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A New Integrated Multi-Criteria Spatial Decision Support System

for urban energy planning in the built environment

By

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Declaration

I hereby declare that the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data. Part of the work described in this thesis was previously published in the publications listed in Appendix C.

Sara Torabi Moghadam

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* This dissertation is presented in partial fulfillment of the requirements for **Ph.D. degree** in the Graduate School of Politecnico di Torino (ScuDo).

I would like to dedicate this thesis to my loving family.

We can't solve problems by using the same kind of thinking we used when we created them

Albert Einstein

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Above all, I extend my special sincere appreciation to my parents for their love, their respect to my choices and confidence in my abilities. Words are not enough to express my gratitude to my mother and father. Special thanks go to my beloved sister, Mana, for her endless love. Each of you can share in this accomplishment, for without your support it would not have been possible. I am also grateful, and forever will be, to my best friend and husband Arash, whose patient and unconditional love enabled me to complete this study.

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Abstract

Sustainability contests represent a fundamental challenge to traditional urban development practices and concepts. Reducing energy consumption and greenhouse gas emissions from urban infrastructure and building stock, towards low-carbon cities requires a supportive planning process. In this regard, the use of appropriate tools and methods for addressing complex interactions of Urban Energy Planning (UEP) processes is needed. In particular, the problem of building stock energy consumption in the urban environment is crucial. The primary aim of this research is to model energy consumption patterns based on bottom-up statistical-engineering combination methods. These methods evaluate the current status of energy consumption and different future energy saving scenarios to promote sustainable urban planning. However, the choice among urban energy planning scenarios is extensively based on multi-actors and multi-criteria aspects. Therefore, to anchor such a sustainable urban planning, a wider societal consensus building with an earnest and active engagement of relevant stakeholders in the city is essential. For this purpose, stakeholder-oriented approach plays a key role in implementing the effective strategies for urban and regional adaptation. The research, therefore, is also dealing with the integration of participative decisional processes of urban energy planning by organizing different focus groups involving real stakeholders. This fact can help to assess, over a short/long term period, the mix of measures by analyzing meaningful scenarios focused on energy consumptions, environmental impacts, economic and social aspects. The result is the development of a new Multi-Criteria Spatial Decision Support System (MC-SDSS), which is an interactive energetic plug-in in GIS environment using CommunityViz. This tool has been applied to a demonstrator case-study, related to a medium-sized city of the metropolitan area of Turin. However, the methodology used for delivering the tool can be applied to other contexts due to its flexibility. The new MC-SDSS is intended to facilitate the decisional process for stakeholders who can ask “what-if” questions and visualize “if-then” scenarios in a real-time. Moreover, it can explore a range of possible futures for assisting urban planners, policymakers and built environment stakeholders in their efforts to plan, design and manage low-carbon cities. This thesis is part of a national Smart City &

Communities project, named “EEB-Zero Energy Buildings in Smart Urban Districts” (www.smartcommunitiestech.it).

Contents

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List of Abbreviations

AB	Apartment Block
ACH	Air Change per Hours
AHP	Analytic Hierarchy Process
APE	Energy Performance Certificate
ARPA	Agenzia Regionale per la Protezione Ambientale
BIM	Building Information Model
DA	Dynamic Attributes
DH	District Heating
DM	Decision Maker
DSS	Decision Support Systems
ELECTRE	ELimination Et Choix Traduisant la REalité
GHG	Greenhouse Gas
GIS	Geographic Information System
IA	Impact Assessment
ICT	Information Communication Technologies
IEP	Integrated Energy Planning
IIA	Interactive Impact Assessment
MAUT	Multi-Attribute Utility Theory
MCDA	Multi-Criteria Decision Analysis
MC-SDSS	Multi-Criteria Spatial Decision Support System
MFH	Multi-Family House
MLR	Multiple Linear Regression
MRSE	Mean Root Squared Error
NN	Neural Network
OLS	Ordinary Least Squares
PBP	Pay Back Period
PROMETHEE	Preference Ranking Organization Method for Enrichment of Evaluations
PSS	Planning Support System
R&D	Research and Development
SA	Suitability Analysis
SDSS	Spatial Decision Support System
SFH	Single Family House
SIM	System Information Model
SODM	Single Objective Decision Making
SWOT	Strengths, Weaknesses, Opportunities and Threats
TH	Terraced House
TMY	Typical Meteorological Year
UEM	Urban Energy Modelling
UEP	Urban Energy Planning
UIEP	Urban Integrated Energy Planning

V-SMART	Visualization-Sustainable Multicriteria Analysis Retrofitting Territory
WLC	Weighted Linear Combination

Part of the work described in this chapter was also previously published in the following publications. Minor grammatical changes and some information extensions have been made to integrate the articles within this dissertation.

Paper 1. S. Torabi Moghadam, C. Delmastro, S.P. Corgnati, P. Lombardi. (2017). Urban energy planning procedure for sustainable development in the built environment: a review of available spatial approaches. Journal of Cleaner Production, vol. 165, pp. 811-827. doi: 10.1016/j.jclepro.2017.07.142.

Paper 2. S. Torabi Moghadam, G. Mutani, P. Lombardi. (2017). A mixed methodology for defining a new spatial decision analysis towards low carbon cities. Procedia Engineering, vol. 198, pp. 375–385. doi: 10.1016/j.proeng.2017.07.093.

Chapter 1

Introduction

1.1 Background and the problem statements

Cities are the main energy consumers in the world, contributing to carbon dioxide (CO_2) emissions and the leading cause of climate change. More than half of the world population settle in urban areas and expecting to have this number increased to 64-69%, or 5.6-7.1 billion by 2050 (IPCC, 2014). Moreover, urban sprawl and the way that cities are growing and operating have a substantial detrimental impact on the environment and its energy demand (Jaeger et al., 2010). Interestingly, urban areas account for about two-thirds of the world energy (United Nations, 2015). Almost always, the most notable source of greenhouse gas (GHG) emissions comes from either energy use in transportation or building sector (IPCC, 2014).

Although built environment sector is very challenging, it provides cities with low-cost and short-term opportunities for emissions reductions first and foremost through the energy performance improvement. In this regard, the European Commission emphasizes that emissions in this area could be reduced by about 90% by 2050 (European Commission, 2011). This fact highlights the significance of attaining the objective of the recast Directive on energy performance of buildings that new buildings built from 2021 onwards will have to be nearly zero-energy buildings (EPBD, 2010). This approach stresses the importance of accelerating renovation development and defining different retrofitting scenarios in the built environment area. An actual reduction of emissions can be realized only by acting on the existing building stock since, the most of the European context is characterized by low energy performance existing building stocks (BPIE, 2011); (Dall'O' et al., 2013). In the literature, many studies deal with the energy consumption modelling for existing building stock (Swan and Ugursal, 2009). Particularly, the focus of these studies is made on the residential stock since this sector is a substantial consumer of energy for any nation (Saidur et al., 2007).

