointly with an analyst to identify the main criteria and constraints for the development of the model (see Chapter 3). However, a narrower analysis is repeated by the user for every project in URB^{io} , in which they identify the perimeter of the project, as well as the main criteria that they will begin by inspecting. Next, the joint *generation-exploration-steering* phase describes the main iterations performed to answer the preliminary (and newly raised) questions. Finally, a *synthesis* of the search process is presented, and the main insights provided by the *systematic experience* are discussed.

6.1.1 Analysis

As identified in Chapter 4, the main questions faced by the planners, and explored in this section, are: *What is the potential for densification?* and *How to reduce the carbon emissions of an existing district?*

Accordingly, in the analysis phase, the user starts by selecting the desired project perimeter—in this case the entire Palettes area—and the criteria with which to begin the search for urban configurations, which can answer the stated questions. After creating a new project, the user faces an empty chart in the GUI (Figure 6.1). This blank chart forces them to think of the most valued aspects in the project, in other words, what they are trying to achieve. For example, to address the first question, the floor area ratio (FAR) axis is added to the chart from the drop-down menu. Regarding the second question, both the total costs of the energy system, as well as the share of renewable energy sources (RES) are also included.

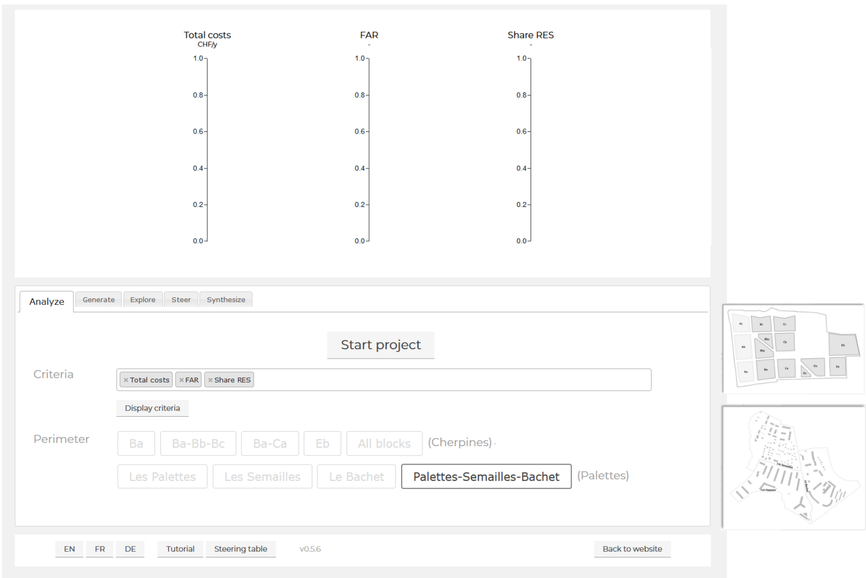


Figure 6.1 – Screenshot of the SAGESSE graphical user interface, showing the tab for the analysis phase. The lateral maps on the right appear as pop-ups to assist in the selection of a perimeter.

6.1.2 Generation, exploration and steering

If they know *a priori* the desired or feasible densities of the project, they can directly specify a range of densities to explore. If not, they can easily compute the minimum and maximum achievable densities of the neighborhood by specifying an objective on the FAR axis (Figure 6.2A). A first time, they rely on the default preference for “more” FAR, and the solver returns the maximum density of 1.27, corresponding to a neighborhood in which additional floors are constructed on all buildings that can legally be heightened. A second time, they set the preference of FAR to “less”, and the solver returns a density of 1.17, which corresponds to the neighborhood’s current density.

A first question here is: *Can high shares of RES be achieved in a high density neighborhood?* Having learned the bounds of achievable densities, they can dismiss them and continue to explore tradeoffs between solutions with densities between 1.17-1.27, RES shares between 0-100%, and minimal costs. This is performed by brushing an objective on the total costs axis, and specifying a range with Sobol sequence on the two other axes (Figure 6.2B).

As the solutions requested in Figure 6.2B appear, the user realizes after only 5 solutions that a

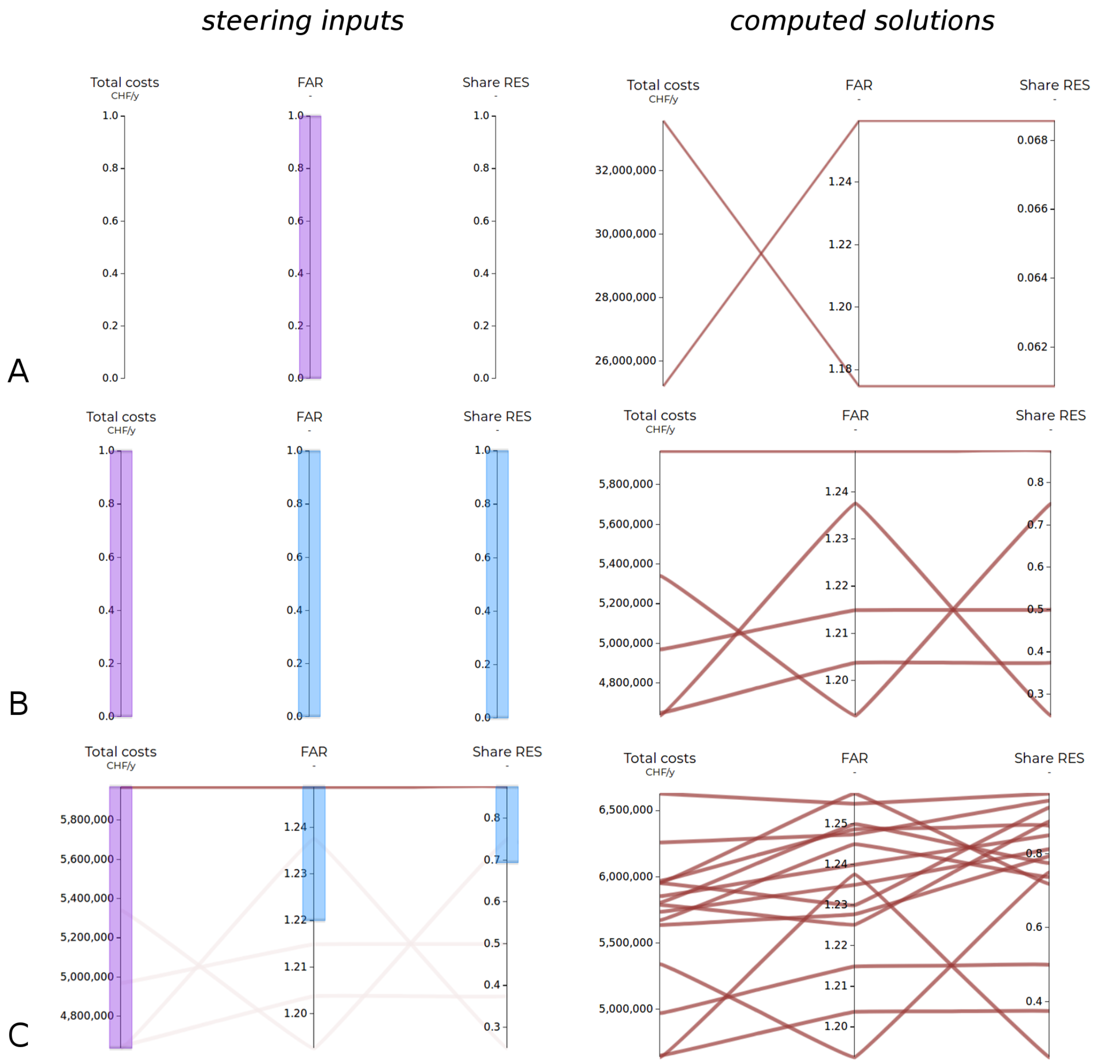


Figure 6.2 – Parallel coordinates charts showing different steering inputs (left) and resulting solutions computed with Sobol sampling (right). A: Set optimize the FAR objective twice, for both less and more as preferred direction, to learn boundaries. B: Request Pareto optimal solutions for all three axes. C: Narrow the search for solutions in the upper parts of FAR and RES. Purple brushes indicates the primary objective in the ε-constraint formulation, and blue brushes indicate the range within which auxiliary constraints are varied.

satisfying RES share (0.88) is compatible with a high density (1.25), although at higher costs (5.97 MCHF/y). The question thus becomes: *How much can the costs be reduced while maintaining an acceptable share of renewable energy and density?* To answer this question, they brush new ranges on the upper parts of the FAR and RES axes, to narrow the search only to those interesting areas, with the expectation to find a configuration which has a lower total cost than the currently most expensive solution (Figure 6.2C). A series of cheaper solutions appear, which the user can filter to reveal the tradeoffs with either FAR or RES that allowed the cost reduction. As visible in the bottom-right chart, the Sobol sequence used to specify constraints guarantees a homogeneous and quick exploration of the areas of interest. As requested by the user, the sampling was first performed on the entire axes, then focuses on the upper areas, as denoted by more compact lines in the upper part of the FAR and RES axes.

Continuing this process, the user can answer further questions, such as: *Which additional aspects explain the costs?* Or: *Which energy technologies lead to these shares of renewable energy sources?* For example, they might be interested in the remaining number of oil boilers in the proposed solutions, as a political target aims at decreasing their amount for environmental reasons. To do so, they type keywords in the drop-down menu to find and display additional criteria (Figure 6.3A). By including the decentralized oil boiler axis, they realize that still around 60 undesirable oil boilers are present in the neighborhood (red polylines in Figure 6.3A), which were initially present in the status quo. To assess the consequences of a drastic reduction in their number, they specify a constraint to prevent oil boilers in all upcoming solutions, while maintaining the exploration of cost-optimal solutions with both high density (> 1.24) and high renewable energy share (> 0.8). This generates ten new solutions with no oil boilers (blue polylines in Figure 6.3A).

The reduction in number of oil boilers has little effect on the total costs and performance of RES share compared to the solutions which included them. To explain this lack of effect, the user could further explore different criteria concerning the oil boilers and other technologies to find out their respective contributions to the neighborhoods energy supply. In this case however, a cartographic representation of the annual energy supply per building and per energy technology is more adapted to provide an overview of all technologies. The maps of solutions containing the oil boilers (not shown) are in fact similar to those without oil boilers (e.g. Figure 6.3C), with a predominance of district heating and wood boilers supplying the buildings. This indicates that oil boilers are only marginally used to satisfy peak loads, and can be substituted by the other installed technologies for only a limited cost increase.

Repeating this process for wood boilers, which are also to be avoided in urban centers because of health-related issues, the user adds a new constraint on the wood boiler axis, and requests five new solutions (Figure 6.3B). Note that in Figures 6.3A and 6.3B, the axes which influenced the generation of the highlighted polylines are colored accordingly, cf. Section 3.2.3. The new constraint on wood boilers leads to a system dominated by solar PV panels and both ground and air source heat pumps. Furthermore, three of the five solutions were infeasible, indicating that shares of RES exceeding 0.88 become difficult to achieve without relying on wood boilers. Overall, the solutions without wood boilers are also more costly than the former solutions which relied on wood boilers and district heating (Figure 6.3B). The reason district heating is no longer chosen after adding the constraint on wood boilers (Figure 6.3D) is that the available centralized technologies used for the district heating do not allow to achieve the higher RES constraints. The inclusion in the model of e.g. deep geothermal or the nearby lake as heat sources could make district heating again a feasible solution for the current problem.

At this point, the user could continue by inquiring e.g. social or economic questions, such as the distribution of costs between building owners and energy provider, the impact of increased density on the view of aesthetic landmarks, etc. As the process evolves however, the number of solutions and criteria rapidly grows. This is where MADA and cluster analysis can further support the exploration. To develop a general understanding of which solutions perform best, the TOPSIS method is applied on-the-fly to the current solutions, and colored accordingly (Figure 6.4A). Because the FAR axis is concentrated on a relatively tight range (1.19-1.26), the "max-min" normalization is adopted to ensure this criterion affects the final score equally to the other criteria (Section 3.2.7). This "score" axis provides support to examine the best performing solutions, i.e. the solutions which are the most balanced, in the case of TOPSIS. For example, by displaying only the solutions with top scores, the user can assess whether (i) the solution reflects their preferences, and (ii) which tradeoffs are required for the improvement of any criterion. For illustration purposes, the score is computed here for only the first three axes, to allow also displaying it also in 3D scatter plots. These plots help to interpret the underlying concept of the TOPSIS approach (Figures 6.4B

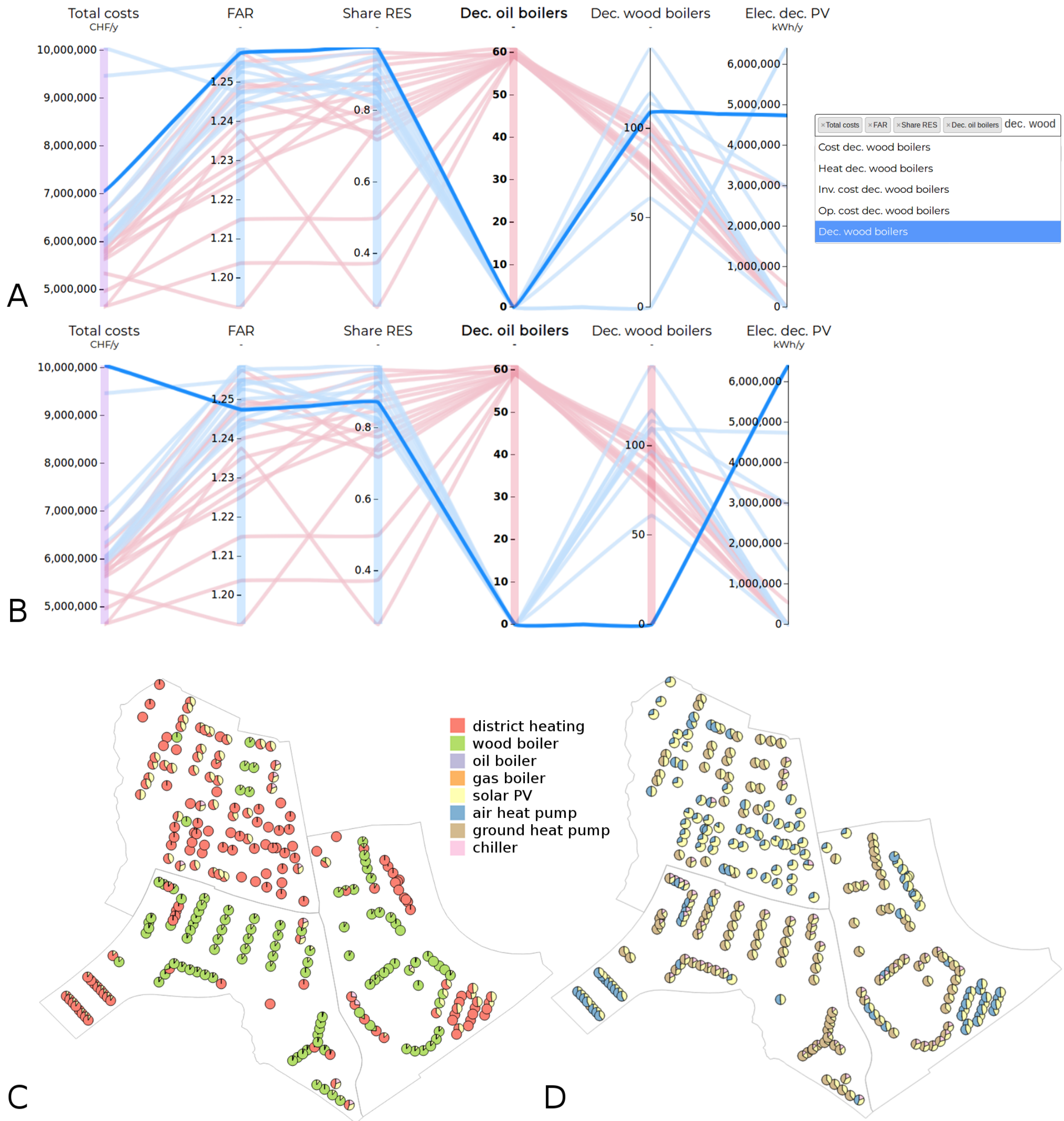


Figure 6.3 – (A) shows a highlighted polyline and the role each axis played in its problem formulation (purple–objective, blue–range, red–constraint), as well as the drop-down menu used to add axes. (B) shows a different highlighted polyline, which is constrained on both fourth and fifth axes. Bold labels indicate the axes based on which a linear gradient coloring is performed. (C) and (D) show the annual energy supply shares by technology per building for the solutions highlighted in (A) and (B) respectively.

and 6.4C). Indeed, the geometrical distance between ideal solutions and actual solutions can more intuitively be grasped in the 3D charts than in parallel coordinates, although this visualization is limited to three axes.

Another way to cope with the many solutions is to perform cluster analysis to identify the few most representative solutions. In Figure 6.5, the user performed three cluster analyses for respectively $k = 2,3,4$ clusters. Depending on the number of solutions for which they are willing to spend time investigating in more detail, or depending on the quality of the clustering (either evaluated visually in the scatter plots or parallel coordinates or by relying on quality indices such as the silhouette

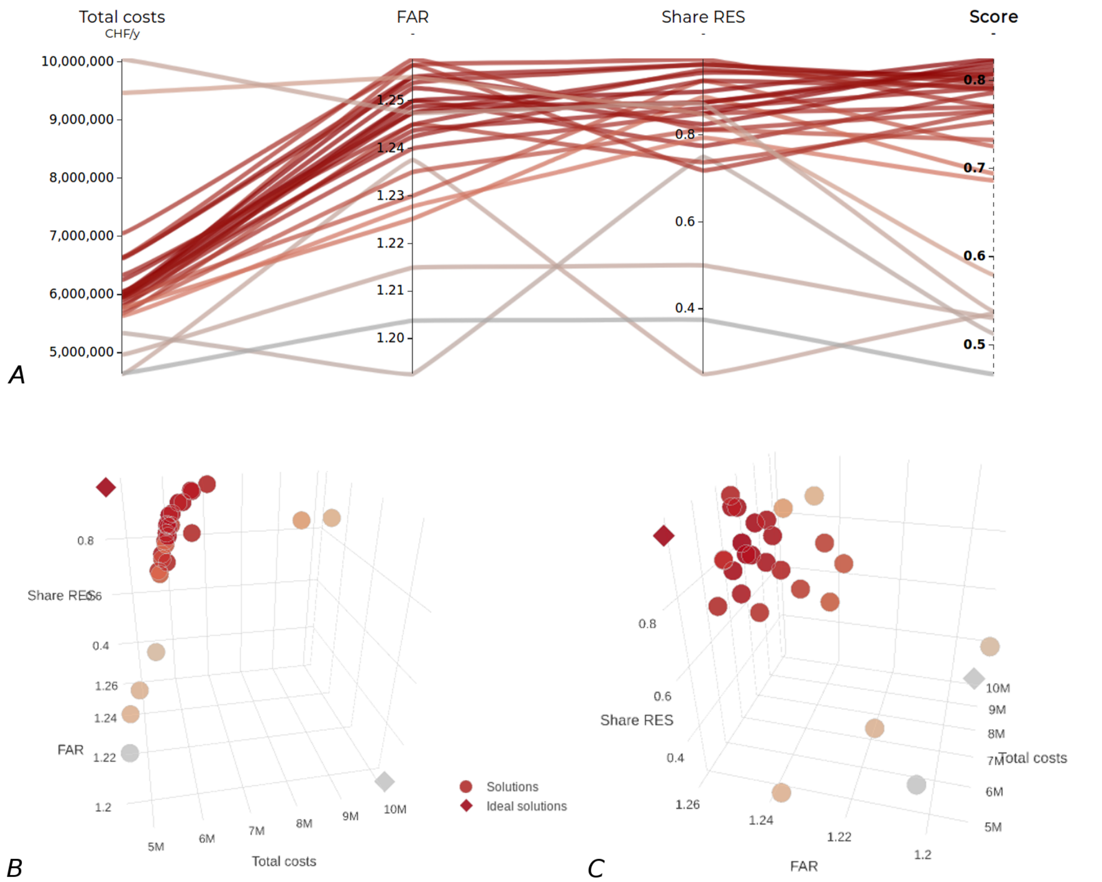


Figure 6.4 – (A) Depiction of TOPSIS score results in parallel coordinates. (B) Lateral view of the Pareto surface in a 3D scatter plot. (C) Frontal view of the Pareto surface. Dark red solutions indicates solutions closest to the positive ideal.

index), a number of clusters–and their corresponding representative solutions (i.e. medoids)–are adopted. Figure 6.5D shows the clustering results for $k = 3$ clusters in parallel coordinates. The color reflects solutions which are part of a same cluster, and the thicker lines indicate the medoids for each cluster.

6.1.3 Synthesis

After generating and exploring several alternatives, the user can narrow down the number of solutions to only a subselection of the most promising ones and add them to the comparer dashboard (Figure 6.6). They select seven axes, including a new criterion ("Share of performance certificates") which indicates the share of buildings which were refurbished according to various energy performance standards. The cartographic thumbnails reflect this criterion, where lighter shades of red indicate buildings refurbished to stricter energy standards. From the 27 solutions generated so far, the three solutions which were added correspond to the three medoids of a cluster analysis performed on the chosen criteria. The first solution (ID 11) is the most cost effective (highlighted in green), but performs the least well in the five last indicators (highlighted in red). In the second solution (ID 10), the neighborhood is almost entirely supplied from renewable energy sources, but

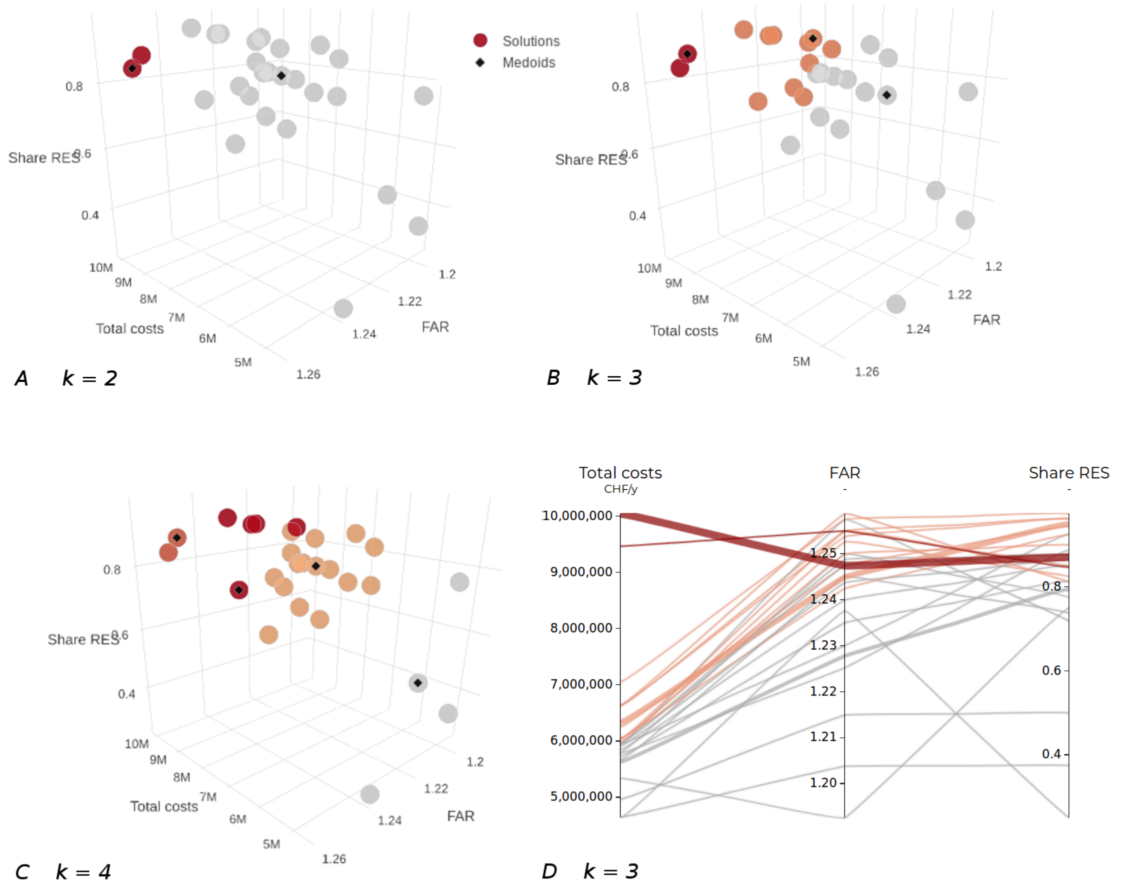


Figure 6.5 – Depiction of cluster analysis results in 3D scatter plots for $k = 2, 3, 4$. Parallel coordinates (D) show the same data set for three clusters, where colors indicate polylines belonging to a same cluster, and thicker lines indicate the representative solutions (medoids).

still relies on oil and wood boilers to satisfy part of the demand. Finally, the third solution (ID 27) is able to achieve 85% of renewable energy, in part by refurbishing 83% of the building stock, but nearly doubling the costs from the first solution.

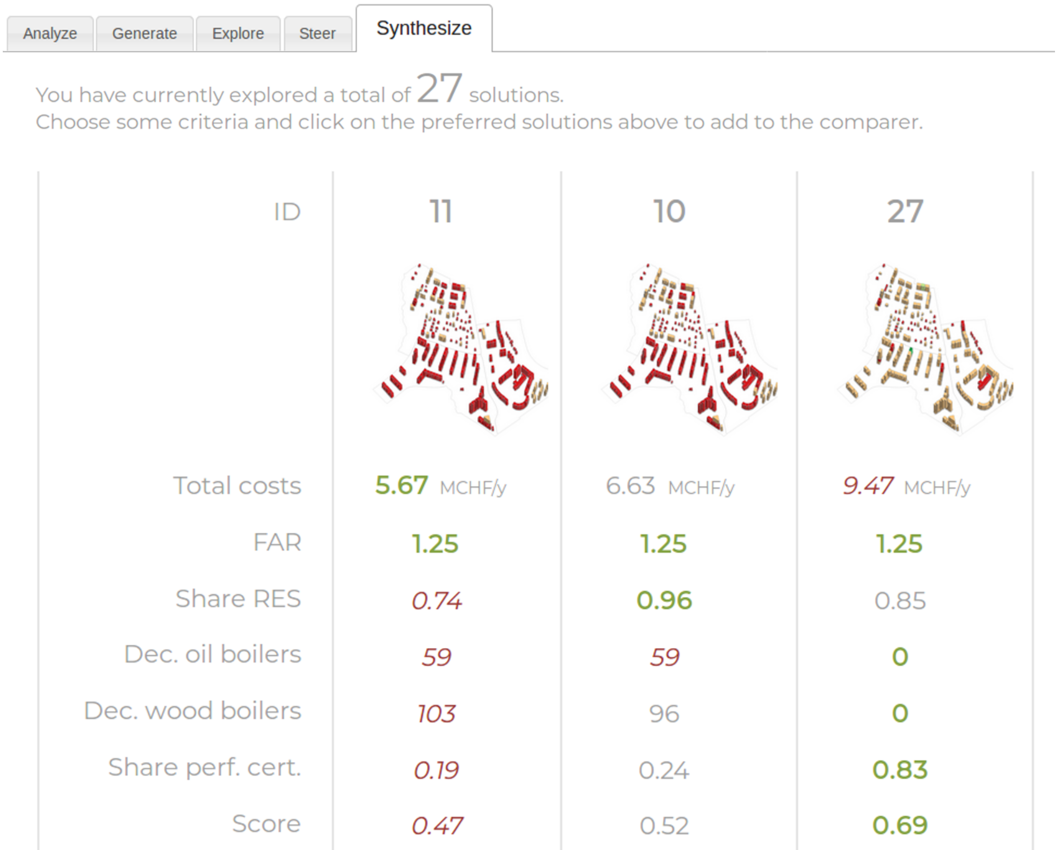


Figure 6.6 – Comparer dashboard containing three representative solutions from a cluster analysis on the chosen criteria. The thumbnails depict the buildings in each solutions, colored by share of energy performance certificates ("Share perf. cert.") adopted. Green fonts indicate the best performing values, red the worst.

6.2 Greenfield application

6.2.1 Analysis

The main questions tackled in this section are based on those identified in Chapter 4. These are: *How can urban planners arbitrate renewable energy targets with traditional urban planning targets such as built density? Which is the relevant perimeter of analysis? What defines the liveability of the neighborhood?*

As a compromise between addressing the entire neighborhood, or just a single block, the present application focuses on the three blocks Ba, Bb and Bc located on the western side of the neighborhood (cf. Table 4.1).

6.2.2 Generation, exploration and steering

Iteration 1 – Exploring basic alternatives

The main purpose of this first iteration is for an urban planner to become familiar with the general tradeoffs between density expressed as floor area ratio (*FAR*), total costs of the energy system (*Total costs*) and share of renewable energy sources (*Share RES*). To begin, sixteen solutions are sampled systematically across the three dimensions, within upper and lower bounds on FAR and Share RES which have been previously calculated (cf. Chapter 5).

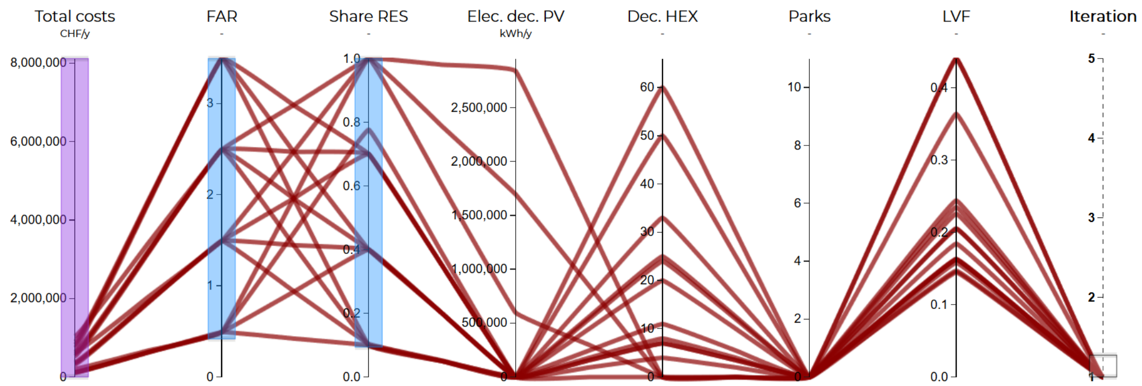


Figure 6.7 – Iteration 1: the user generates basic solutions according to three objectives, using systematic sampling. Purple indicates the specification of the main objective in Eq. 3.1, while blue indicates the specification of ranges.

In Figure 6.7, the parallel coordinates reveal that the optimization successfully identified solutions for all desired densities and RES shares, except one. Out of the sixteen requested solutions, only fifteen solutions were found, due to the combination of the highest density (3.5) with the highest share of RES (100%) being infeasible (cf. also Figure 5.1).

In order to visualize the relationships between two axes and the rest, line color and width are applied respectively to the FAR and Share RES axes. While the chart could be sequentially colored according to each axis, the ability to also resize the line width allows to visualize both relationships simultaneously in a single chart Figure 6.8.

The line width reveals a positive correlation between Share RES and electricity from PV (as denoted by the thicker lines in the upper part of both axes), and a negative correlation between the share of RES and the connection rate to a DH network (as denoted by the thinner lines in the upper part of *Dec. HEX*). The relationship with the landmark view factor (*LVF*) however is fairly random. This means that a satisfying configuration in terms of LVF (i.e. which promotes views towards the

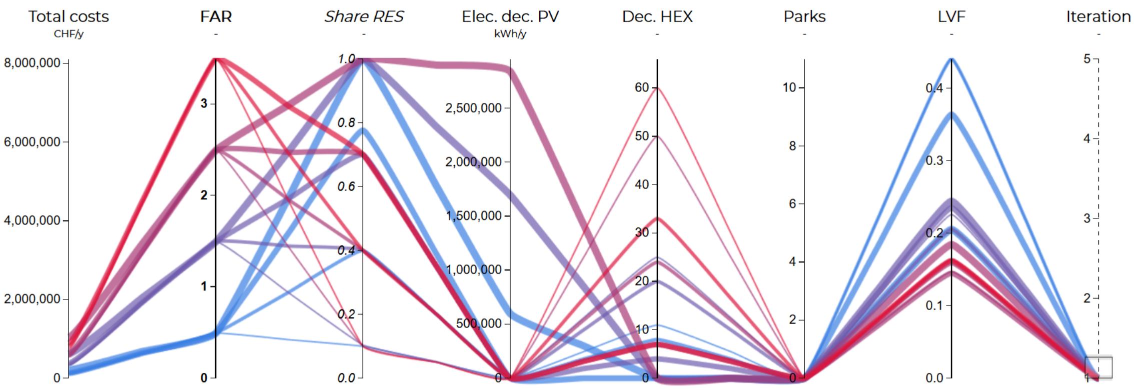


Figure 6.8 – Iteration 1: The color of polylines indicates the value of FAR, revealing a positive correlation with Total costs, and a negative correlation with the landmark view factor (*LVF*). The width of polylines is proportional to the share of RES, and indicates a positive correlation with Electricity from decentralized PV systems, and a negative correlation with decentralized heat exchangers (*Dec. HEX*).

mountain landscape north of the district) could be selected, which also achieves a relatively high RES share.

The same cannot be said about the relationship between density and LVF (Figure 6.8). Indeed, the lines colored by floor area ratio (*FAR*) show a negative correlation between FAR and LVF: this is rather expected, as the denser the configuration, the fewer floors are likely to enjoy the view without being obstructed by another building. This indicates a contradiction between two planning goals, for which a compromise must be considered.

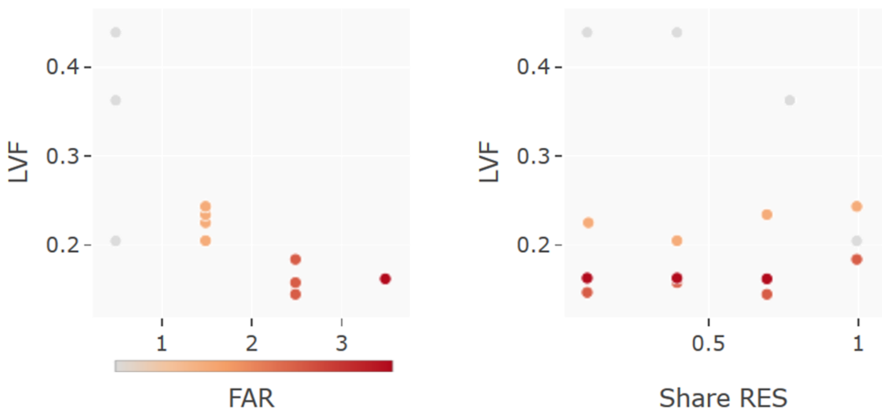


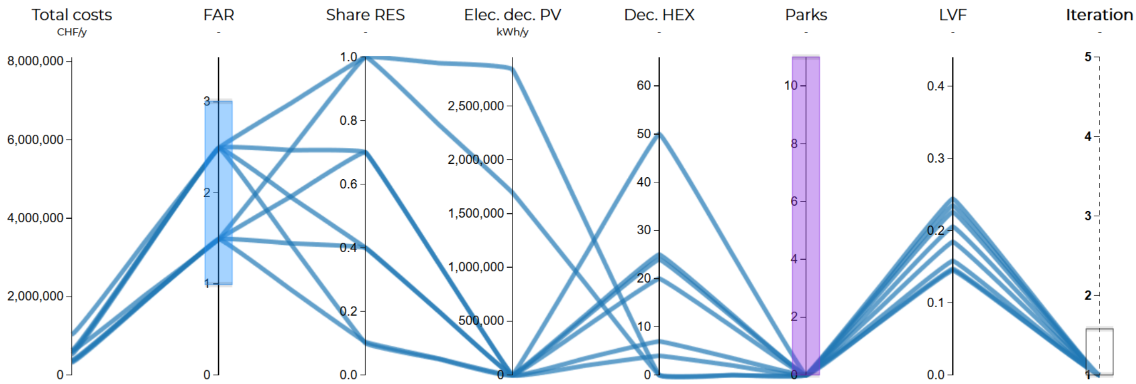
Figure 6.9 – Iteration 1: Depiction of the Pareto front for FAR and LVF (left) and absence of correlation between RES and LVF (right). Points are colored according to FAR.

For comparison with the parallel coordinates visualization, the same relationships between LVF and FAR and Share RES are shown in 2D Cartesian axes (Figure 6.9). While the left chart shows decreasing LVF values with FAR, there is no such trend with RES shares. This contradiction should be resolved e.g. between the planners and local developers to determine an acceptable tradeoff.

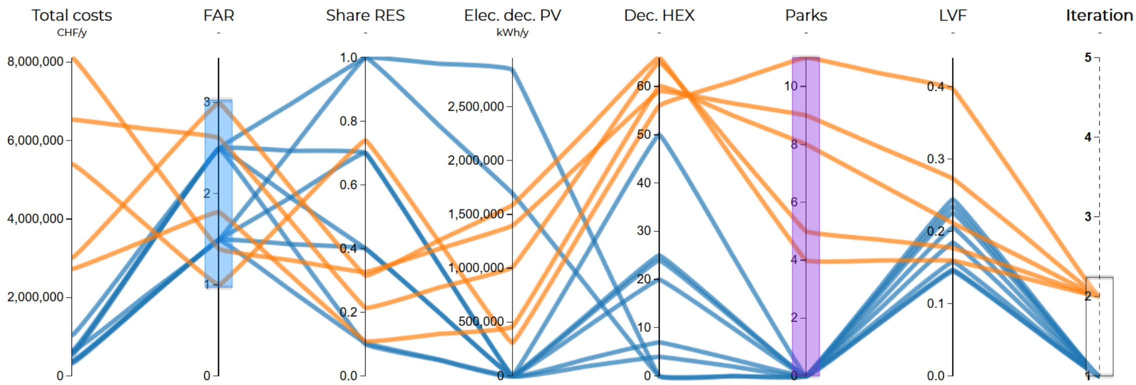
Iteration 2 – Including parks

Next, the planner tackles another issue observed in the previous charts: none of the calculated solutions provide sufficient parks, expected by the specifications of the master plan (Figure 6.8).

This is addressed by brushing the corresponding *Parks* axis as the objective to be maximized



(a)



(b)

Figure 6.10 – Iteration 2: (a) Requesting solutions which contain parks, for a range of different densities. (b) Depiction of the requested solutions containing parks.