As the GHG emitters and energy consumption reduction targets are to be met, it is required that Decision Makers (DMs) tackle emissions from the building sector. The problem is that, traditionally, the scenarios for energy and environmental planning have considered a single measurement criterion, costs benefit maximization, to make their decisions (Greening and Bernow, 2004). However, the complexity, conflicting and multidimensionality concept of long/medium-term sustainable development of urban energy planning matters cannot rely upon just single criterion alternatives. Moreover, an urban and regional planning should be sustained by earnest collaborative and inclusive processes since cities are dynamic living and continuously evolving organisms (Lombardi and Ferretti, 2015). In this regard, the use of the appropriate tools and methods for addressing complex interactions of energy planning problems including a high level of uncertainty, a different type of data, multi-interests and conflicting objectives is needed.

Moreover, the transition toward a sustainable urban development requires the definition of a set of strategies considering national priorities. Since the late '50s, an Integrated Energy Planning (IEP) has been recognized to support the strategic planning process of urban areas. During these years, various energy supply companies had to make appropriate decisions to solve the massive growth of the energy demand (Herbst et al., 2012). Currently, Urban Integrated Energy Planning (UIEP) has been developed as the new generation of IEP (Mirakyan et al., 2009). UIEP asks for a comprehensive vision of urban sustainable energy policies and a strong co-operation between local and national governments. It involves many aspects (e.g. economic, societal, and environmental), different energy sources (e.g. electricity, gas, and oil), multiple actors (e.g. citizens, experts, and public entities) and different sectors (e.g. residential, commercial, and transportation), which leads to be considered as a very complex problem (Albeverio et al., 2008). Setting up an effective UIEP requires appropriate approaches to support DMs in defining a policy development strategy. These approaches help DMs to choose the "best" alternative among different alternatives (Løken, 2007a). However, from the systematic literature review conducted by Torabi Moghadam et al. (2017a) during the development of current research, emerged that there is still not a well-recognized procedure and an integrated framework to support the UIEP. In this study over the

146 articles, 80 papers on the UIEP application have been identified and analysed. These papers then have been classified based on three criteria for the purpose of presenting results effectively: the year of publication, the level of integration of UIEP phases and the types of combination of methodology. Chapter 2 is dedicated to illustrate this study and its results. One can say that although there are several examples of urban energy planning approaches there is still not a well-recognized procedure and an integrated method to face the UIEP. This fact leads to neglect some important aspects of current urban energy planning practices (Lombardi and Trossero, 2013).

Considering that energy planning is complex and multi-disciplinary (Torabi Moghadam et al., 2017a), the main challenge for research is to integrate the existing different methodologies in an agreed structure in order to enhance the quality and robustness of the planning results. In fact, although the research field of energy planning has become progressively important at urban and regional scales, performing the entire energy planning process by integrating different approaches is still not a common practice. An IUEP is an opportunity through which it is possible to contribute towards a greater sustainability. Indeed, UIEP has to take into consideration an integrated approach. To achieve such a sustainable, integrate urban planning, a wider societal consensus building with an earnest and active engagement of all relevant actors and interest stakeholders in the city is essential. For this purpose, a stakeholder-oriented approach plays a key role in implementing the effective strategies for urban and regional adaptation.

The whole process is essential to guarantee a future sustainable urban transformation by investing responsibly in alternative consumption patterns and greener strategies; speeding the decision-making process through participation and intuitive visualization; strengthening the collaboration and relationship between research and private and public local authorities; leading to various new commercial consequences for the environment, economy and society at the national level down to the city level; offering the opportunities of engaging stakeholders in the planning process by establishing a shared framework between them. According to the given background, the lack of well-recognized of integrated approaches in UIEP need to be further studied.

1.2 Research objectives and questions

The primary goal of this study is to develop a new interactive urban energy building retrofitting system, which can strongly support the participative spatial decision process for relevant stakeholders. More specifically, the research first aims at performing energy consumption patterns modelling based on bottom-up statistical-engineering methods. These methods evaluate the current situation of building stock energy consumption and they are able to predict also different future energy saving scenarios to promote sustainable development. However, the choice among urban energy planning scenarios is extensively based on multi-actors and multi-criteria aspects. The core objectives of this research are listed below:

a. Conduct a review of the literature regarding different phases of UIEP, which consist in (a) the spatial modelling approaches that can be applied to the energy use of building stock (b) Multi-Criteria Spatial Decision Support System (MC-SDSS) tools for energy planning;
b. Create a supportive Geographic Information System (GIS) database including a broad number of data and information regarding the building stock that helps to identify and locate hot-spots area;
c. Develop a geospatial statistical model of the building stock that is able to give a representative picture of the current energy consumption performances and locate on maps the targeted areas that need to be energetically improved;
d. Explore how to reduce the energy demand of building stock in the future by developing simulations models that save the computations time;
e. Develop a new MC-SDSS integrated into the GIS considering the socio-economic, technical and environmental aspects;
f. Identify the opportunities and challenges of creating different interactive energy consumption retrofitting scenarios side-by-side with stakeholders;
g. Explore and test an interactive energy visualization tool forming different workshops with real stakeholders and using questionnaires and structured discussions.

Concerning the current field of research limitations, this Ph.D. study has identified three main questions that need to be addressed in order to create a comprehensive framework for UIEP.

1. Are current research studies able to support the challenges provided by Urban Integrated Energy Planning (UIEP) taking into account the variety of all the sustainable planning aspects? What are current challenges and barriers in this research field?
2. How to model the energy consumption at urban scale in a spatial way for the current and future scenarios? Which kinds of data are needed? How to connect different data type from different and scattered sources?

3. How useful are interactive MC-SDSS tools in supporting the stakeholders in urban energy planning decisions? How their usability can be improved?

These questions will be answered through methodological approaches and procedural steps as illustrated in section 1.3 below.

1.3 Methodological approach and expected result

This Ph.D. work assembles research outcomes aiming to illuminate innovative solutions bridging the limitations of the current field of research of UIEP, which consists in four main phases of planning according to Mirakyan and Guio (2013):

- Phase I: Preparation and preliminary analysis;
- Phase II: Detailed urban buildings energy modelling;
- Phase III: Prioritization and decisional process
- Phase IV: Implementation and monitoring.