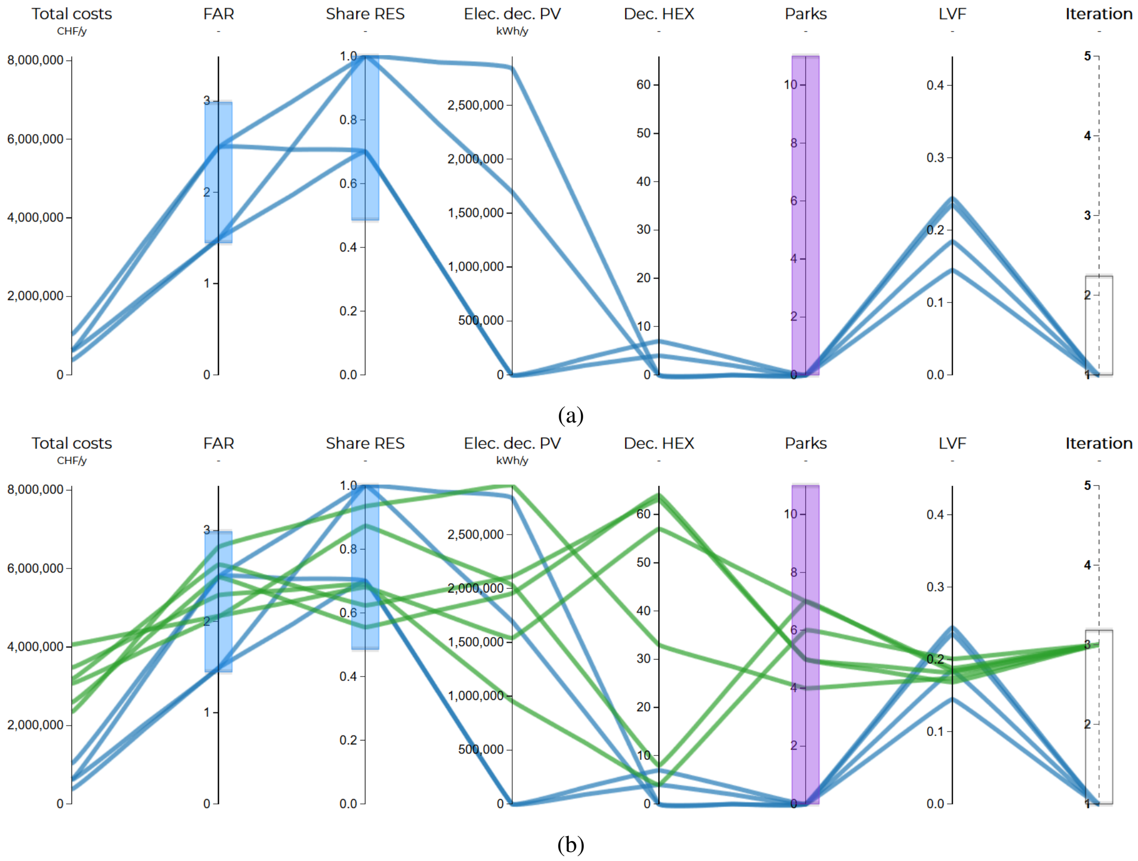


Figure 6.11 – Iteration 3: (a) Requesting solutions which contain not only parks, but also achieve at least 50% RES. (b) Depiction of the requested solutions containing parks and at least 50% RES.

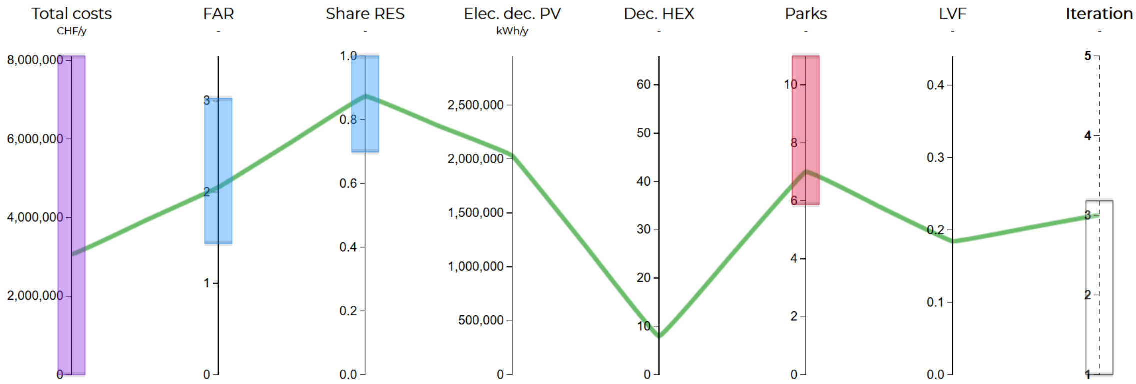
(Figure 6.10a). Without any other constraint, this single-objective optimization problem would lead to a neighborhood consisting of only green areas. Therefore, additional constraints must be specified to better reflect the expectations. A range is therefore brushed on the FAR axis (in blue), sampling the range with 5 solutions, in order to investigate the tradeoff with the number of parks. While the initial range on FAR was covering the entire feasible range, here a tighter range is used between 1-3.

The solver identified 5 new solutions which contain parks, according to the requested densities (Figure 6.10b). While up to 11 parks can be built for the lowest density (1), this number diminishes to 4 with increasing density. However, most of these new alternatives do not satisfy requirements of renewable energy, and appear more expensive than the options identified so far. The only solution which achieves more than 50% of RES only presents a density of 1, which is considered unsatisfactory. In the two next iterations, renewable energy sources are increased, followed by an improvement in the total costs.

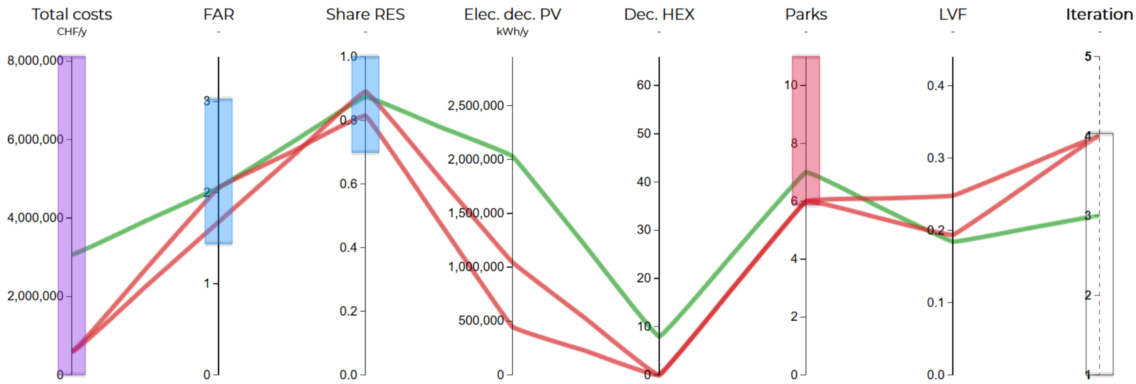
Iteration 3 – Improving the share of renewable energy

The RES objective is improved by applying a range to ensure that upcoming alternatives achieve at least 50% of RES (Figure 6.11a). To get a quick overview of solutions across all three dimensions (parks, FAR and RES), the Sobol sampling method is used until the user finds a satisfying tradeoff between number of parks, density and RES.

After the generation of only a few new solutions, the area of interest is populated with interesting



(a)



(b)

Figure 6.12 – Iteration 4: (a) Requesting solutions to minimize costs, while achieving comparable values than in the previous iterations in other criteria. (b) Depiction of the requested solutions containing cost-effective solutions.

solutions, which not only have parks, but also achieve densities above 1, and shares of RES above 50% (Figure 6.11b). So far, the costs have not been optimized, and can thus likely be improved, and are tackled next.

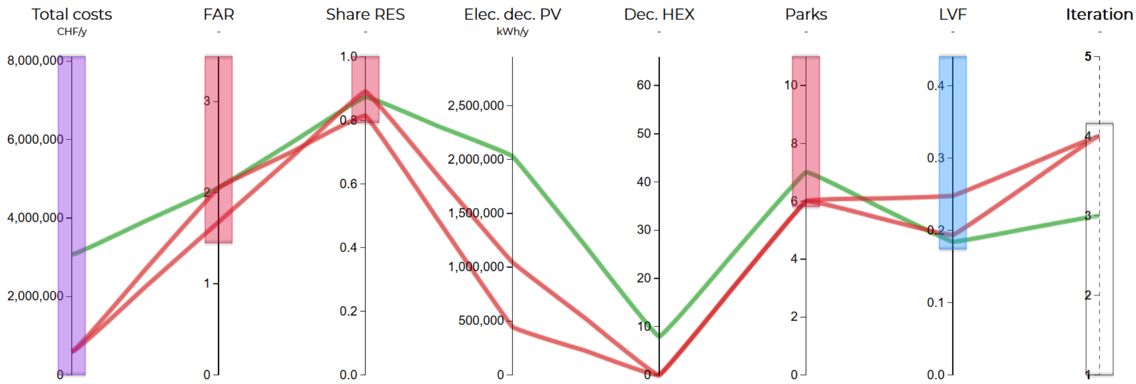
Iteration 4 – Reducing costs

Because the user learned that 6 parks are feasible for the other objective targets, they can replace the “objective” brush with a single constraint specifying the desired lower threshold (Figure 6.12a). This will ensure that any upcoming solution contains at least 6 parks. The main objective in turn becomes the total costs, and ranges are applied to explore (with Sobol sampling) a few solutions in the same range of density, while further tightening the range of RES to at least 70%.

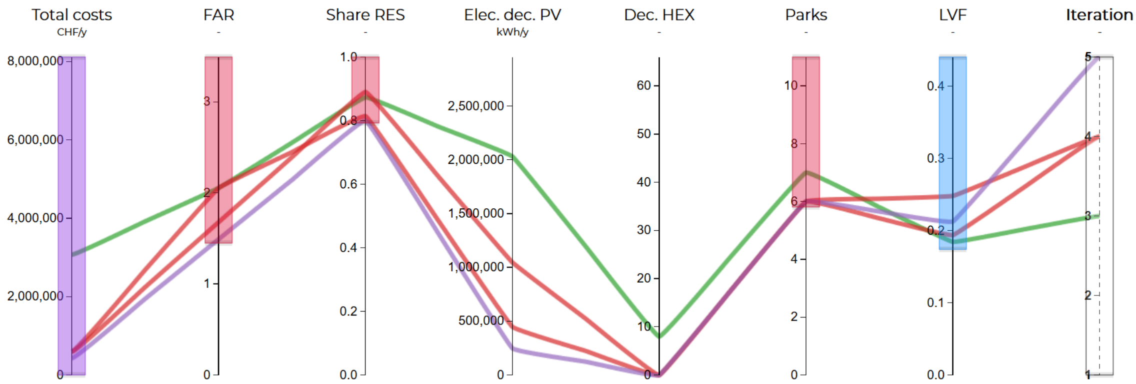
The goal of reducing costs was highly successful: new alternatives were found with a threefold reduction in costs (Figure 6.12b). However, after 7 computed solutions, only two converged to a feasible solution within the time limit. This likely indicates that the combination of constraints could be slightly relaxed to ensure a greater diversity in solutions. In this case however, more diversity is not sought, instead, the current solutions will try to be optimized with respect to the LVF, which so far has only been post-computed.

Iteration 5 – Improving the view towards landmarks

To achieve this, fixed constraints are set on FAR (1.5), RES (0.8) and parks (6) based on the identified feasible solutions, while costs are optimized, and a sensitivity analysis is performed on



(a)



(b)

Figure 6.13 – Iteration 5: (a) Requesting solutions to improve the LVF, while achieving comparable values than in the previous iterations in other criteria. (b) Depiction of the requested solution containing an increased LVF.

the LVF to see the extent to which it can be increased (Figure 6.13a). The lower bound of the LVF is set to the current minimum value, and the upper bound is set to the current maximum value found so far. At this point it is not clear how high the LVF might reach, and therefore setting a realistic upper bound is not obvious. However, it is reasonable to set it equal to the current maximum value achieved since the beginning, i.e. 0.44. In the case where infeasible solutions are encountered already at a point below 0.44, this would confirm that there is no point in exploring higher values without changing at least some other constraint. In the case where the solver is able to return values up to 0.44, then the user knows that it may be worth setting a higher bound, if they are still not satisfied with the obtained solutions.

Only one solution could be found, which improved the LVF slightly beyond 0.2 (purple line) (Figure 6.13b). Because the time limit was reached, this does not exclude the possibility to further improve the current objectives. In the context of this example, it seems acceptable to settle for the slightly more expensive red line, which also achieves more FAR and RES, but the DM could alternatively decide to dedicate more time in searching for these solutions.

At this point of the search, still many aspects could be explored with respect to the original questions. One aspect would be to improve the layout of various building uses and their distribution across the district, in order to improve the proximity of dwellers to shops and tram stops. Another aspect would be to adapt the default model parameters relative to the park model (cf. Chapter 4). For example, these could be changed to require more or less surrounding diversity or number of buildings. A third aspect could distinguish the investment costs for specific users, which were so far only considered in an aggregated way. By analyzing costs for building owners and the energy utility separately, one could aim to find a fair distribution of costs in the chosen energy system. Yet another aspect considers the best allocation of roof surface usage, i.e. between PV, greenery, or other social uses.

Instead, the next section focuses on some additional considerations regarding the energy system, demonstrating how SAGESSE can be used to perform sensitivity analysis on input parameters.

Iteration 6 – Sensitivity analysis of heat prices

In this section, the goal is to determine the sensitivity of the choice of energy conversion systems when the price of energy sources change. A first example varies the price of wood to determine the threshold for which the next resource—in this case gas—becomes competitive. A second example varies the price of the waste heat which could be used from a neighboring industrial zone. The currently estimated price of 0.06 CHF/kWh makes it less competitive than both gas and wood.

Wood price sensitivity analysis

Figure 6.14a shows that when simply generating cost-optimal districts for various densities, the most competitive energy conversion technologies to supply both heat and electricity is a centralized combined heat and power (CHP) plant, fueled by natural gas. In this configuration, the neighborhood is a net exporter of electricity.

As soon as a constraint on RES is specified, the CHP configuration is no longer systematically chosen (Figure 6.14b). As early as 30% share of RES, gas is progressively replaced by the next most competitive renewable option, which is wood. A threshold is reached around 80% RES: beyond this point, the centralized CHP is no longer economically viable for the limited energy it is "allowed" to supply. Instead, decentralized wood boilers are chosen.

At this point, a sensitivity analysis is performed on the price of wood, to determine how much cheaper wood should be for it to be economically competitive with the gas-fueled CHP alternative. By default, a price of 0.065 CHF/kWh is assumed for wood pellets (Schüler and Cajot, 2018). While a detailed sensitivity analysis performed for a wide range of wood prices could be executed,

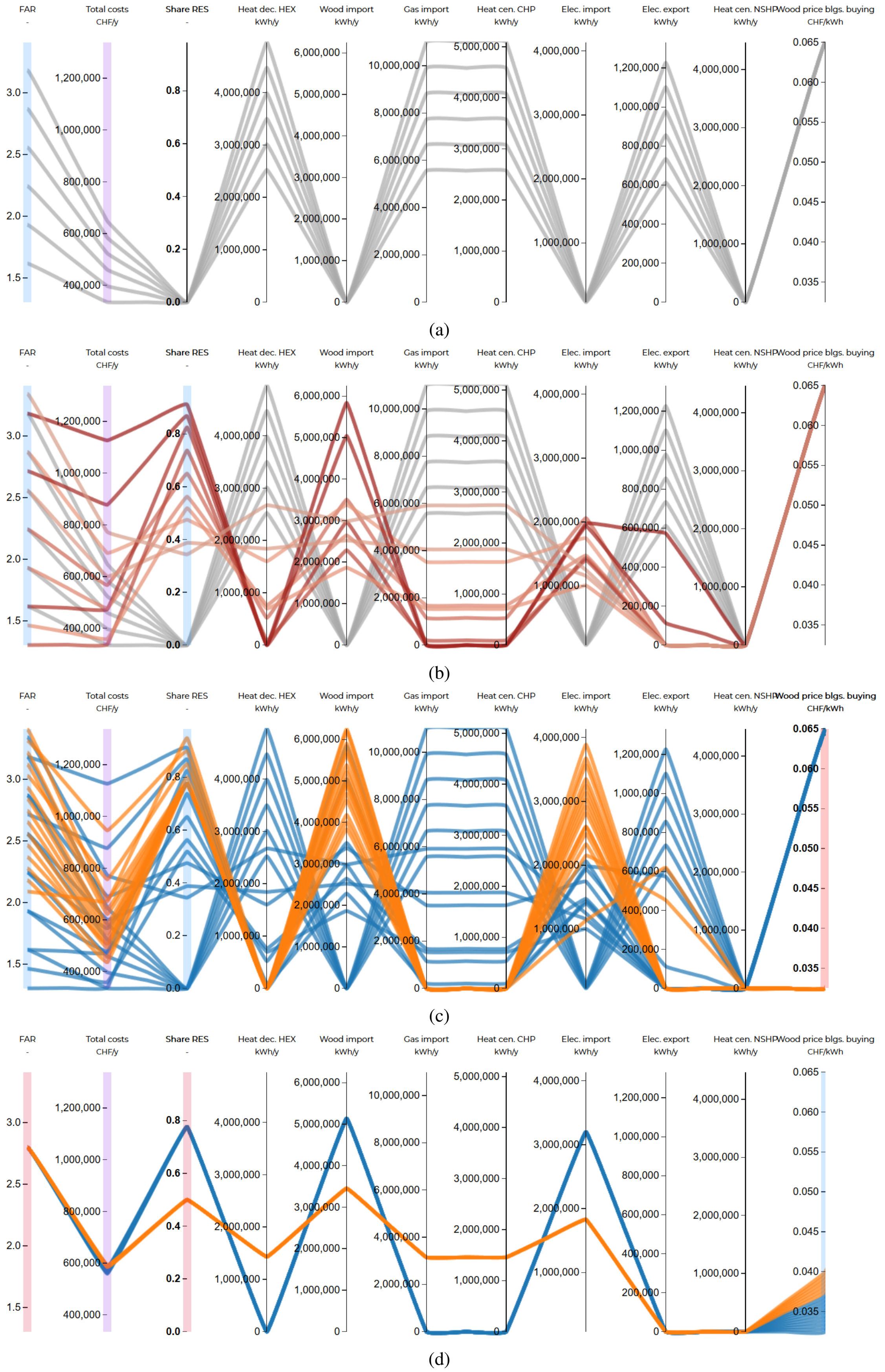


Figure 6.14 – (a) By default, cost-effective neighborhoods rely predominantly on gas-fueled CHP. (b) Constraints on RES lead to the progressive replacement of gas by wood. (c) For a 50% reduction in wood price, it becomes the most competitive resource, regardless of RES targets. (d) A sensitivity analysis shows that, for a density of 2.8 and share RES target of 50%, a wood energy price of 0.037 CHF/kWh or less (blue lines) is the threshold before which gas becomes competitive (orange lines).

the interactive framework allows to quickly verify if—and where—a tipping point occurs. This is performed in three steps. First, the price of wood is divided by two to verify that in this case, wood is always preferred. As illustrated in Figure 6.14c, all solutions with a wood energy price of 0.0325 CHF/kWh (colored in orange) lead to systems which relies solely on wood and electricity imports, but no gas. Second, three prices are sampled between 0.0325 and 0.065, namely for 0.040, 0.050 and 0.060. Already for 0.040, there are some options which favor gas CHP when low RES shares are requested. This means the threshold occurs somewhere between 0.0325 and 0.040. This range is now reasonably small to perform a more detailed systematic sampling to determine the exact price for which wood becomes competitive. So in the third step, the user sets a systematic sampling of 16 points on the price, between 0.0325 and 0.040 CHF/kWh. The threshold is found at 0.037 CHF/kWh. This means that if wood could reach such a price (e.g. via subsidies), there would be no more economical incentive for the gas option. One can further notice that the effect of changing the price of wood has little effect on the overall costs of the project: a decrease of 6.25% in the price leads only to a decrease of 1.45% in total costs.

Waste heat price sensitivity analysis

As mentioned in Chapter 4, an industrial zone located south of the planned neighborhood could provide residual heat from the industrial activities, which would otherwise be dissipated into the environment. Due to the low temperatures in the industrial heating network, a centralized "network source heat pump (NSHP)" should be installed in order to increase the temperature of for the supply of the neighborhood (Cajot et al., 2016). Thus, by expanding the perimeter of the analysis and including this option, a potentially cleaner option could be effectively used by the neighborhood. Compared to wood, such an option would imply less impacts on health due to lower emissions of particulate matter, and compared to gas, residual heat is arguably considered renewable (Schüler et al., 2018b).

The question addressed here is "*What should the price of residual heat be for the local energy provider to decide to implement a network source heat pump system?*" To answer this question, a sensitivity analysis similar to the one performed on the price of wood is repeated for the price of residual heat (Figure 6.15). The results show that for a 90% reduction in the residual heat price (down to 0.01 CHF/kWh), the NSHP becomes the most competitive option to provide heat, inc combination with large imports of electricity from the national grid (red line in Figure 6.15). Yellow lines show that for prices between 0.02-0.04 CHF/kWh, it is worth also producing some electricity with the gas-fueled CHP engine, as far as permitted by the 50% RES target. Finally blue lines indicate that from prices of 0.05 CHF/kWh and above, the residual heat is no longer competitive, and gas- and wood-based options are preferred.

6.3 Discussion

This chapter illustrated how interactive optimization allows to efficiently explore multiple dimensions to answer urban and energy planning questions. By personally *experiencing* the systematic search process, the user has gained a better understanding of the problem and of their own preferences. New questions were raised along the way, which could be answered on-the-fly.

The different examples showed the steering mechanisms adopted to generate solutions in areas of interest. The procedure is inherently a learning one, which explains the need for multiple iterations and the progressive refinement of the problem formulations. On several occasions, the problems led to infeasible solutions, which contributes to developing a better understanding of what is achievable, and where compromises must be made.

The number of iterations was kept purposely low for conciseness. However, the search processes

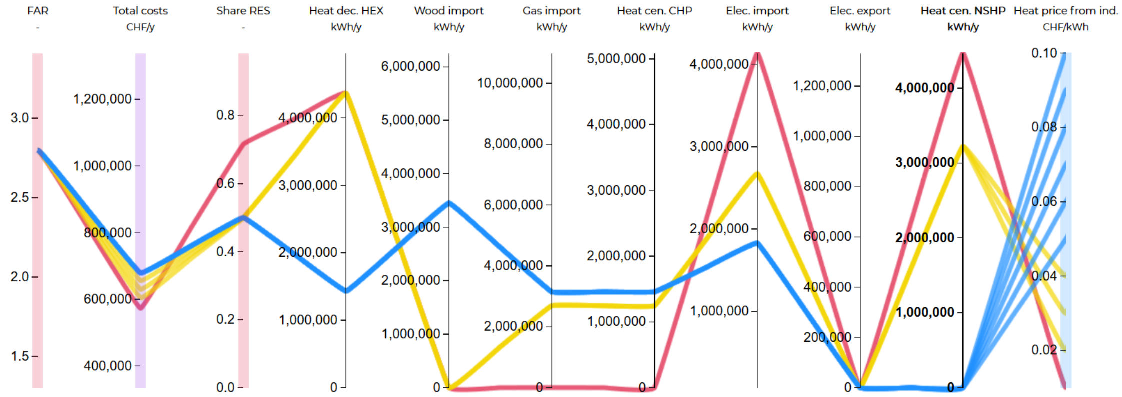


Figure 6.15 – Results of the sensitivity analysis performed on the price of residual heat from the nearby industrial activities (*Heat price from ind.*). Colors indicate the three amounts of heat supplied by the centralized network source heat pump (*Heat cen. NSHP*).

initiated in this chapter should not be considered "complete", and several outlooks were identified, which could be further explored (regarding the diversity of building functions, the quality of parks, multi-actor cost allocation, optimal building stock refurbishment, etc.). Such questions have been partly tackled elsewhere (Schüler and Cajot, 2018).

Learning points from the examples

The main learning points from the brownfield application can be summarized as follows: knowledge of the maximum achievable density, required costs to achieve a highly renewable energy neighborhood, and the corresponding density threshold, as well as the maximum RES share achievable in the absence of wood boilers.

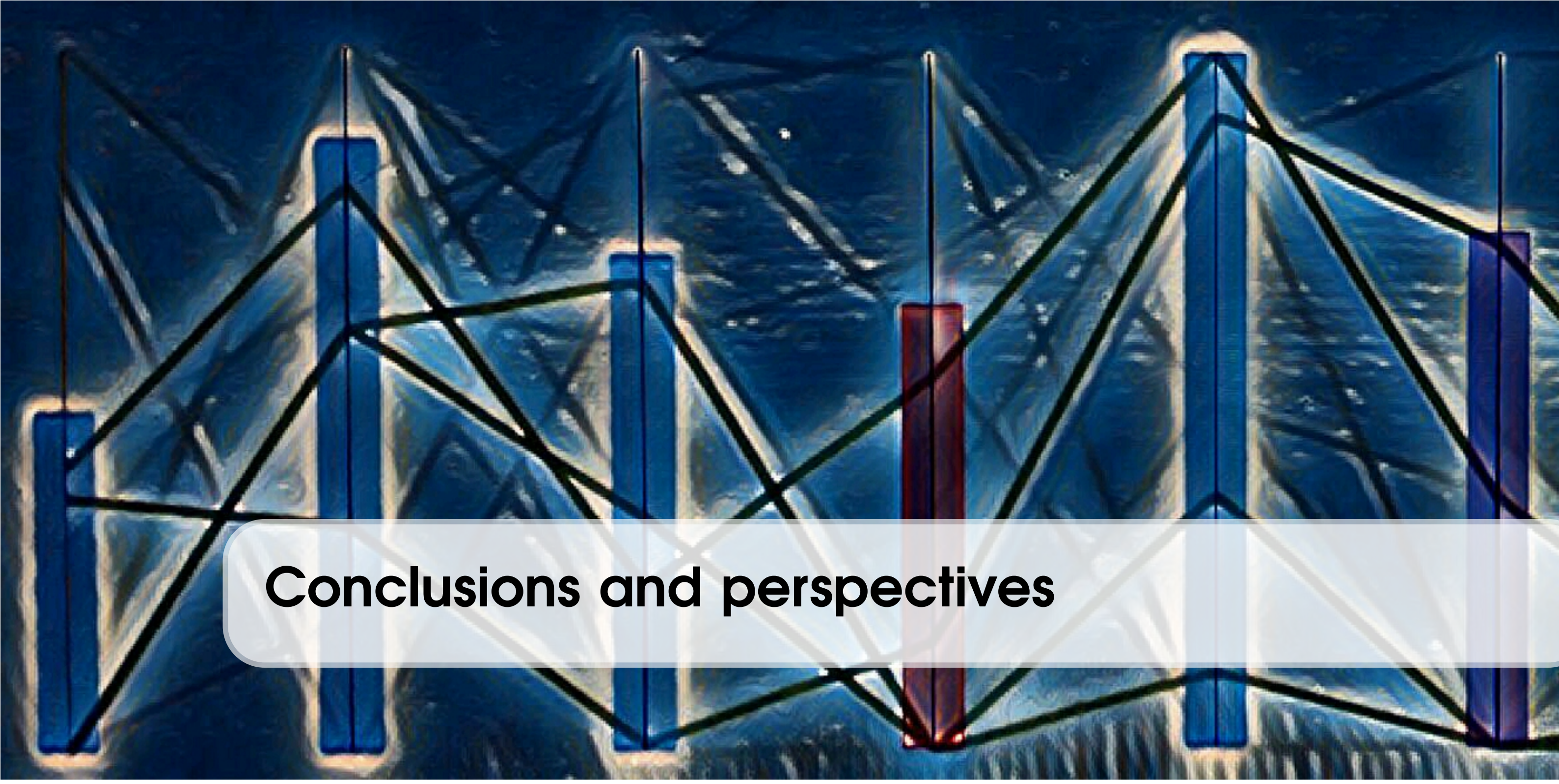
In the case of the greenfield application, the user started with (i) a set of cost-effective urban configurations, and progressively refined the search to (ii) include more parks, (iii) increase the share of renewable energy sources, (iv) reduce the costs of the solutions, and (v) improve the visibility of the surrounding landmark. At each iteration, tradeoffs and synergies could be identified. Finally, a systematic sensitivity analysis was performed to answer more specific questions regarding the competitiveness of wood and industrial waste heat compared to existing options.

General outcomes of the methodology

Compared to the a posteriori approach in Chapter 5, the examples in this chapter demonstrated how it is possible with SAGESSE to efficiently explore many objectives, while including also variations in the model parameters for sensitivity analyses. Although the explored solutions represent only a fraction of the total solution space, they are sampled according to the decision maker's preferences, and therefore allow to answer specifically their questions, as they arise.

Overall, the acquired knowledge of extreme cases, but also the finer understanding of tradeoffs and tipping points between conflicting objectives gained during the search phase, give the user more confidence in justifying the chosen solutions, or the reasons why other solutions were discarded.

In addition, by visualizing the results in adapted forms (parallel coordinates, 3D charts, 2D scatter plots, maps), and by eventually laying down side-by-side the main criteria for a subselection of solutions in the synthesis phase, the user is equipped to take an informed decision, and justify and communicate it to other stakeholders.



Conclusions and perspectives

The goal of this thesis was to develop a decision support methodology to facilitate the integration of energy issues in urban planning processes. This was achieved mainly through the development of SAGESSE, an interactive optimization methodology, and URB^{io} , a planning support system combining SAGESSE with the multiparametric mixed integer linear programming (mpMILP) model implemented by Schüler et al. (2018b). The methodology was successfully applied to answer practical questions which arose from two different case-studies.

While previous urban planning studies adopting optimization tend to focus either on the energy system, or the urban one, the developed approach allows to consider both jointly. The resulting complexity, size of the problem and uncertainties were handled by relying on interactive multiobjective optimization, and involving the user "in-the-loop". Compared to the literature in the field of interactive optimization, the innovative features of SAGESSE are (i) the use of parallel coordinates to simultaneously explore and steer the search as solutions are generated, (ii) the application of a Sobol sequence for efficiently and interactively sampling the solution space, and (iii) the integration of multiobjective decision analysis (MODA), multiattribute decision analysis (MADA), clustering techniques and linked views for interactive data visualization.

Going back to the formulated questions, several insights can be drawn from the performed work:

> *Which obstacles are preventing the integration of energy issues in urban planning processes, and which improvements can be made?*

Chapter 1 clarified the scope and phases of urban planning, and introduced a framework to identify the main challenges which arise when considering energy beyond the building scale. Nine interdependent conditions were identified, which collectively contribute in hindering the appropriate integration of energy in urban planning processes. A review of common responses to challenges was presented. As it is, there does not appear to be any silver bullet to addressing the multi-faceted problem of urban energy system planning. Instead, a combination of responses must be devised to tackle the problem in its entirety, namely recognizing the presence of multiple actors and values, of uncertainties in available data and decisional processes, and of unpredictable evolutions in the planning context. The findings of this review inspired the present work to strive for a comprehensive modeling approach, capable of capturing multiple domains of urban planning jointly, while resolving conflicts between scales and phases. While this approach can be considered an *ideal* response to wicked problems, the adoption of interactive optimization allows to *realistically* adapt the problem size, and focus the exploration of only the most relevant subset of the solution space. In turn, interactive optimization can potentially disrupt traditional planning practices. Today, the elaboration of plans can be loosely summarized as being incremental, alternative-focused and often intuition-based, and whose process spans over months. Conversely, interactive optimization has the ability to increase the reactiveness of planners to cope with the dynamic context and rapidly changing goals, to explore a larger and more diversified number of alternatives, and to provide accountable planners and politicians with rational insights into why certain decisions were taken. The improved decision making approach is expected to increase the acceptability of plans by a majority of stakeholders.

> *What requirements do multicriteria decision analysis methods have to meet to support decisions in urban energy system planning?*

In Chapter 2, a review of MCDA studies applied to urban energy planning problems was carried out. This led to a systematic classification of methods, accessible in an online parallel coordinates interface, which allows to answer the formulated research question. In particular, the expected decision problematic, number of criteria and alternatives considered, scale of the problem and motivations for combining various methods are all aspects to consider before identifying an appropriate method. Accordingly, the insights from the review motivated the development of a decision support methodology combining MODA (for its ability to generate "value-focused" alternatives) and MADA (for its ability to support the analysis of existing solutions, based on a large number of criteria).

> *How to efficiently generate and visualize a set of Pareto optimal solutions given the elusive nature of urban planning goals, and the large problem size?*

Because of the large size of the problem, and the assumed limited time of the decision maker, a new way to explore the solution space interactively was developed. This was done by combining the ε-constraint method with a quasi-random sampling technique based on the Sobol sequence. By adopting this approach in interactive optimization, the user can efficiently and intuitively explore a variety of solutions which answer new questions as they arise from exploring the existing solutions. Thus, even if the values are elusive and difficult to quantify *a priori*, the use of the methodology promotes learning and clarifies the preferences progressively, based on the knowledge of tradeoffs. Furthermore, the methodology remains accessible to practitioners, by adopting parallel coordinates, known for being efficient and intuitive to visualize multidimensional data. The input of preferences is further simplified, contrary to other methods, by merging the steering and exploration tasks: brushing axes to *filter* data is indeed the same action as that to *specify the boundaries* in which new solutions are to be generated. To cope with the large amount of generated solutions and interpret them, the exploration is done with linked views between the parallel coordinates and GIS maps, 3D scatter plots, and 2D scatter plot matrices. In addition, clustering and multiattribute decision analysis allows to manage and interpret the generated data in real-time.

> *Which practical questions arise in urban energy system planning, and which criteria can be used to evaluate the success of the proposed solutions ?*

This question was mainly answered through the collaboration with urban and energy planning practitioners throughout the duration of the research. Four workshops revolving specifically around two case-studies served to define the issues and criteria in greenfield and brownfield cases. The main questions in the greenfield case involved determining the tradeoff between density and share of renewable energy. Indeed, during the elaboration of the neighborhood's master plan, new political ambitions required to rapidly revise the initial density targets. In the brownfield case, the main questions dealt with how to optimally reduce carbon emissions in an existing neighborhood. In particular, questions of heritage conservation, building refurbishment and increasing floors of existing buildings had to be considered. As the workshops revealed, the identification of relevant criteria is an iterative process. It is not trivial to know *a priori* the criteria which will be useful, until after the alternatives have been generated—and have sparked new questions. Furthermore, the exploitation of the generated optimization results is not necessarily straightforward. Going beyond the simple application of a computer model, the workshops also began to address the questions of usability, interpretability and applicability in the planning process. The early stages of vision setting, and strategic planning were found most relevant for the current contributions of the methodology, while applications to other stages are left for future work.

Perspectives

Both the literature research, and the insights from the workshops allow to propose several perspectives for future work.

Expanding the methodology. SAGESSE could potentially be extended in regard to four different aspects: targeted user type, number of users, application domain, and underlying optimization procedure.

i. *User types.* The target audience of the methodology in the present work was urban and energy planners. It is not expected, nor required of the practitioners to have the technical background in the underlying optimization procedure for them to benefit from the generated results. This was in fact a main motivation for the development of an accessible interface, with limited technical jargon, many predefined default values (both regarding the optimization procedure and the model), tooltips and dialogs, as well as controls mainly via GUI buttons and menus (Shneiderman, 2010; Cohon, 1978; Spronk, 1981). Nevertheless, the tool was found to be particularly useful also from a "developer's" point of view, i.e. the analyst or the person developing the models. For example, the ability to closely monitor solve durations, solve results, and optimality gaps in the parallel coordinates is an effective way to detect any bugs or oddities in the optimization model or procedure. The framework allows the "modeler" to quickly diagnose any issues and remedy them accordingly. This topic should be further developed, and adaptations be made in the interface. Shneiderman (2010) notes "know thy user" as one of his guiding interface design principles. He advocates multi-layered interfaces targeted respectively at first-time, knowledgeable and expert users. While first-time users should be protected from making mistakes, e.g. by limiting the number of actions or the density of data displayed, and including sufficient dialogs and feedback, experts require instead less distracting dialogs and pop-ups, and shortcuts for frequent commands. At the time of writing, the SAGESSE interface contains a simple layering which displays key actions by default (e.g. steering actions, polyline coloring options), and masks secondary or advanced actions (e.g. the time limit setting, or toggling the visibility of incomplete or infeasible solutions). This avoids overcrowding the interface with too many actions, also following the motto "overview, filter, details on demand" (Shneiderman, 1996). Following this principle, a clearer distinction could be made between a "practitioner mode" and a "developer mode".

The former would contain only the basic steering and exploration features required to solve context-specific problems. Arguably, planners—and even more so non-professional users such as citizens—should not need to pay attention to any procedural aspects (e.g. choice of sampling method, definition of objectives or ranges, solver limits, etc.): brushing the axes of interest and interpreting the results should be their main concern, and future developments should strive to accommodate this. On the other hand, the "developer mode" would contain a more detailed set of actions, allowing to control the model more precisely. For convenience, the development of an application programming interface (API) would also be desirable, in order to execute tasks via command line and programmatically. Overall, these adaptations would require involving users with different backgrounds and studying their difficulties, habits and preferences. For example, the qualitative and quantitative research methodology carried out by Piemonti, Macuga, and Babbar-Sebens (2017) and Wolf, Simpson, and Zhang (2009) could be repeated for a well-defined case-study using SAGESSE. Insights would allow to improve the current interface and better target future developments.

ii. *Number of users.* The assumption that there is only one user involved is often unrealistic, given that decision makers are typically either proxies influenced by and representing the interests of a larger group, or actually are a group (Zionts, 1994). While multi-user applications of the methodology have not been tested, the web interface and underlying data model have been designed with the intent of handling multiple users per project. Future research should thus investigate how the tool could be used either by multiple users in a same room (e.g. during interdisciplinary workshops) for consensus building, or by multiple users from remote locations. Some research has already been done in this area and provide useful starting points. Babbar-Sebens et al. (2015) studied multi-user applications of their interactive optimization tool. They proposed a "democratic" approach, in which the ratings of multiple users are aggregated into a common preference model, used to steer the search. Ferreira, do Nascimento, and de Albuquerque (2006) also proposed a multi-user framework for the User Hints interactive optimization tool developed by do Nascimento and Eades (2005). They studied the effect of competition and cooperation in identifying new solutions, and proposed several mechanisms to share the best performing solutions from individual searches among a group of users. Various approaches could be envisaged for the use of parallel coordinates, such as highlighting lines which are most frequently requested by a group of users, recommending axes based on those which other users deemed important or allowing multiple users to interact with a same chart, jointly specifying ranges of interest.

iii. *Optimization procedures.* In URB^{io}, efficient solutions are found by using linear programming and deterministic solving algorithms. However, the interactive optimization methodology is developed in a way that other solution generators could be employed, such as stochastic solvers (e.g. genetic algorithms). As discussed in Chapter 3, this can be relevant for addressing e.g. problems involving non-linear objective functions, though at the price of requiring many iterations, and slowing down the search process and possibly hindering the quality of solutions.

iv. *Domains.* In this thesis, the developed methodology was applied to the field of early stage urban and energy planning, and used with models corresponding to that context. A first expansion of the model and visualization of results would investigate the applicability of the tool to questions in localized planning and design of the urban form. Second would be to expand the addressed questions to cover also urban issues and planning processes specific to other parts of the world, extending from the European focus in this thesis. More generally, the context of urban planning is in no way a constraint, and in principle, any type of application could be considered. The main requirement for the use of SAGESSE is that the solution times to run the model remain sufficiently low. For problems which take longer to solve, the interface could nevertheless be considered for exploring the solutions a posteriori, as was done in Chapter 5. Current work is being done to apply the methodology to the Swiss national energy system modeling tool Energyscope (Codina Gironès et al., 2015).