The methodological framework of this study responds to the first three main phases of UIEP presented above, wherein each phase several steps, tools and methodologies are involved (Mirakyan and De Guio, 2013); (Cajot et al., 2017). The Ph.D. research offers a specific methodology for each phase of planning as shown in Figure 1.

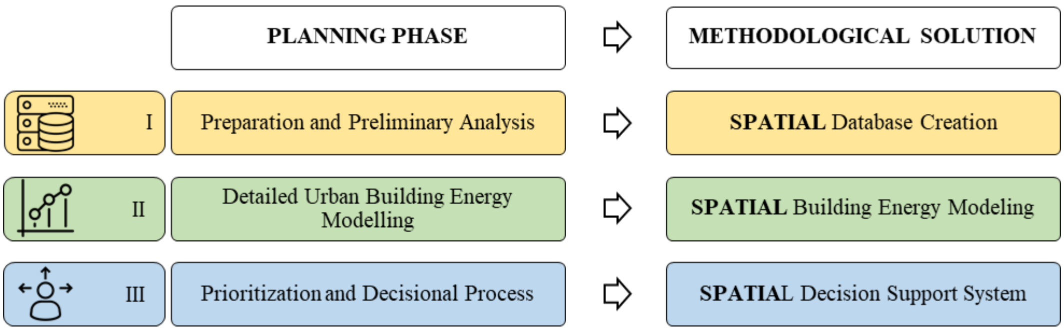


Figure 1: Summary of methodological framework solution for each phase of planning through this thesis.

In the first Phase, a GIS-data collection procedure and preliminary analysis is done in order to have a supportive basis for the analysis. The second Phase consists in a methodology, which is developed to assess the energy consumption for the current and future city performances. Finally, in the third Phase, stakeholder-oriented scenarios are promoted for urban energy saving in the built environment.

The expected result of this thesis is a new Multi Criteria Spatial Decision Support System (MC-SDSS) that is able to aid and support the stakeholders in defining urban energy scenarios and strategies for the building sector.

It is notable to say that the concept of Spatial Decision Support System (SDSS) is strictly related to Planning Support System (PSS) (Li and Jiao, 2013). In 2004, Geertman and Stillwell stated that similar specifications of PSS and SDSS help decision makers (DMs) and planners to gain more efficient and accurate planning and decision-making outcomes. This understanding relates these two concepts, PSS and SDSS, which are able to analyze the variety of alternatives on future development strategies, in order to compare, interactively discuss and communicate (Geertman and Stillwell, 2004). According to Geertman et al. (2015), "*PSS are also related to so-called spatial decision support systems (SDSS), which are also designed to aid particular decision tasks. These two types of systems differ in that PSS generally pay particular attention to long-range problems and strategic issues whereas SDSS are generally designed to support shorter-term policy making by independent individuals or business organizations*". Given this definition, in this study the terminology of SDSS is interconnected with PSS, however, the author used SDSS rather than PSS because: (i) the focus is specifically on the urban energy planning rather than generally, spatial planning; (ii) this research takes into account the built environment and not only of urban planning purposes; (iii) the scenarios are valid for short/mid-term decisions rather than long-term ones since they are based on current data and stakeholder preferences.

The proposed MC-SDSS increases the data readability and robustness by using a GIS plugin and combining of several visualization approaches. The MC-SDSS is created to visualize the results of each scenario and to effectively make the comparison among them (Aydin, 2014). Table 1 summarizes the research objectives, questions, UIEP phases, relevant chapters and published papers in line with the conducted fieldwork.

Table 1: Research objectives, questions and related data collection methodologies, relevant chapters and corresponding papers.

Research objective	Research questions	UIEP phase	Relevant chapters	Corresponding papers	Adopted methods
a	1	-	Chapter 2	Paper 1	-systematic review -SWOT analysis -meta-analysis
b c d	2	Phase I Phase II	Chapter 4 Chapter 5	Paper 2 Paper 3 Paper 10 Paper 13	-data collection (quantitative) -data analysis -data geo-referencing -statistical model -engineering model
e f g	3	Phase III	Chapter 6 Chapter 7	Paper 4 Paper 5	-impact assessment (quantitative and qualitative) -MCA -semi-structured focus groups with real stakeholders -playing card game -questionnaire

The complete list of the author's papers is attached in Appendix C, which are organized based on the investigated research objectives and questions. Table 2 shows the lists the selected publications used in this dissertation.

Table 2: List of research papers relevant to the Ph.D. dissertation.

Paper	Title
Paper 1	S. Torabi Moghadam, C. Delmastro, S.P. Corgnati, P. Lombardi. (2017). Urban energy planning procedure for sustainable development in the built environment: a review of available spatial approaches. Journal of Cleaner Production, vol. 165, pp. 811-827.
Paper 2	S. Torabi Moghadam, G. Mutani, P. Lombardi. (2017). A mixed methodology for defining a new spatial decision analysis towards low carbon cities. Procedia Engineering, vol. 198, pp. 375–385.
Paper 3	S. Torabi Moghadam, J. Toniolo, G. Mutani, P. Lombardi. (2018). A GIS-Statistical Approach for Assessing Built Environment Energy Use at Urban Scale. Journal of Sustainable Cities and Society, vol. 37, pp. 70-84.
Paper 4	P. Lombardi, F. Abastante, S. Torabi Moghadam, J. Toniolo. (2017). Multicriteria Spatial Decision Support Systems for Future Urban Energy Retrofitting Scenarios. Sustainability, vol. 9, n. 7. pp. 1-13.
Paper 5	S. Torabi Moghadam, C. Delmastro; P. Lombardi; S.P. Corgnati. (2016). Towards a New Integrated Spatial Decision Support System in Urban Context. Procedia Social & Behavioural Sciences, vol. 223, pp. 974-981. ISSN 1877-0428.
Paper 10	S. Torabi Moghadam, G. Mutani, P. Lombardi. (2016). GIS-Based Energy Consumption Model at the Urban Scale for the Building Stock. JRC Conference and Workshop Report, Paolo Bertoldi. European Union, Luxembourg, pp. 56-63.

Paper 13	S. Torabi Moghadam, S. Coccolo, G. Mutani, P. Lombardi, J.L. Scartezzini, D. Mauree. A new clustering and visualization method to evaluate urban energy planning scenarios. Submitted, Under revision.

1.4 Thesis structure

This Ph.D. dissertation is a monograph that presents in structured form the Ph.D. candidate researchers around the development of a new MC-SDSS for energy retrofitting of existing residential buildings. However, most of the Ph.D. research results were also published in international scientific journals, that follow the same research path. In both monograph and the publications, the contents are organized to answer to each of the three research questions listed in section 1.2. This dissertation consists of eight chapters including the research work performed, the results and the conclusions (Figure 2).