Use of different scalarization functions. Scalarization is used to convert the multiobjective problem into a set of parametrized single-objective problems. While the ε-constraint method was favored for the reasons discussed above, it could nevertheless be interesting to explore other methods, which are widely discussed by Branke et al. (2008). For example, Cohon (1978, p. 157) noted that a potentially useful by-product of the weighted sum method is the weights themselves. It could be interesting and insightful to inform the user of the implicit objective weightings which lead to their preference for a solution, not only in the a posteriori TOPSIS method as performed in Chapter 5, but also for any solution returned by the optimization procedure.

Improving parallel coordinate features. The presented methodology only exploited a few of the many possible functionalities for parallel coordinates. Future work could involve and test:

i. smart ordering of axes, e.g. by exhaustive pairwise depiction (Heinrich and Weiskopf, 2013), by conflicting objectives, prioritizing those with most convex Pareto fronts (Unal, Warn, and Simpson, 2017), by similarity-based reordering (Lu, Huang, and Zhang, 2016), by use of 3D parallel coordinates (Johansson and Forsell, 2016), or by visual (Keeney, 1992, p. 57) or automatic dimensionality reduction techniques (Copado-Méndez et al., 2016),
ii. improved visualization of polylines and patterns, e.g. visually bundling clusters into compact polygons (Palmas et al., 2014)), or using polynomial curves and other line styles to emphasize various data properties (Franken, 2009; Heinrich and Weiskopf, 2013),
iii. handling of time series, e.g. using the third dimension to display temporal evolutions (Gruendl et al., 2016), by plotting several time steps on adjacent axes (Franken, 2009) or by animating a series of charts for each time-step (Heinrich and Weiskopf, 2013)),
iv. dynamic rescaling of axes, to allow brushing beyond the visible values (currently brushing beyond the visible axis requires manually editing the numerical brush bound in an ad hoc table).

Criterion builder. As discussed in Chapter 4, SAGESSE is an effective approach to progressively identify new criteria which allow to answer the stated questions. Currently, the addition of new criteria relies on the analyst, who implements them in the computational framework. Depending on the nature of the criterion, it is either modeled in the mathematical programming model, or alternatively, it is post-computed further down the workflow (e.g. in a dedicated "view" in the database). For the latter, simpler case, a "criteria builder" on the client side could replace the need for the analyst, by providing more flexibility to the user, and enriching the exploration of results. Such a tool would allow to recombine existing criteria with basic mathematical and logical operators, in order to reflect specific questions. This is particularly relevant given the potentially large number of criteria, not all of which would benefit from a permanent integration in the common list of criteria. For example, a user could create a criterion "number of PV panels on office buildings", or "share of park area per residential floor area", by combining the underlying criteria accordingly.

Combining MADA methods. For demonstration purposes, only the TOPSIS method was implemented. Including additional methods would let the user choose the one which they are most comfortable with, or which is most adapted to their needs. The synthesis in Chapter 2 could help in this regard. For example, the weighted sum method might be preferable as it is more popular, while the outranking ELECTRE method or analytical hierarchy process might lead to more reliable results, at the expense of taking more time to elicit pairwise preference information from the user (Zanakis et al., 1998). The ability to visualize and compare the results of multiple MADA methods, as well as their adoption for real-time assessment of MODA results opens also potential axes of research.

As Guitouni and Martel (1998) wrote: "In practice, many analysts and researchers are incapable of justifying clearly their choice of one MCDA method rather than another". This is supported by the finding in Chapter 2 which shows that triangulation is the third leading cause for combining several methods, i.e. the comparison of different methods to study convergence and corroboration of results. Many studies indeed have compared two or more methods on similar problems (Zanakis et al., 1998; Nigim, Munier, and Green, 2004; Medineckiene and Björk, 2011; Carriço et al., 2014; Feo and De Gisi, 2014; Banar, Özkan, and Kulaç, 2010; Vadiati et al., 2012; De Feo, De Gisi, and Galasso, 2008; Tzeng, Lin, and Opricovic, 2005; Dehe and Bamford, 2015). The implementation of multiple methods in the SAGESSE framework would allow to partly automatize the comparison process, while allowing to apply the methods to a variety of problems and domains.

Simplifying the steering process. Currently, the user still has specific control over the steering actions influencing the search. This makes sense in particular for an experienced user who aims to achieve specific outcomes. It is questionable whether a novice user actually requires such detailed control, and whether the distinction between objectives, ranges and constraints could be abolished (Wolf, Simpson, and Zhang, 2009). Future work could explore a more complete automation of the steering process, in which regular "filter" brushes drawn by the user are automatically interpreted as steering actions, i.e. objectives and ranges. In this context, the Sobol sampling could be applied by default to all visible criteria to the largest known bounds, and the explored space is reduced as soon as the user applies a brush. The main limitations in this approach is that the user loses touch with the underlying mechanisms, and has less control over specific actions (e.g. set a constraint), which could potentially lead to wasted computational effort on less relevant solutions. Liu et al. (2018) argue that the interaction with the solver is key in building trust both in the model and the outcomes, and that the more opaque the approach, the greater the risk of non-acceptance and misunderstanding from the user.

Machine learning. The fact that this methodology produces large amounts of data makes it well suited to exploit machine learning. Merkert, Mueller, and Hubl (2015) highlight three main contributions which machine learning can bring to decision support systems: (i) higher effectiveness, (ii) efficiency and (iii) degree of automation. By learning from actions performed by the user (selected objectives, upper and lower bounds of brushes, axes toggled on or off, solutions added to the comparer dashboard, etc.), these could be at least partly automatized to support the user. Shneiderman (2010, p. 78) notes that "automation increases over time as procedures become more standardized and the pressure for productivity grows". Arguably this can accelerate the process, avoid errors and reduce the user's cognitive effort. On the other hand, the benefits should be weighed against the risk of alienating the user from the process, hindering the trust they may have in the resulting solutions (Liu et al., 2018). Ultimately, the purpose of human-machine interaction is to best allocate tasks to each party according to their respective abilities (Scott, Lesh, and Klau, 2002). The fact that computers are increasingly outperforming humans in a growing number of tasks (e.g. image and pattern recognition) requires to rethink the role of the human in interactive methods, and how such methods are designed. A question is whether or not let the user perform some tasks for the sake of learning, even though the computer might do it better or faster than them.

Outlook

Human-machine thinking

Whereas traditional interactive methods tend to clearly distinguish the learning phase, the preference articulation phase, and the generation of solutions, the methodology proposed in this thesis blends these three phases into an integrated, more immersive experience. Indeed, the exploration of solutions need not be interrupted while the optimization is running: as soon as a solution is found, it is directly included into the chart—and into the user's mind—for the user to interpret. Through various exploratory features, the user becomes mindful of the relationships between criteria, and how much they are willing to sacrifice in one, in order to gain value in others. Each new solution makes more clear the critical contradictions to be resolved, allowing to refine the search towards areas which are found most relevant.

Because both the phases concerning the human and those concerning the computer occur at the same time, the whole can be considered an "optimization-based thought process". The computer optimization becomes an extension of the user's mind, while at the same time, the user's mind becomes an extension of the optimization. Vinge (1993) anticipated the need for less "oracular" and more symmetrical decision support systems, where the program provides the user with as much information as the user provides the program guidance. He wrote that "computer/human interfaces may become so intimate that users may reasonably be considered superhumanly intelligent". The direct and symmetrical link between human and computer offered by SAGESSE can be considered a step in that direction.

A source of wisdom

Finally, the acronym of SAGESSE (French for *wisdom*) was chosen deliberately. According to the Merriam-Webster dictionary, wisdom concerns in particular "the ability to discern inner qualities and relationships", which is precisely what the methodology provides. It is hoped that the appealing nature of parallel coordinates and the powerful insights made possible by optimization, combined in the proposed methodology, will promote learning from even the most wicked problems. As the Greek philosopher Plato hinted:

> *Is not the love of learning the love of wisdom, which is philosophy?*
>
> Plato, *Republic*, 2.376b

A. Urban planning processes review data

This appendix complements Chapter 1 by providing the methodological details of the performed review of urban planning processes. It also contains additional information regarding the tasks performed at each phase, as well as common supporting tools or methods mentioned in the reviewed studies.

A.1 Methodology of review

The results presented hereafter are a synthesis of urban planning process depictions found in literature This review was carried out for 20 scientific and practice-based references involving explicit urban planning depictions (Table A.1), answering the questions “What are the typical phases in urban planning?”, “Which tasks are carried out at each phase?”, and “Which methods and tools exist to support each task?”. The published material was collected using the search terms “urban planning process” in the Scopus database, and scanning the 263 references by availability, language and relevance (i.e. containing explicit discussion and/or depiction of urban planning processes). Research projects were found on the European CORDIS database, using the keywords “urban planning” and “energy”, and returning 89 projects, three of which contained planning process depictions. Two internal studies from the European Institute for Energy Research were also included in the research project set. Finally, three practice-based references were considered: the sustainable energy action plan guidelines from the EU Covenant of Mayors initiative, and two Swiss references addressing urban planning.

In the scope of this review, the studied processes focus on the *sequential model* (Masser, 1983). This representation of planning as a sequence of delimited events has the advantages of being widespread (which is suitable for a systematic comparative review), and inherently simple (which allows a straightforward categorization of tasks in each phase). As Masser (1983) notes, “models of this kind provide a useful starting point for a more detailed analysis of tasks within this general framework”, which is precisely what is intended here. Other models include the contextual model, which rejects the notion of an ideal, universal model, describing planning instead as deeply influenced by contextual conditions, including social, political, economic and traditional aspects. Another model, the interaction model, focuses essentially on the stakeholder relationships within the planning process. Planning and Implementation Process (PIP) diagrams can be cited as a combination of interaction and sequential models (Di Nucci and Pol, 2010). Though such models would undeniably enrich the discussion to come, their systematic review in literature is out of scope, and focus is set on the sequential models.

The various sequences of events observed in the reviewed documents were compiled and synthesized into five generic phases, and the corresponding tasks were classified accordingly. Tools were then mapped to each task. Additional meta-information regarding the process (iterative nature, duration, participation, thematic focus), as well as any mention of decision support tools or methods was also collected and discussed.

Table A.1 – List of references analyzed in this work.

Published scientific material (articles, books, thesis)	Research projects	Practice-based references
- (Banfield and Meyerson, 1955) - (Yeh, 1999) - (Amado et al., 2010) - (Teriman, Yigitcanlar, and Mayere, 2010)* - (Wallbaum, Krank, and Teloh, 2011) - (Mirakyan and De Guio, 2013) - (Nault, 2016) - (Masser, 1983) - (deVries, Tabak, and Achten, 2005) - (Yigitcanlar and Teriman, 2015)*	*EU-CORDIS database* - (Di Nucci, Gigler, and Pol, 2009; Di Nucci and Pol, 2010) - (Gaffron, Huismans, and Skala, 2008; Gaffron, Huismans, and Skala, 2005) - (STEP-UP, 2015)* *EIFER studies* - (Cassat et al., 2015)* - (Sipowicz, Ge, and Bahu, 2016)*	*EU initiative* - (Covenant of Mayors, 2010)* *National references* - (SIA, 2003, p. 110) - (Roulet and Liman, 2013)

*These references present similar planning phases and tasks and as such are reviewed jointly (respectively (Teriman, Yigitcanlar, and Mayere, 2010; Yigitcanlar and Teriman, 2015); (STEP-UP, 2015; Covenant of Mayors, 2010) and (Cassat et al., 2015; Sipowicz, Ge, and Bahu, 2016). However, they are kept distinct in the review as they do propose different support tools and methods.

A.2 Results of review

Although some clear patterns emerge in the depiction of urban planning steps, there are some notable disparities across the different sources (Figure A.1). Gaffron, Huismans, and Skala (2008), Teriman, Yigitcanlar, and Mayere (2010), and Yeh (1999) propose the most fragmented and detailed processes with up to 9 steps. For example, they include steps such as plan selection, detailed design, or project delivery. On the other extreme, (deVries, Tabak, and Achten, 2005; Nault, 2016) only use 2 or 3 steps to describe the process. Furthermore, some references view urban planning as disconnected from the more practical phases of implementation and operation (Banfield and Meyerson, 1955; deVries, Tabak, and Achten, 2005; Nault, 2016) and do not mention any steps related to those phases.

Inferring from the observed patterns (Figure A.1), all steps were aggregated and classified into five main phases:

(1) Initiative & vision: Identification of needs for action, description of a vision
(2) Strategic planning Formulation and prioritization of objectives or goals
(3) Design Elaboration, evaluation and comparison of solutions
(4) Implementation Implementation of plan
(5) Operation & monitoring Operation of infrastructure and services and monitoring

These were chosen as a compromise between a too general subdivision of the process, and a too detailed one, both of which would be unpractical for a deeper analysis of tasks and tools. In addition, most references can be closely mapped to these five phases, while three are nearly identical (Cassat et al., 2015; Masser, 1983; Roulet and Liman, 2013).

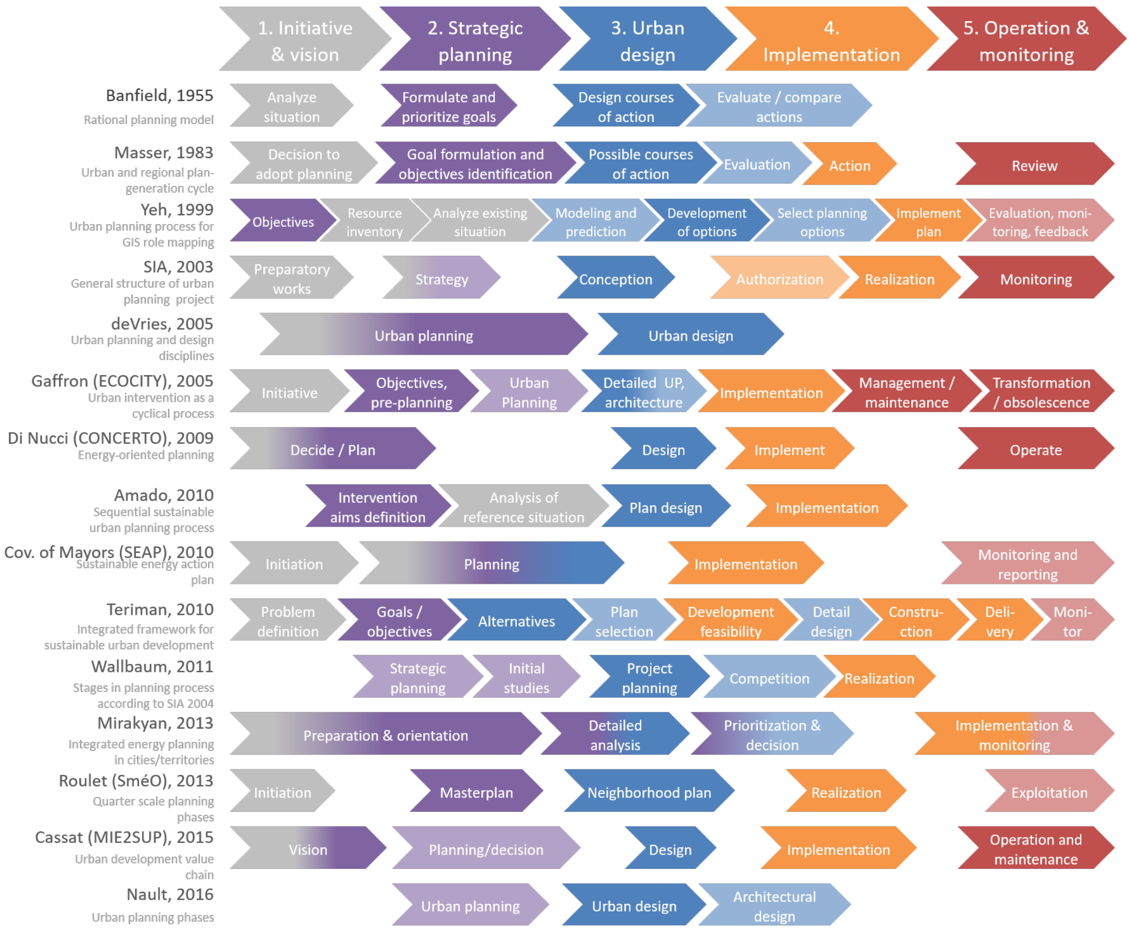


Figure A.1 – Compilation of planning steps as depicted by the references on the left, and classified according to five generic phases (top row). Key: pale colors indicate secondary steps within a phase; gradients indicate overlapping steps. Note: ((Sipowicz, Ge, and Bahu, 2016; STEP-UP, 2015; Yigitcanlar and Teriman, 2015)) are not depicted (cf. footnote on Table A.1).

Additional information regarding the focus, iterative nature, and planning horizon of the processes was also collected (Table A.2). Nearly all references explicitly recognized the need for some form of iteration in the process, either with stepwise iterations between phases, or as an entire repetitive cycle. Even more consensual was the advocacy of public participation in urban planning. Several temporal indications show the long-term investment of planning, up to over a decade for the entire process. Six references were specifically concerned with sustainability aspects, and four with energy. Regarding physical scales, planning focus ranged from building to neighborhood, and up to regional scales.

Table A.2 – Additional information regarding the planning processes in the reviewed documents.

Ref.	Short description	Iterative nature[1]	Special focus
(Banfield and Meyerson, 1955)	Rational planning model	→	Rational – Urban
(Masser, 1983)	Urban and regional plan-generation cycle	↻	Regional – Urban
(Yeh, 1999)	Urban planning process for GIS role mapping	↻	Urban – GIS
(SIA, 2003)	General structure of urban planning project	↔	Urban
(deVries, Tabak, and Achten, 2005)	Urban planning and design disciplines	↔	Design – Urban
ECOCITY, 2005	Urban intervention as a cyclical process	↻	Sustainable – Urban
CONCERTO, 2009	Energy-oriented planning	↔	Energy – Urban – Neighborhood
(Amado et al., 2010)	Sequential sustainable urban planning process	→	Sustainable – Urban
SEAP, 2010	Sustainable energy action plan	↻	Sustainable – Energy
(Teriman, Yigitcanlar, and Mayere, 2010)	Integrated framework for sustainable urban development	↻	Sustainable – Urban
(Wallbaum, Krank, and Teloh, 2011)	Stages in planning process according to (SIA, 2004)	→	Sustainable – Urban
(Mirakyan and De Guio, 2013)	General procedure for integrated energy planning in cities/territories	↔	Energy – Integrated – Long-term – Model-based
SméO, 2013	Quarter scale planning phases	↔	Building – Neighborhood – Sustainable – Urban
(Cassat et al., 2015)	Urban development value chain	↻	Energy – Urban
(Nault, 2016)	Urban planning phases	→	Design – Urban

[1] →: *Sequential process*, ↔: *Stepwise iterations*, ↻: *Cyclical process*

Mapping of urban planning tasks and supporting tools

Using the planning phases established in the previous section, it is possible to map in more detail the various tasks which have been mentioned in the reviewed documents (Table A.3).