Chapter 2 is devoted to systematically review a literature related to UIEP approaches. The review specifically emphasizes the importance of the integration of GIS with the bottom-up statistical-engineering energy consumption modelling approaches at the urban scale. Moreover, the importance of the MCA and Spatial Decision Support System (SDSS) in helping in the visualization and decision-making processes in the urban energy planning procedure is presented. This chapter shows the lack of a well-organized UIEP framework in the current study field, which includes all phases of spatial planning.

Chapter 3 describes in detail, an integrated methodological framework of this thesis and all its phases and steps to fulfil the objectives of the research. This chapter attempts to summarize the complex interdisciplinary methodology proposed for this thesis, illustrating all the software used and methodological approaches for each phase of work. The study area is also represented in this chapter. The application of the proposed methodology on the case study and the relative results will be present in the further chapters.

Chapters 4 and 5 illustrate the result of Phase I and Phase II (see Figure 1) and their applications. First, the procedure of geospatial data collection is illustrated, which belongs to the Phase I. This Phase is the basis of all further Phases. Next, two different modelling approaches were followed during the research activities:

a) The modelling approach of the current status by the geospatial “statistical” method over the entire city, which is shown in chapter 4. This chapter illustrates the integration of GIS and a robust Multiple Linear Regression (MLR).

b) The future energy consumption scenarios assessments are based on the “engineering” method by defining an archetype of the city, which is illustrated in chapter 5. This chapter attempts to investigate the potentials of reducing the energy demand using mainly GIS and CitySim tools to explore two (standard and advanced) possible retrofitting future scenarios.

Chapters 6 and 7 demonstrate the outcomes of Phase III of the planning procedure (see Figure 1). These two chapters embrace the development of a new MC-SDSS using the basis created in the previous chapters:

a) The definition of evaluation criteria is first introduced in chapter 6 through organizing the first workshop. This chapter demonstrates the importance of participative and collaborative approaches in defining evaluation criteria from an early phase of planning. After defining the definitive version of evaluation criteria, this chapter assesses the impact of each multiple criteria, including technical, economic, social and political issues.
b) The next step after defining evaluation criteria is how the new MC-SDSS is developed. A new MC-SDSS is able to define different stakeholders-oriented scenarios in UIEP as reported in chapter 7. A new MC-SDSS tool is based on adapting, coding and modelling an existing interactive plug-in in ArcGIS environment, named CommunityViz. The developed MC-SDSS tool is tested and evaluated through the second organized workshop consisting of two semi-structured focus groups and distributed questionnaires. The main goal was to improve the usability of a new developed MC-SDSS tool and its functionality for the future developments.

Chapter 8 is the last chapter of this dissertation and discusses the conclusive summary as well as suggestions for future research developments.

In the appendices are added the envelope physical properties considered for simulations of Chapter 5 (Appendix A) and material used in the application of the second workshop during the Ph.D. research (Appendix B). Furthermore, the full list of the papers that have been written during this research project is attached in Appendix C. Additionally, each chapter is introduced by a schematic summary table in order to guide the readers through the text. Each schematic table illustrates the related phases (I, II and III) of UIEP and it introduces the research limitation which led to formulate the research question, research question and summarizes the Ph.D. proposals to address the problem. In the scheme, reference is made to the published papers proposing the corresponding contents.

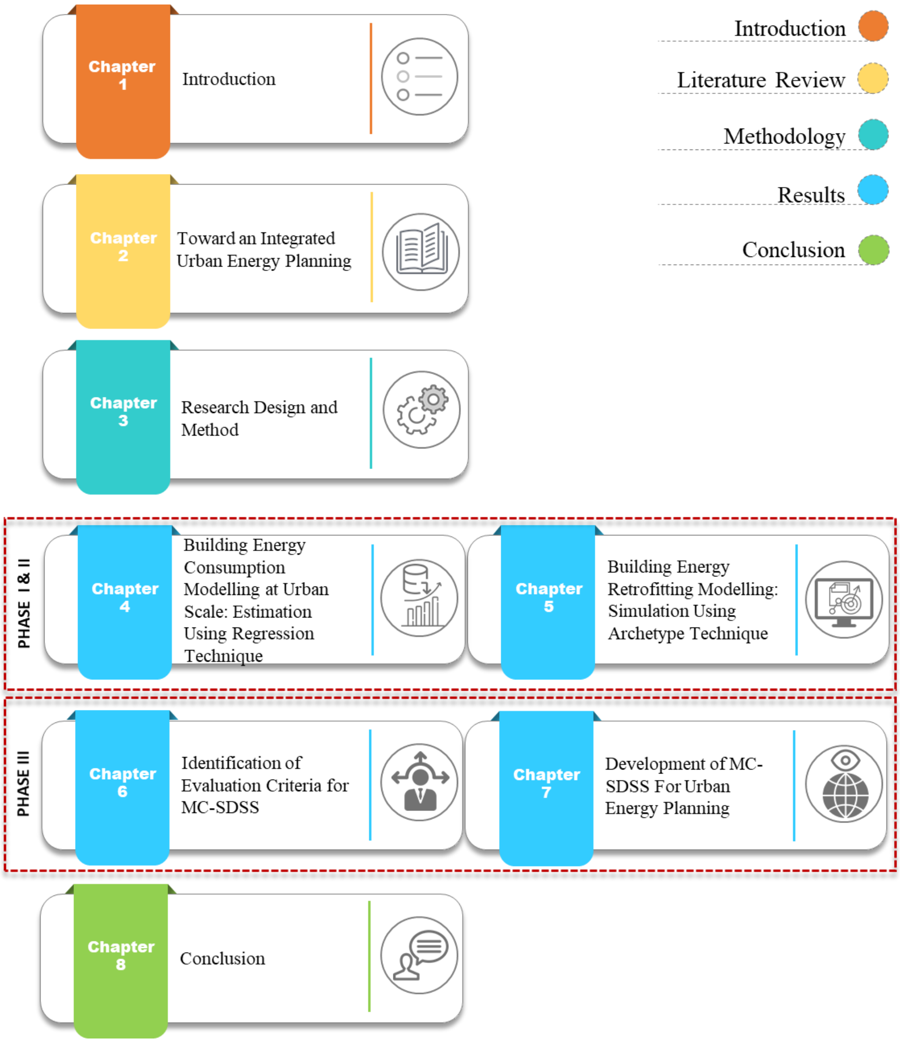


Figure 2: Thesis structure.