Table A.3 – Synthesis of tasks after aggregation across all references (darker shades mean more references mention the task, white indicates one reference; the darkest shade indicates twelve references).

1. Initiative & vision	2. Strategic planning	3. Design	4. Implementation	5. Operation & monitoring
Characterize past and present situation	Determine objectives of intervention	Design different alternatives	Implement plan and construct	Monitor implemented plan against objectives
Establish a shared vision	Prioritize objectives	Evaluate, compare and select alternatives	Engage public for validation, training and organization	Adapt, rectify, maintain infrastructure and site
Involve specific stakeholders and citizens (identify requirements and get feedback)	Elaborate master plan	Communication of results and exchange with public and DM	Create implementation program (budget, timing, resources)	Operate the systems (infrastructure, services..)
Identify needs for intervention	Public participation	Detailed design of single alternative	Decide to carry out plan	Engage, inform stakeholders and train them on new technologies
Store and analyze physical, social and economic data (GIS)	Define measures and policies	Competition/tender	Monitor development to ensure plan compliance	Identify new intervention needs when obsolescence is reached, define new urban context
Identify areas of environmental sensitivity (GIS)	Define spatial aspects	Create scenarios	Coordinate development operations and construction	Reporting and submission of implementation report to political authorities
Contract definition	Establish budget, timing and responsibilities	Establish/revise implementation program (budget, timing, resources)	Legally formalize project	Update plan periodically according to feedback
Cost estimations	Perform initial studies	Dispatch lots and projects to developers	Select appropriate site	
General deadline calendar	Describe barriers preventing goals from being reached.	Determine detailed conceptual model of planning process and formalize in tool	Analyze market trends	
Select neighborhoods	Define eco-district program	Collect, describe and interpret the information	Follow administrative procedures	
Get political commitment for plan	Publish energy concept	Examine strategies by impact assessment, review results and goals	Deliver project	
Adapt city administrative structures for sustainable energy planning	Launch international urban planning competition	Implement the objective hierarchy in a MCDA approach for each scenario		
Initiation		Operationalize the quality targets and the measurable indicators		

A.2.1 Urban planning tools and methods

Many tools and methods exist to support urban planners in the tasks described in Table A.3. The list presented in this chapter does not claim to be exhaustive, but rather shows an overview of tools which are mentioned in the reviewed urban planning documents. This overview is therefore purposely limited to reveal common tools and methods which are currently used or advised in the urban planning field.

Consequently, the same references used for the review of planning process and tasks are used to identify relevant tools and methods (cf. Table A.1). These are organized into the five following categories:

(i) problem structuring and project management
(ii) data collection and visualization
(iii) public participation
(iv) alternative generation and
(v) evaluation

The categories are defined loosely, and one method or tool could belong to different categories. For example, some methods in the first and second categories could also be considered helpful for the generation of alternatives (e.g. SWOT analysis, GIS tools) or evaluation (e.g. checklists, certifications, MCDA). These latter categories are chosen to better emphasize the role of computer tools – particularly optimization and simulation – which shall be discussed in Section 4.2.

Figure A.2 shows the intensity of use of each category along the planning phases. Problem structuring, project management and public participation are the most evenly used throughout the process. Data collection and visualization is most used in phases 1 and 3. Alternative generation is predominant in the strategic planning and design phases, while evaluation is found essentially in the design phase. Figure A.3 provides the names of tools and methods found at each phase.

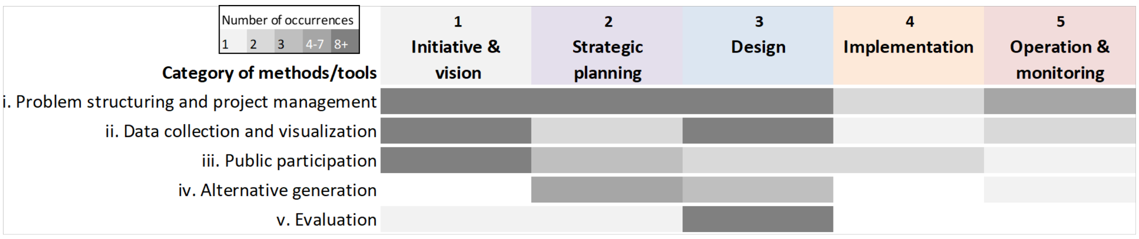


Figure A.2 – Intensity of use of methods and tools in reviewed documents, by category, throughout the urban planning process.

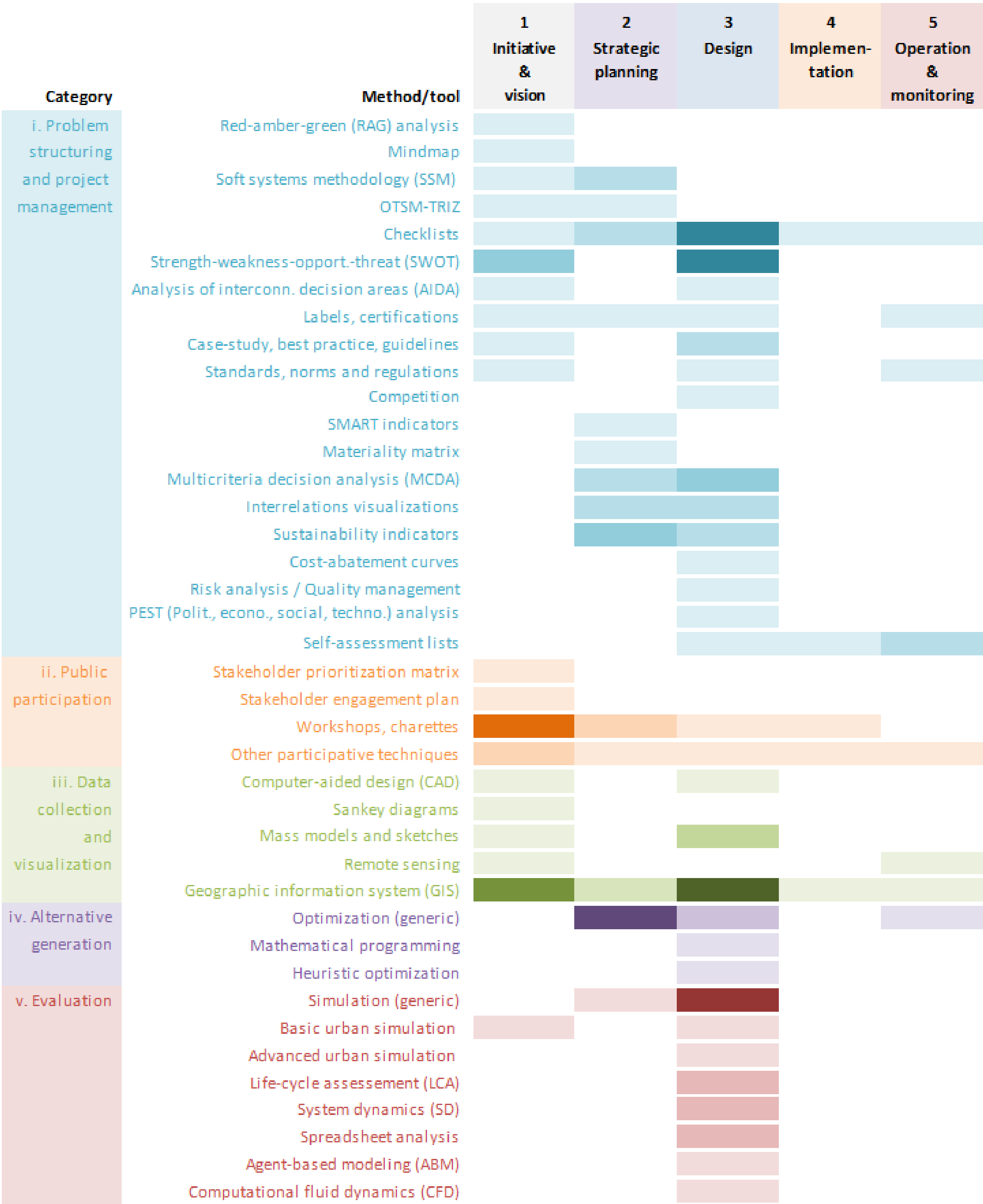


Figure A.3 – Detailed heat map of specific methods and tools mentioned in reviewed documents for each planning phase. Adapted from Cajot, Peter, and Koch (2017).

B. Multicriteria decision analysis review data

This appendix complements Chapter 2 by providing additional methodological details and results from the performed review of multicriteria decision analysis methods used for urban energy system planning. It also provides links to the raw data from the review, as well as to an interactive visualization of the data in parallel coordinates.

B.1 Static and interactive data from the review

The data collected during the review of 89 studies can be accessed in the following XLSX file provided as supplementary material to (Cajot et al., 2017b) :

www.frontiersin.org/articles/file/downloadfile/247141_supplementary-materials_tables_1_xlsx/octet-stream/Table%201.XLSX/1/247141

An interactive chart can also be accessed online to explore the data using parallel coordinates (Figure B.1):

infoscience.epfl.ch/record/228830/files/Interactive_results_1.html

infoscience.epfl.ch/record/228830/files/Interactive_results_annex_with_ref.html

B.2 Supplementary figures and tables

Figure B.2 illustrates the search process in the Scopus database which led to the 87 papers reviewed in Chapter 2.

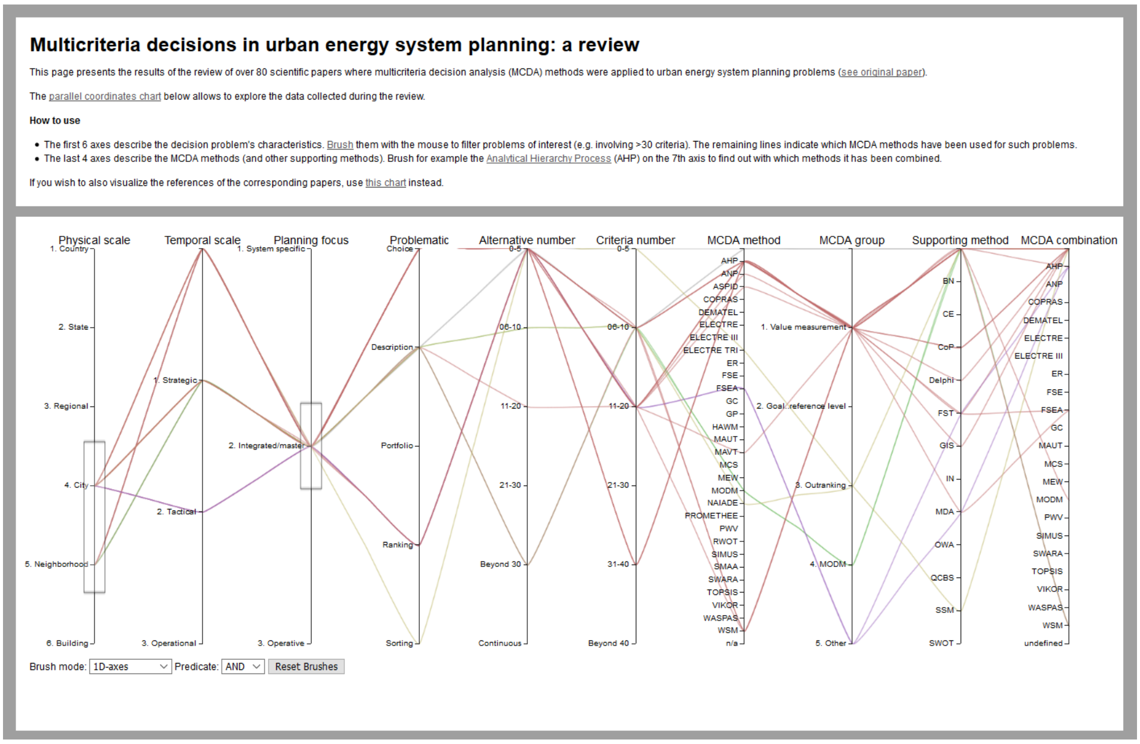


Figure B.1 – Screenshot of the online parallel coordinates interface containing the results from the review.

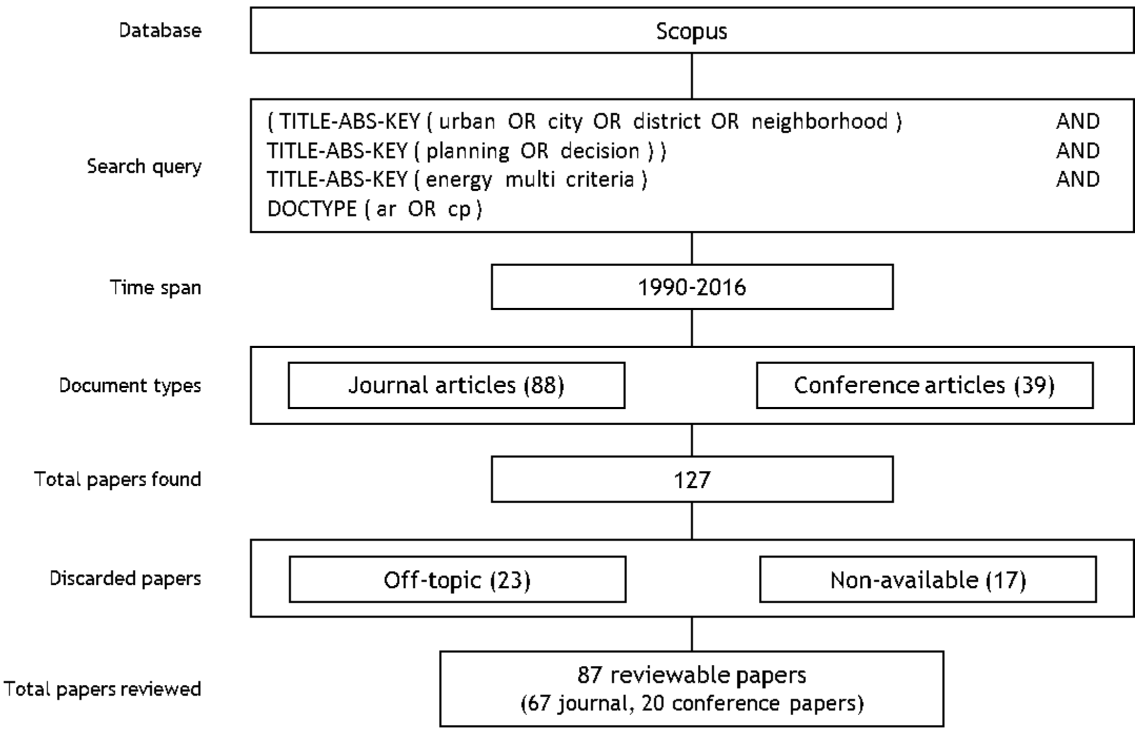


Figure B.2 – Depiction of the methodological steps and results involved in collecting the studies to be reviewed. The search query was performed in March 2016, returning initially a total of 127 papers.

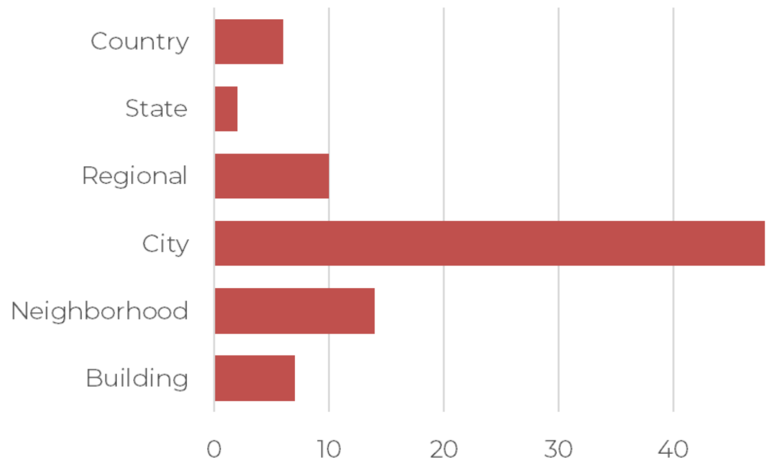


Figure B.3 – Number of studies reviewed distributed by planning scale.

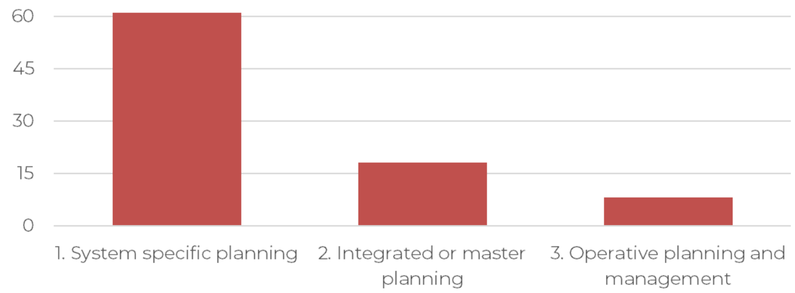


Figure B.4 – Number of studies in each planning focus category.