Part of the work described in this chapter was also previously published in the following publication. Minor grammatical changes and some information extensions have been made to integrate the articles within this dissertation.

Paper 1. S. Torabi Moghadam, C. Delmastro, S.P. Corgnati, P. Lombardi. (2017). Urban energy planning procedure for sustainable development in the built environment: a review of available spatial approaches. Journal of Cleaner Production, vol. 165, pp. 811-827. doi: 10.1016/j.jclepro.2017.07.142.

Chapter 2

Toward an Integrated Urban Energy Planning (IUEP)

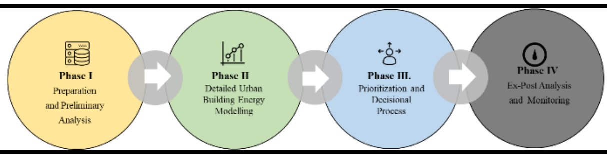
2.1 Introduction

This chapter overviews the three main phases of a UIEP for the built environment sector according to Mirakyan et al. (2009)[1]. It provides an extensive revision of existing UIEP applications toward sustainable built environment for each phase of the UIEP, highlighting the most relevant spatial approaches (Torabi Moghadam et al., 2017a). Accordingly, section 2.2 illustrates some important concepts that are needed for better understanding the present research work. Section 2.3 presents the proposed methodology to review an existing review of UIEP. First Phase, entitled “Preparation and Preliminary Analysis” is described in section 2.4. The preliminary UIEP phase consists of creating a supportive GIS database involving stakeholders. This Phase should be well-defined to proceed with phases II and III. Section 2.5 builds the principal part of the literature review of the UIEP, and it illustrates different approaches regarding the “Detailed Urban Energy Modelling”. Finally, section 2.6, entitled “Decisional and Prioritization Process”

[1] This Ph.D. Research does not consider the Phase IV “ex-post analysis and monitoring”, because it is not functional to the strategy definition.

presents the last and complementary phase of the UIEP, illustrating some of the most significant MC-SDSS for UIEP processes. For schematic summary of this chapter refer to Table 3.

Table 3: Schematic summary of chapter 2.



Research limitations	Research questions	Addressing the questions	Related publications
a lack of an integrated framework for urban and regional energy planning.	Are current research studies able to support the challenges provided by Urban Integrated Energy Planning, taking into account the variety of all the sustainable planning aspects? What are current challenges and barriers in this research field?	Systematic literature review through SWOT analysis and Meta-analysis.	[Paper 1] Urban energy planning procedure for sustainable development in the built environment: a review of available spatial approaches.

2.2 Some important concepts

From the literature basing on a compilation of fragmented definitions, the section puts forward a synthetic description of key terminologies used, in order to facilitate and improve the debates on this emerging field (Cajot et al., 2017). UIEP is defined by Mirakyan and De Guio (2013), as a model-based energy planning process. This is divided into the following four main phases: Phase I: Preparation and Preliminary Analysis; Phase II: Detailed Urban Buildings Energy Modelling; III: Prioritization and decisional Process and Phase IV: Implementation and monitoring. The focus of this research is mainly the ‘Spatial’ or “Spatial-Integrable” approaches of UIEP (Figure 3).

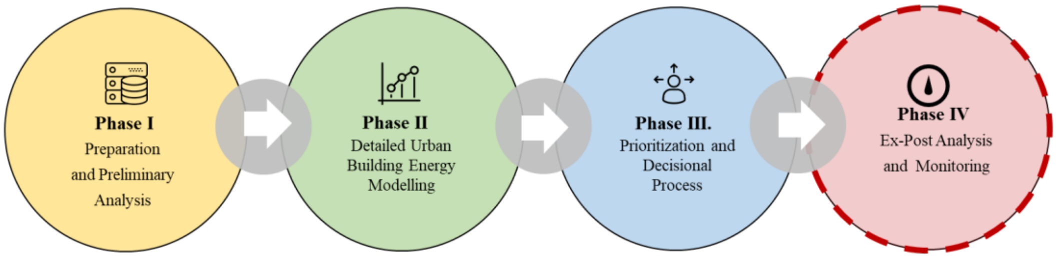


Figure 3: Urban Integrated Energy Planning (UIEP) phases, adopted from (Mirakyan and De Guio, 2013).

The concept of sustainable development dates back to 1970s and since then it has been widely the subject of public, private and academic sectors concerns, being the main effort of national and international economic, social and environmental agendas (Brandon et al., 2016). According to Brandon and Lombardi (2011) and Rad (2010), sustainable development is a continuous process that is able to balance between all the environmental, economic and social aspects related to a living environment, in order to improve present or future generations. A sustainable energy development means balancing energy production and consumption, along with having the minimal impact on the environment and giving the opportunity to employ social and economic activities (Hofman and Li, 2009).

Moreover, scenarios analyses can be defined as a way to create and predict future alternatives and their impacts, providing policy decisions framework (Miola, 2008); (Mistry et al., 2014). Indeed, the major purpose of energy modelling is to understand the possible future trends of certain energy-related variables, planning new strategies, and adaptation. Future studies comprise of a huge number of approaches as is introduced in 1996 as a “very fuzzy multi-field” (Marien, 2002). One of the most basic concepts in this field is “Scenario”. Future scenarios analyses can be defined as a way to create and predict the future alternatives and activities and their impact, providing policy decisions framework (Mistry et al., 2014); (Miola, 2008). The aim of future studies is supporting decision-making under uncertainty which is to be defined as indeterminacy (Dreborg, 1996). In the scenario literature various classifications exist (Mannermaa, 1986); (Rotmans et al., 2000); (Börjeson et al., 2006); (Marien, 2002). Following the classification defined by Börjeson et al. (2006) scenarios studies are classified into three principal categories in order to answer three main questions.

- Predictive-what will happen? For example, forecasting predicts the possible future, depending on the degree to which it accurately proposes what is plausible happen under specified conditions (Robinson, 2003).

- Explorative-what can happen? For instance, one way to do scenario planning is creating the business strategies that are robust among different possible future developments (VanderHeijden, 1996). These scenarios are descriptive and explore several plausible configurations for identifying main drivers and their linked dynamics (IEA, 2003).
- Normative-how can a specific target be reached? For instance, backcasting was introduced by Robinson (1982) as an approach to long time-term (over 20-100 years) future studies with the aim at exploring the implications and feasibility of desired policy goals and with a discussion of what changes would be happened in order to reach the images (Robinson, 1990). They are strategic and, according to the analyst, assume to simulate some necessary norms and to identify the most suitable ones (IEA, 2003).

Furthermore, scenarios can be classified taking into account their time horizon perspective, scales, and the level of integration; vertical and horizontal integration. Concluding, it can be found further information in the comprehensive Börjeson et al. (2006) study for guiding how scenarios can be developed and used as shown in Table 4 (Börjeson et al., 2006); (Banister and Stead, 2004).

Table 4: Future scenarios classification according to (Börjeson et al., 2006); (Banister and Stead, 2004).

Scenarios type	**Quantitative/ Qualitative**	**Time-frame**	**Main Techniques**	
			Generating	**Integrating**
PREDICTIVE-what will happen? (Probable futures)				
Forecasts	Typically, quantitative, sometimes qualitative	Often short	Surveys, Workshops, Original Delphi method	Time series analysis, Explanatory modelling, Optimizing modelling
What-if	Typically, quantitative, sometimes qualitative	Often short	Surveys, Workshops, Delphi method	Explanatory modelling, Optimizing modelling
EXPLORATIVE-what can happen? (Possible futures)				
External	Typically, quantitative, qualitatively possible	Often long	Surveys, Workshops, Delphi method	Explanatory modelling, Optimizing modelling
Strategic	Quantitative and qualitative	Often long	Surveys, Workshops, Delphi methods	Explanatory modelling, Optimizing modelling
NORMATIVE-how can a certain target be reached? (Preferable futures)				
Preserving	Typically, quantitative	Often long	Surveys; workshops. Transforming	Optimizing modelling

Transforming	Typically, quantitative with qualitative elements	Often very long	Surveys; workshops, Backcasting Delphi.	-

2.3 Systematic review methodology

This section illustrates hereafter the systematic literature reviews methodology, which is conducted by Torabi Moghadam et al. (2017a). The methodology has been adopted in this research for reviewing the journal articles and conference papers. According to Prasara-A and Gheewala (2016), this is structured as a four-stage analysis framework. In the earliest stage of the review process, named “Literature search”, the Scopus database has been chosen to support the literature search. Moreover, conference papers and many different tools and applications developed by Research and Development (R&D) projects have been scattered across different websites through Google search engine.

The second stage is the “Screening process”. In this, the review has been organized according to three UIEP process phases, as presented, with the aim of illustrating an in-depth state of the art on available approaches, in the specific context. In each phase, the principal keywords have been used, in combination with the literature search. As this research focuses on the “UIEP”, which is a multi-disciplinary and multi-phases topic, the relevant keyword combinations have been checked as follows: Urban /Building/ Energy Modelling/ Multi-Criteria/ Spatial/ Decision Support System/ GIS/ Energy System. The time period sets in the search engine for the academic publications is between 1970 and 2016.

In the third stage, “Selection of literature”, the abstract of all the references have been read in order to select and identify the most related studies on the topic. Furthermore, the full paper texts of those more appropriate papers have been included in the database. Finally, this selection of papers has been filtered by considering the following criteria: (i) English language papers; (ii) the study must be related to energy sustainable development; (iii) the approach presented in the paper must be “spatial” or “integrable spatial”. A total of 146 papers, ranging from 1970 to 2016, have been selected at this stage.

The fourth stage, named “Including literature”, consists of reading the 146 selected papers in order to collect the information about existing approaches for supporting the UIEP in the sustainable built environment and urban development.

In total, the 146 reviewed papers are composed of two groups as follows: 66 papers that describe the state of art and theoretical background and 80 articles that show the urban applications of the described approaches. However, in this dissertation, the author intended to extend the literature review. A summary of the main features of each section is shown in Figure 4 to help the readers.

Section 2.4. Phase I-Preparation and Preliminary Analysis
preliminary required actions to create a supportive base of data and information to perform the Phases II and III

Major characteristics	• Creation of a supportive spatial database collecting and elaborating the data • Identification of major criticalities and constraints • Definition of a common vision of the city planning involving stakeholders
Involved actors	• Experts • Researcher • Decision makers
Major viewpoints	• Importance of GIS usage to store, manage, pre-process and visualize data • Importance of stakeholder's involvement

Section 2.5. Phase II-Detailed Urban Building Energy Modeling
building stock energy assessment approaches and their applications for predicting building stock energy demand, with a particular focus on methodologies that can be linked with GIS tools

Major characteristics	• Assessment of building stock energy consumptionBuilding physics methods • Statistical methods
Involved actors	• Experts and analysts • Researcher
Major viewpoints	• Top-down approaches have not been considered suitable for urban analysis • Bottom-up approaches have been recognized appropriate for urban analysis • The archetype and regression models have been the most used modeling techniques due to their suitability for energy savings potential assessment

Section 2.6. Phase III-Prioritization and decisional process
analyses different scenarios through multiple criteria spatial decision support systems, with particular emphasis on visualization features

Major characteristics	• Participatitive and stakeholders oriented approach • Decisional processes • Visualization opportunities
Involved actors	• Experts and analysts • Researcher • Decision makers
Major viewpoints	• Importance of the integration of GIS and multi-criteria • Importance of identifying the critical zones through visualization features

Figure 4: Outline of section 2, adopted from (Torabi Moghadam et al., 2017a).

2.4 Phase I: preparation and preliminary analysis

The Phase I is crucial in creating a supportive data and necessary information to perform the next phases of the UIEP. The most relevant activities included in Phase I consist of data collection and stakeholders' involvement processes (Mirakyan and De Guio, 2013). Data collection consists of collecting the historical and current building stock data (e.g., building level data and census level data). A high data disaggregation may represent wider possibilities of investigations, however, very detailed data collection may be very challenging and takes too much time (Kelly, 2011). Accordingly, the data collection process can be divided into:

- Geo-referenced data collection: the collection of existing building-related data such as geometrical and demographic information.
- Non-geo-referenced data collection: the collection of available data which should be further geo-referenced such as energy consumption and temperature information.

2.4.1 Geographic Information System (GIS) for urban energy planning

An urban structure has a very evolving nature and dynamic organism within several various subsystems in which interacted together. To address this challenge, GIS as a comprehensive tool provide a city model structured including several layers and geo-referenced data to support the urban planning analysis (Azzena, 1995). Many cities have already started to shift the representation and analysis of territorial processes from analogue cartography analysis to digital geoprocessing (Campagna, 2016). In this phase, therefore, the use of GIS is significantly beneficial to store, manage, and visualize a broad number of spatial data for urban planning purposes.