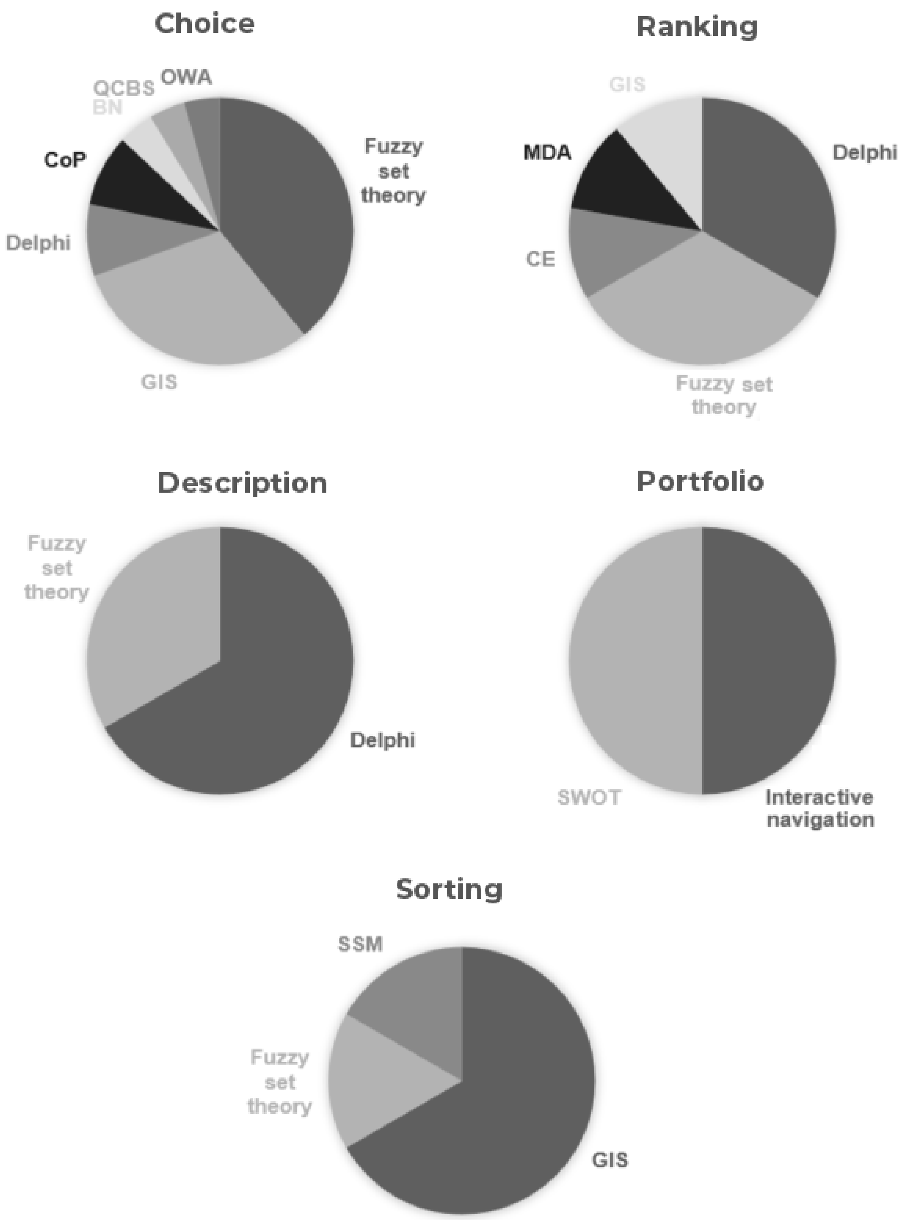


Figure B.5 – Supporting methods per decision problematic.

Table B.1 – Classification of MCDA and supporting methods and share of each class in the 89 studies reviewed.

MCDA methods					Supporting methods
1. Value measurement models	2. Goal, aspiration and reference level models	3. Outranking models	4. MODM	5. Other	- *(supporting methods)*
AHP (Al-Yahyai et al., 2012; Beccali, Cellura, and Mistretta, 2002; Chrysoulakis et al., 2013; Daim, Bhatla, and Mansour, 2013; De Feo, De Gisi, and Galasso, 2008; Duan, Pang, and Wang, 2011; Dytczak and Ginda, 2006; Ekmekçioĝlu, Kaya, and Kahraman, 2010; Feo and De Gisi, 2014; González et al., 2013; Hsu and Lin, 2011; Hsueh and Yan, 2011; Idris and Abd. Latif, 2012; Jain et al., 2014; Karatas and El-Rayes, 2013; Kaya and Kahraman, 2010; Khoshsolat et al., 2012; Koo and Ariaratnam, 2008; Madadian, Amiri, and Abdoli, 2013; Massara and Udaeta, 2010; Medineckiene and Björk, 2011; Meney and Pantelic, 2015; Nigim, Munier, and Green, 2004; Nigim, Reiser, and Luiken, 2009; Reza, Sadiq, and Hewage, 2011; Rochas, Kuzņecova, and Romagnoli, 2015; Tzeng, Lin, and Opricovic, 2005; Wang, Xu, and Song, 2011; Yedla and Shrestha, 2003; Ziemele et al., 2014)	TOPSIS (Ekmekçioĝlu, Kaya, and Kahraman, 2010; Guo and Zhao, 2015; Khoshsolat et al., 2012; Tzeng, Lin, and Opricovic, 2005; Ziemele et al., 2014)	ELECTRE III (Banar, Özkan, and Kulaç, 2010; Carriço et al., 2014; Frijns et al., 2015; Karagiannidis and Perkoulidis, 2009)	MIN(L)P, EA (Al-Ani and Habibi, 2013; Aydin, Mays, and Schmitt, 2014; Ayoub et al., 2009; Fonseca et al., 2016; Goe, Gaustad, and Tomaszewski, 2015; Karatas and El-Rayes, 2014; Karmellos, Kiprakis, and Mavrotas, 2015; Ma, 2012; Ma, Jin, and Lei, 2014; Nowak, Bortz, and Roclawski, 2015; Pérez-Fortes et al., 2012; Rager, Dorsaz, and Maréchal, 2013; Ribau, Sousa, and Silva, 2015; Videla et al., 1990; Wu et al., 2012; Yokoyama and Ito, 1995; Zheng et al., 2015)	WASPAS (Vafaeipour et al., 2014)	Geographic information system (Al-Yahyai et al., 2012; Al-Yahyai and Charabi, 2015; Arampatzis et al., 2004; Awad-Núñez et al., 2015; Colantoni et al., 2016; Feo and De Gisi, 2014; Goe, Gaustad, and Tomaszewski, 2015; González et al., 2013; Grubert, Stillwell, and Webber, 2014; Hsu and Lin, 2011; Idris and Abd. Latif, 2012; Van Haaren and Fthenakis, 2011)

Table B.1 – (continued)

1. Value measurement models	2. Goal, aspiration and reference level models	3. Outranking models	4. MODM	5. Other	- *(supporting methods)*
WSM (Afify, 2010; Arampatzis et al., 2004; Awad-Núñez et al., 2015; Aydin, Mays, and Schmitt, 2014; Bauer and Brown, 2014; Beccali, Cellura, and Mistretta, 2002; Carriço et al., 2014; De Feo, De Gisi, and Galasso, 2008; Dombi, Kuti, and Balogh, 2014; Feo and De Gisi, 2014; Fonseca et al., 2016; Frijns et al., 2015; Haruvy and Shalhevet, 2007; Jovanović et al., 2009; Koo and Ariaratnam, 2008; Medineckiene and Björk, 2011; Rochas, Kuzņecova, and Romagnoli, 2015; Vadiati et al., 2012)	VIKOR (Kaya and Kahraman, 2010; Tzeng, Lin, and Opricovic, 2005)	PROMETHEE II/GAIA (Ghafghazi et al., 2010; Zhang, Pan, and Kumaraswamy, 2014)		SWARA (Vafaeipour et al., 2014)	Fuzzy set theory (Al-Yahyai et al., 2012; Al-Yahyai and Charabi, 2015; Colantoni et al., 2016; Duan, Pang, and Wang, 2011; Ekmekçioĝlu, Kaya, and Kahraman, 2010; Fetanat and Khorasaninejad, 2015; Guo and Zhao, 2015; Hsu and Lin, 2011; Hsueh and Yan, 2011; Kaya and Kahraman, 2010; Khoshsolat et al., 2012; Wang, Xu, and Song, 2011)
ASPID (Jovanovic, Afgan, and Bakic, 2010; Jovanovic et al., 2011; Lipošćak et al., 2006; Vučićević et al., 2014)	SIMUS (Nigim, Munier, and Green, 2004)	ELECTRE (Fetanat and Khorasaninejad, 2015)		COPRAS (Medineckiene and Björk, 2011)	Delphi (Awad-Núñez et al., 2015; Bauer and Brown, 2014; Haruvy and Shalhevet, 2007; Hsueh and Yan, 2011; Jain et al., 2014; Tzeng, Lin, and Opricovic, 2005; Vafaeipour et al., 2014)
ANP (Banar, Özkan, and Kulaç, 2010; Bottero and Mondini, 2008; Fetanat and Khorasaninejad, 2015)	GP (Nixon et al., 2014)	ELECTRE TRI (Coelho, Antunes, and Martins, 2010)		FSE (Duan, Pang, and Wang, 2011)	CoP (Chrysoulakis et al., 2013; González et al., 2013)

Table B.1 – (continued)

1. Value measurement models	2. Goal, aspiration and reference level models	3. Outranking models	4. MODM	5. Other	- *(supporting methods)*
MAUT (Karatas and El-Rayes, 2013)	GC (Ribau, Sousa, and Silva, 2015)	NAIADE (Browne, O'Regan, and Moles, 2010)		FSEA (Wang, Xu, and Song, 2011)	OWA (Al-Yahyai et al., 2012)
MAVT (Phdungsilp, 2010)				PWV (Ribau, Sousa, and Silva, 2015)	BN (Awad-Núñez et al., 2015)
MEW (Medineckiene and Björk, 2011)				RWOT (Öztürk, 2015)	CE (Dombi, Kuti, and Balogh, 2014)
HAWM (Sheykhdavodi et al., 2010)				DEMATEL (Fetanat and Khorasaninejad, 2015)	SSM (Coelho, Antunes, and Martins, 2010)
				SMAA (Kontu et al., 2015)	SWOT (Öztürk, 2015)
				MCS (Ribau, Sousa, and Silva, 2015)	MDA (Wang, Xu, and Song, 2011)
				ER (Zheng et al., 2015)	IN (Nowak, Bortz, and Roclawski, 2015)
					QCBS (Vadiati et al., 2012)
Share of all studies [%]					
69	13	10	19	12	37

C. Case-studies: complementary material

This appendix complements Chapters 4 and 5 with the detailed references of the documents reviewed for the problem analysis, slides containing the questions and answers from the live poll performed during a workshop, and with complementary figures of the computed three-dimensional solutions spaces.

C.1 Urban and energy planning documents

Table C.1 contains the documents reviewed as part of the planning framework analysis and led to the development of the mpMILP model described in Schüler et al. (2018b).

C.2 Questions and answers from the live poll

Figures C.1, C.2 and C.3 show the slides describing the interface related questions asked in the live poll, as well as the results of the poll processed in real time. Figures C.4, C.5, C.6 and C.7 show the slides describing the model-related questions.

C.3 Case-study solution space visualization

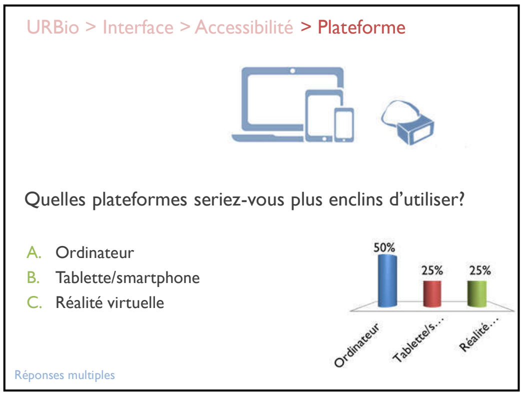
Figures C.8 and C.9 show the solutions spaces computed for each subsector, comparing the way in which both sampling methods cover the space.

Table C.1 – Urban and energy planning documents reviewed to describe the case-studies. (C) and (P) indicate documents relative to the Cherpines and Palettes case-studies respectively.

Name	Type	Description
		Laws and standards
LAT	National law	Spatial planning law (LAT, 2016)
OPB	National ordinance	Ordinance on noise protection (OPB, 2018)
SIA norms	Norm	Set of standards and requirements for planning and construction in Switzerland (SIA, 2001; SIA, 2006; SIA, 2011; SIA, 2016)
LaLAT	Cantonal law	Application of the federal spatial planning law (LaLAT, 1987)
LGZD	Cantonal law	Development zone law (LGZD, 1957)
LCI	Cantonal law	Construction and installation law (LCI, 1988)
RCI	Cantonal regulation	Regulation on the construction and installation law (RCI, 1978)
LEN	Cantonal law	Energy law (LEn, 1987)
REN	Cantonal regulation	Regulation on the energy law (REn, 1988)
		Urban planning instruments
PDCn 2030	Cantonal directive plan	Sets and coordinates strategic goals as well as measures to reach them (DALE, 2013)
PDCom Plan-les-Ouates 2009 (**C**), Confignon 2006 (**C**), Lancy 2008 (**P**)	Communal directive plan	Provides a global vision of a commune's development over 10-15 years, coordinating with canton and neighboring communes. Contains a concept and synthesis map, as well as measures to reach the objectives. (Plan-les-Ouates, 2009; Confignon, 2006; Lancy, 2008)
PDQ Les Cherpines 2013 (**C**), Les Semailles 2013 (**P**)	Neighborhood directive plan	Depicts the evolution of a neighborhood in the mid-term, setting the project principles, but not the details of layout and construction. Contains layout alternatives, objectives and synthetic map, as well as measures to reach objectives. (Confignon and Plan-les-Ouates, 2013; Lancy, 2013)
		Energy planning instruments
PDE	Energy directive plan	Sets the energy policy goals on the canton level, and establishes desired shares of energy resources, including renewable energy sources. (ScanE, 2005)
CET: Secteur Cherpines (2011)(**C**), Secteur élargi Semailles (2011)(**P**)	Territorial energy concept	Organizes and coordinates actors to reduce energy needs by developing energy efficient infrastructure and promoting the use of local energy sources. (ScanE, 2011)

Figure C.1 – Interface-related questions 1-5 from live poll performed during the first brownfield workshop.

Figure C.2 – Interface-related questions 6-11 from live poll performed during the first brownfield workshop.



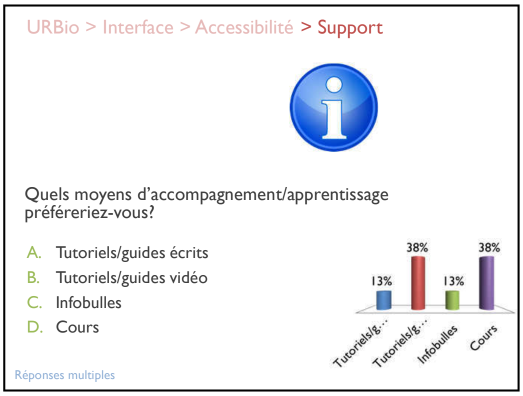
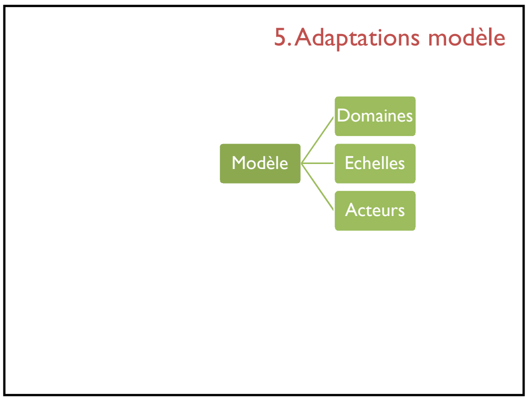
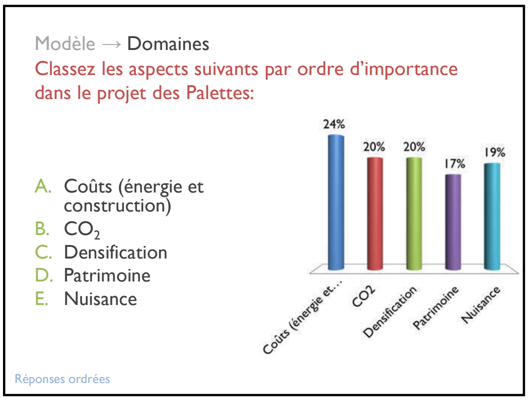
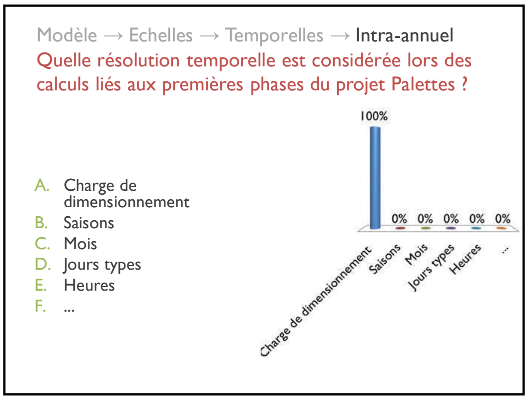
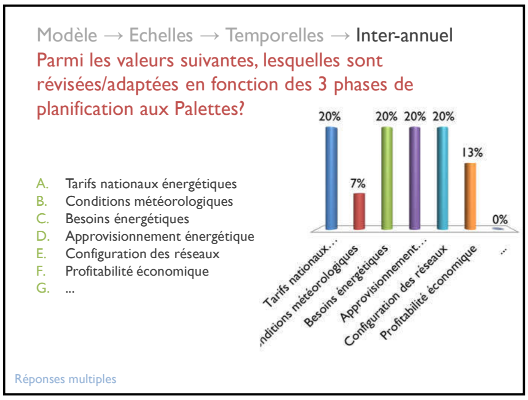


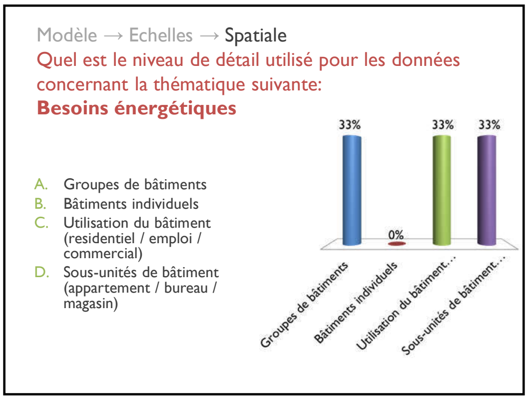
Figure C.3 – Interface-related questions 12-13 from live poll performed during the first brownfield workshop.











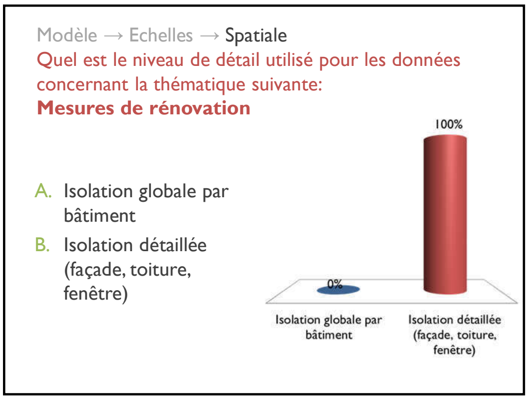


Figure C.4 – Model-related questions 1-5 from live poll performed during the first brownfield workshop.