Through the representation of multiple layers, city development can be represented, where each item is associated with a geometric entity in a proper system of coordinates (Bugs et al., 2010). Particularly, the GIS allows Geo-referencing all the available energy data to develop energy consumption models to characterize the building stock for the whole city fully. Data need to be carefully elaborated and analysed to create a strong supporting data set. GIS techniques were born due to a necessity to have a supportive tool for collecting, processing, analysing and visualizing a huge number of territorial spatial information both alphanumerically and graphically at the cities. These techniques have become crucial to operating decisions involving territory, allowing to collect all data and information for analysing future scenarios related to different possible alternatives to single out the best one (La Gennusa et al., 2011). By geo-referencing the data, each item is placed in a proper location-system of coordinates, being associated with a geometric entity. Indeed, the GIS techniques development shifts from not integrated into an integrated data information management in the designing, planning, and management of territory and environmental processes (MUTATE, 2005).

Therefore, the creation of a GIS is a useful tool for an urban energy planning, regarding both territorial management and evaluation of energy retrofits potential (Ascione et al., 2011). At the urban scale, GIS helps with regards to identifying critical points of possible areas that necessitate improvement concerning energy performances (Chalal et al., 2016). Moreover, this digital environment is mainly used for buildings' storage data and consequently helps to determine their energy performance of buildings. In this regard, it can implement the most effective strategy for each scenario and verify the energy consumption saved after some steps in related areas. Geo-referencing process manages and analyses the large volume of data with the aim of better understanding the urban transformation and the modifications induced by selected interventions (Ascione et al., 2011). Since built environment data and information at the local level are significantly scattered among several entities, and there is a lack of interoperability among the data sources, one of the most challenging barriers to developing a robust and detailed analysis is data collection (Caputo and Pasetti, 2015). In this regard, an enormous effort is required to provide a supportive and comprehensive accessible building stock database, at the local level for different goals and various stakeholders, gathering all the necessary data from different sources (Caputo and Pasetti, 2015).

Sometimes, information about building stock and their energy performances are derived from different regional and local authorities and often are not homogeneous (Caputo et al., 2013b). In this context, GIS helps to identify and visualize buildings data and their distribution, supporting decision-making, at urban and regional scale. This approach can manage location-based information, linking databases to maps to create dynamic displays. Moreover, GIS highlights the high energy use hotspots that need to be renovated (Chalal et al., 2016). GIS is principally used for buildings geometrical data; however, it significantly assists also their energy performance determination. Accordingly, there are many opportunities to achieve a better level of sustainability by making better decisions and by supporting proper urban planning.

The other fundamental action to be considered from the earlier phase of integrated UIEP is the involvement of stakeholders. This fact helps to obtain the existing data, determine important sustainable objectives, and propose a common strategic vision (Bottero et al., 2015); (Linnenluecke et al., 2016); (Pelzer et al., 2015). In order to involve multiple stakeholders and experts in the planning procedure is necessary to organize the collaborative events such as workshop organization, focus groups, questionnaires, and interviews. The GIS supportive database aids the stakeholders to visualize the current urban energy situation and therefore to reshape the sustainable objectives. In sum, the creation of a geo-referenced urban energy inventory establishes the primary step of the strategic planning. According to Girardin (2012), this stage aims to achieve:

- The creation of a set of necessary information and data;
- The identification of the entities and sources of local information;
- The collection and integration of scattered information within the data storage;
- The production of the integrated spatial information, making it available for every new work and research;
- The management of data;
- The presentation of the current state of the balance of energy and emissions;
- The smart electronic access to geo-referenced energy data layer.

It is notable to say that the geodatabase will not only be used to evaluate the present situation of the building energy modelling in the early phase but also support the assessment of energy performance and scenarios visualization for the future visions.

2.5 Phase II: detailed urban buildings energy modelling

This section aims at providing a comprehensive overview of the existing building stock energy consumption assessment approaches and their applications to model energy consumption. According to Yu et al. study (2011), existing studies with regards to energy consumption can be classified into two types:

- Aggregate analysis for which researchers performed energy consumption aggregate analysis at national, regional and do not differentiate each energy end-uses such as the works conducted by Schipper and Ketoff (1983); Unander et al. (2004); Zhang (2004); Lenzen et al. (2006).

- Disaggregate analysis started from the 1980s for which researchers have developed energy consumption disaggregate approaches, estimating and analysing energy consumption for a specific individual end-uses as the works conducted by Moller (2003); Vringer and Blok (1995).

In other classification regarding previous comprehensive surveys the modelling energy use for residential building sector are classified into “top-down” (aggregate) and “bottom-up” (disaggregate) (Swan and Ugursal, 2009); (Kavgic et al., 2010).

The top-down approach is based on the historical aggregate energy values as energy reported by energy suppliers and estimates the energy consumption as a function of top-level variables. These models specify the energy consumption energy value affected by long-term changes in the building stock. At the large level, there are many different studies of residential energy demand system such as for Spain (Labandeira et al., 2006); for the UK (Summerfield et al., 2010), and for the USA (Hirst et al., 1977). The top-down method has been recognized suitable for a broad national scale analysis and not for the identification of the possible improvements to the building at urban and regional levels (Lenzen et al., 2006); (Zhang, 2004). Hence, this research focuses on the urban and regional scale; the top-down models are not reviewed and discussed.

In counterpart, the bottom-up approach has been identified more appropriate with the aim of evaluating the energy consumption at a smaller scale. These methods require a high level of detailed data and the specific expertise to model technological systems (Nouvel et al., 2015). Several studies are also conducted to define the energy modelling stock for the large scale such as a national (Farahbakhsh et al., 1998); (Huang and Broderick, 2000); (Shipley et al., 2002); (Wan and Yik, 2004); (Parekh, 2005); (Yao and Steemers, 2005); (Petersdorff et al., 2006); or provincial (MacGregor et al., 1993).

Bottom-up models are divided into two Engineering (i.e., Sample, Archetype, and Population Distribution) and Statistical (i.e., Regression, Conditional Demand Analysis, and Neural Network) groups (Swan and Ugursal, 2009); (Kavgic et al., 2010). The bottom-up models differ in calculation methodology, time and spatial resolution, disaggregation level of input data and results. Figure 5 illustrates the energy consumption modelling categories according to the existing classification (Swan and Ugursal, 2009); (Kavgic et al., 2010). Even if previous studies are focused on the same classification mentioned in this thesis, the focus here is to understand if the methodologies can be applied at urban scale and coupled with

GIS. In other words, this research emphasizes the importance of spatial approaches for urban energy modelling and re-classify them considering an existing classification in the literature.

2.5.1 Building energy consumption modelling using the bottom-up approach

Since bottom-up building energy consumption modelling are appropriate for urban and local scale analysis, this section focuses only on these approaches and their use for spatial energy-planning purposes. The section will start with a short presentation of these models and their background as shown in Figure 5.