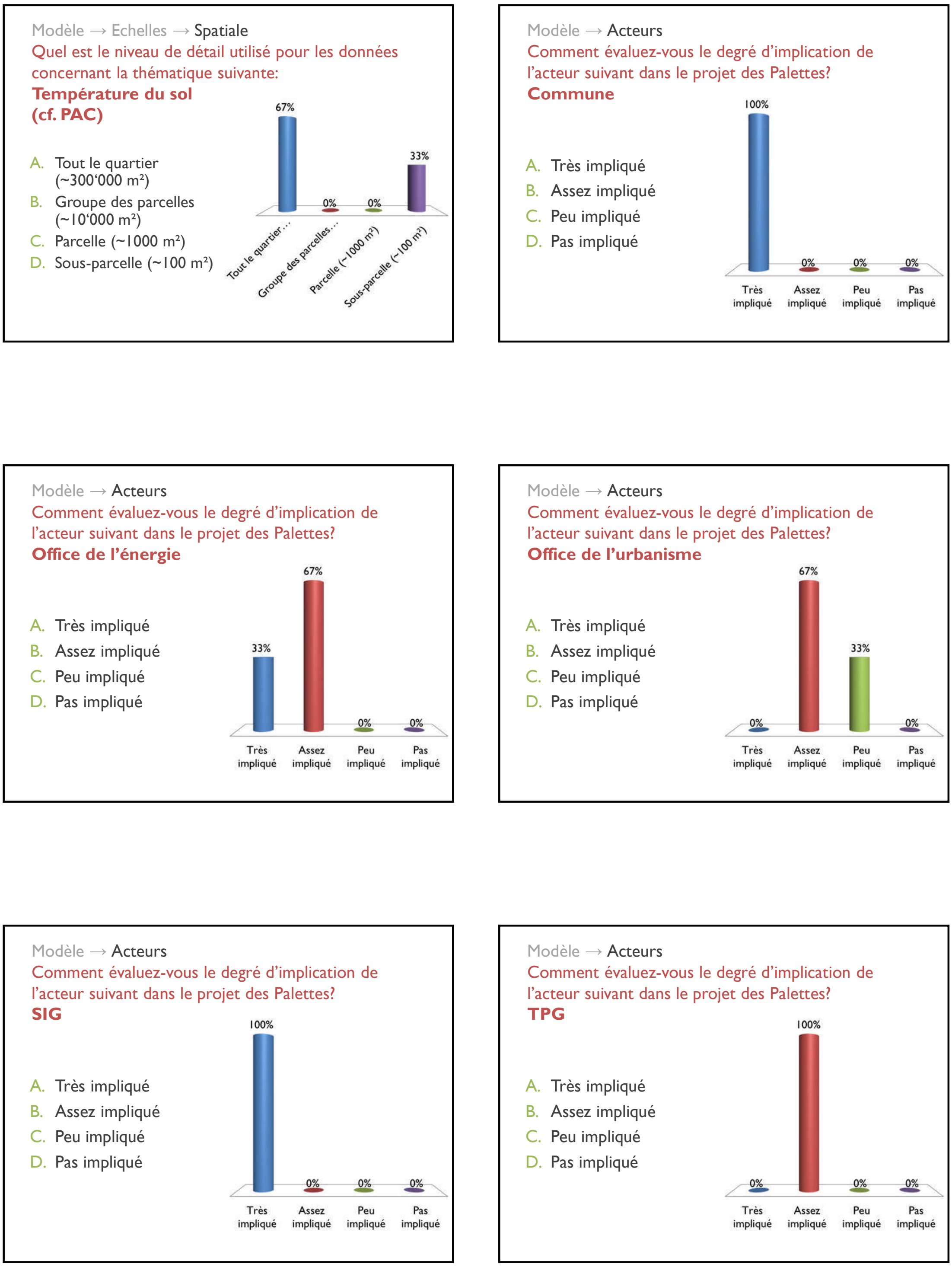


Figure C.5 – Model-related questions 6-11 from live poll performed during the first brownfield workshop.

Figure C.6 – Model-related questions 12-17 from live poll performed during the first brownfield workshop.

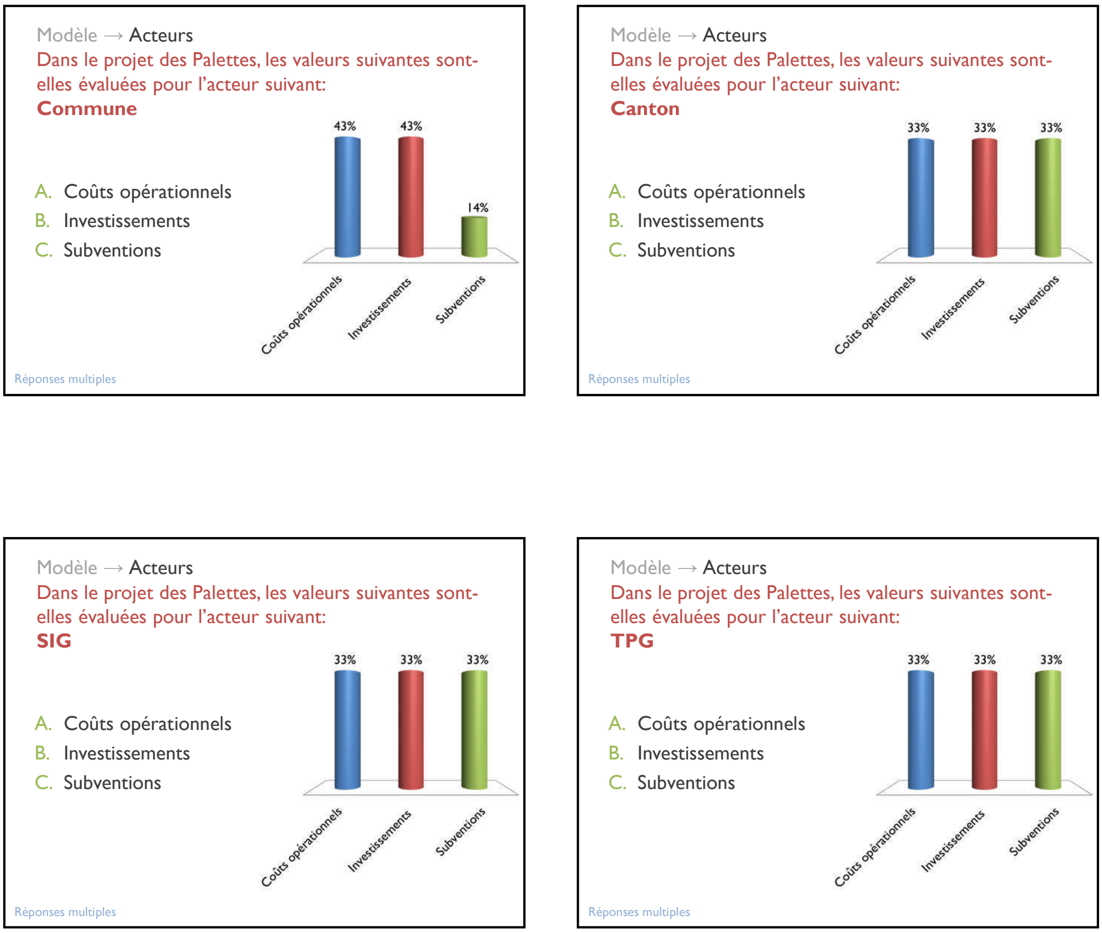


Figure C.7 – Model-related questions 18-21 from live poll performed during the first brownfield workshop.

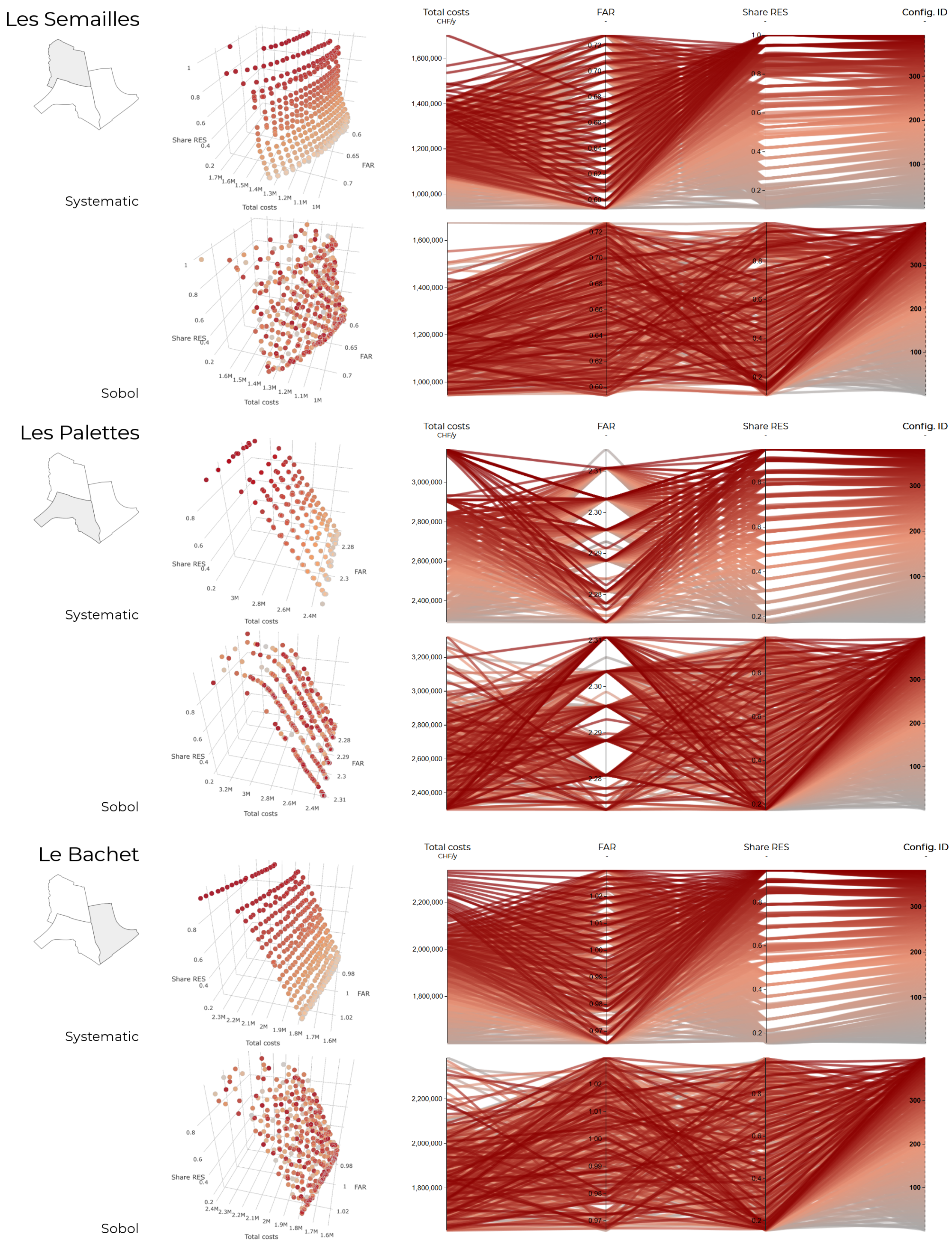


Figure C.8 – Comparison of systematic and Sobol sampling techniques for exploring the FAR and RES dimensions while minimizing total costs in each subsector of Palettes. The color of the points/polylines indicates the order in which they were generated, from light to dark.

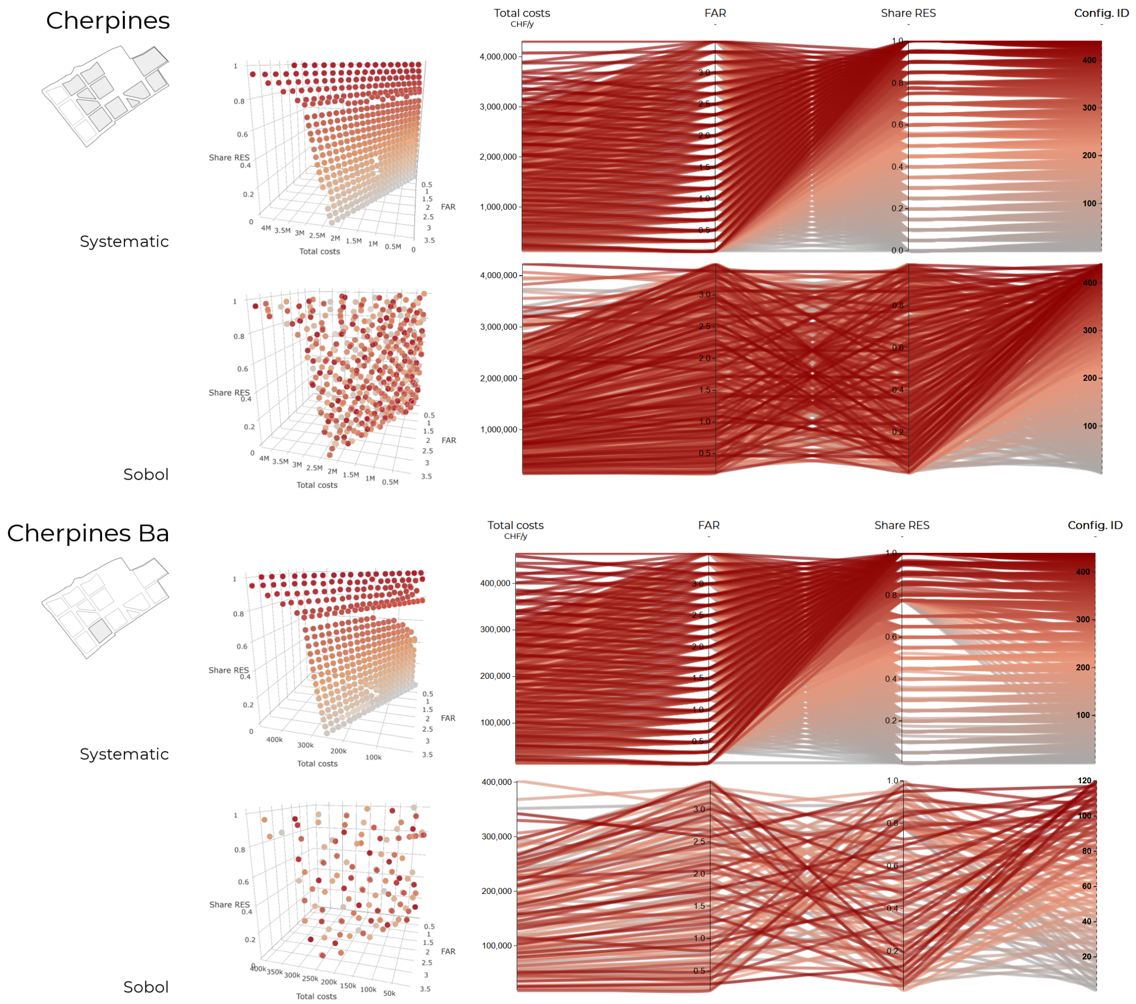
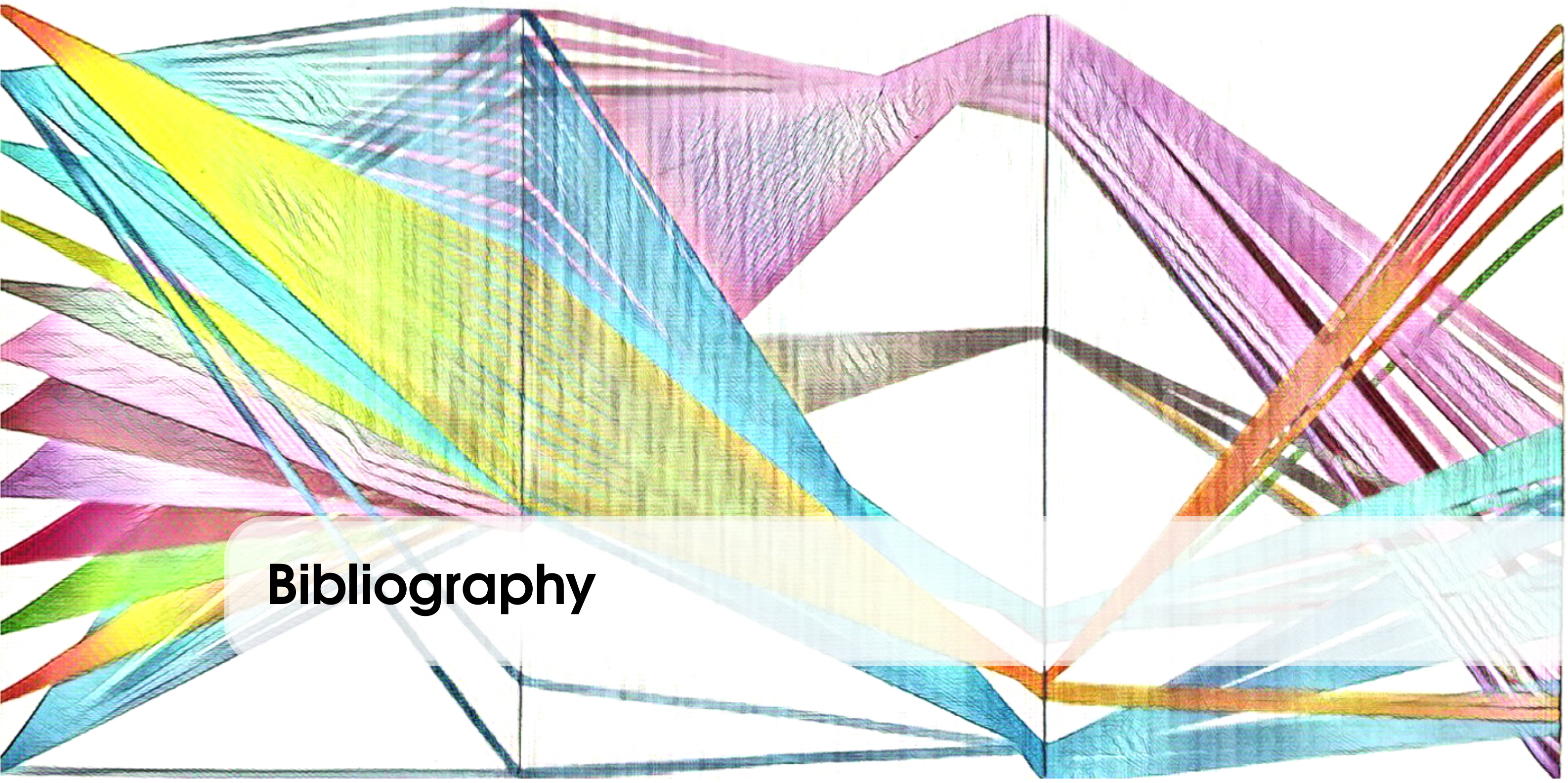


Figure C.9 – Comparison of systematic and Sobol sampling techniques for exploring the FAR and RES dimensions while minimizing total costs in each the Cherpines project, and for one of its subsectors (block Ba). The color of the points/polylines indicates the order in which they were generated, from light to dark.



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Environmental engineer

Education

2014–2018 **PhD Energy**, *École Polytechnique Fédérale de Lausanne (EPFL)*.

2006–2011 **Msc Environmental Engineering**, *École Polytechnique Fédérale de Lausanne*.
Master project carried out at Kyoto University, Japan, EPFL

Professional Experience

2014–2017 **Research engineer**, *European Institute for Energy Research (EIFER)*, Karlsruhe, Germany.
- Engaged in the European International Training Network "CI-NERGY"
- Collaborated with urban and energy planning departments in Geneva

2012–2014 **Junior project manager in process analysis**, *Direction générale de l'environnement (DGE)*, Vaud, Switzerland.
- Developed a system of energy indicators to monitor the cantonal energy policy
- Planned the restructuring of the energy, nature, and urban environment departments (>300 collaborators)
- Defined the canton's priority research topics for the Swiss Federal Institute for Forest, Snow and Landscape Research (WSL)

2011–2012 **Junior project manager in forest biodiversity**, *Service des forêts, faune et nature (SFFN), and ILEX sàrl*, Vaud, Switzerland.
- Developed a computer tool to raise biodiversity awareness among forest professionals and students
- Moderator for the professional training courses on forest biodiversity

2012 **Organizer and contributor at international symposium and congress**, *International Commission on Large Dams (ICOLD)*, Kyoto, Japan.
- Active member in the local hosting team for an event of 1300 participants

Awards and grants

2011 Master thesis grant at Kyoto University, CHF 3'000, Zeno Karl Schindler Foundation

2010 Best "Design Project 2010" poster, titled "Evaluating the integration of rainwater harvesting for Geneva International Airport", School of Architecture, Civil and Environmental Engineering, EPFL

Languages

French	**Native language**	
English	**Native language**	
German	**Intermediate**	*8 years scholarship, 3.5 years in Germany*
Italian	**Basic**	*A1*

Publications

Journal articles

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