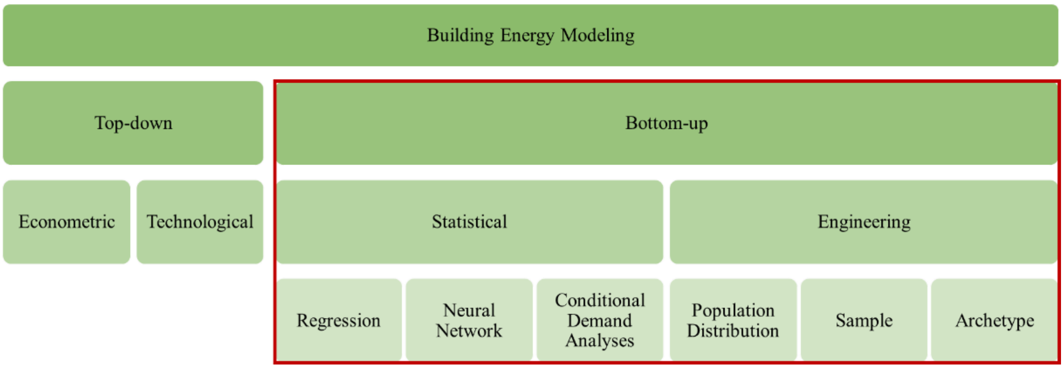


Figure 5: Energy consumption classification, source (Swan and Ugursal, 2009); (Kavgic et al., 2010).

2.5.1.1 Statistical models

According to the rapid growth of data availability sources, statistical techniques can extensively identify the associations and correlations among various variables influencing building energy performances. These methods search for correlations, utilizing a sample of information in energy bills as a source of data for energy modelling and analysing the link between energy consumption and a range of different variables (e.g. building shape, age, and occupant behaviour) (Nouvel et al., 2015). They calculate reliable consumption based on the available information on the current status of buildings potential after applying refurbishment measures (Torabi Moghadam et al., 2018). They perform reliable consumption information about the current status of buildings and for the calibration process of engineering-based models.

However, due to their strong dependency on available historical consumption data, these methods are not able to predict the impact of new retrofitting solutions and the amount of energy saving. One of the major strengths of statistical analysis is the widespread familiarity with this methodology and its simplicity. According to Swan and Ugursal (2009), the statistical methods can be divided into:

Regression analyses: regression methods fit the relation between energy consumption and its identified appropriate drivers (Dascalaki et al., 2010); (Fracastoro and Serraino, 2011). In this context, Theodoridou et al. (2011) conducted a statistical analysis of the features of the residential building stock relative to energy consumption and potential of energy savings to classify the building typologies in Greece. They do not require very detailed data about the building structure and envelope system, but they need a high amount of data to develop the model. In 2008, the statistical method for space heating carried out by Caldera et al. (2008) was based on a dataset of 50 multi-family residential buildings, finding out a simple correlation between space heating energy demand, construction age and thermos-physical and geometrical features. Results of the correlations can be spread to the whole stock buildings with the same boundary conditions to find out the energy performance for space heating of the major real estates.

Another study based on a field survey was carried out by Corgnati et al. (2008) to collect and analyse the actual heating space energy consumption data for about 140 buildings in the metropolitan city of Turin. They introduced a "*specific conventional coefficient of energy supplied for heating"* which could be used for analysing the building stock energy performance, providing a cost analysis and helping in planning retrofit solutions. This methodology is suitable for long-term assessments of building stocks, while it is necessary to consider an upper accuracy for single buildings. A study conducted by Dascaloaki et al. (2010) introduced the approach to collect and to analyze the energy data for Hellenic building stock that demonstrate relevant characteristics. The database comprises a sample of 250 buildings from different regions in Greece. The work aimed to provide a management tool for the procedure of construction. The database used for this study includes a total of 255 realistic range of building characteristics.

In 2011, Fracastoro and Serraino (2011) developed an analytical method, starting from census data and energy statics to define the statistical distribution of residential buildings according to heating demand. In this study, the principal source of data was the Italian Census, but it should be integrated into laws and energy standards, literature and the data derived from the authors' experience, and also, in situ analysis. Their study did not offer a physical model but specified the overall primary energy demand basing on statistical information such as typologies, climatic areas. The model is applied at the national level but can be scaled to local and urban level. This approach requires a low level of input data and provides more aggregated results.

Another interesting statistical modelling and analysis of energy consumption for the buildings sector have been conducted by Hsu (2015). This study highlighted the interactions of several parameters, both technical and non-technical, for developing accurate analysis and policy formulation at the local level. In 2016, Walter and Sohn (2016) developed a multivariate linear regression model with numerical variables and categorical indicators to estimate energy use intensity. The model quantifies the contribution of building characteristics and systems to energy consumption. Furthermore, in this study the cross-validation has also been applied for validating the model in a more accurate way.

Conditional Demand Analysis (CDA): CDA method is a regression-based method suitable for analysing large datasets. Due to the lack of flexibility, the analysis of energy conservation measures upon request variation is not allowed (Swan and Ugursal, 2009).

Neural network models (NN): NN find the relationship between a wide range of variables and parameters. They have been widely used for prediction problems at the individual building level, but also at a larger scale (Aydinalp et al., 2004). This method is proper for the evaluation of energy consumption and the impact of socioeconomic factors (Aydinalp-Koksal and Ugursal, 2008), but they are not suitable for defining energy conservation measures even if some applications exist (Krarti et al., 1998). There are some NN regression algorithms that have been performed by previous studies in building energy-related studies (Asadi et al., 2014); (Siami-Irdemoosa and Dindarloo, 2015); (Siami-Irdemoosa and Dindarloo, 2015). Recently in 2016, Ma and Cheng (2016) proposed a spatial integrated NN regression algorithms methodology framework for estimating the building energy use intensity in the urban scale of New York City. However, there is still an inadequate integration between energy data and spatial planning (Zanon and Verones, 2013).

2.5.1.2 Engineering models

Engineering methods are very detailed models based on traditional thermodynamic relationships and heat transfer calculations (Robinson et al., 2009). The main advantage of an engineering-based method is the capability of predicting energy savings for buildings after the application of renovation solutions (Mauree et al., 2017). Although the historical data can be used for the comparison against measured consumption data, this method is able to assess energy consumption without any historical information. However, these modelling approaches require a high quantity of information about building structure and parametric input to calculate the energy consumption of a set of reference buildings of the stock based on a numerical model. Additionally, the evaluation of urban planning scenarios is computationally very extensive, and the availability of construction and geometrical data needed as input for the models is very scarce. Into this, simplified 3D city models can significantly help (Aydinalp-Koksal and Ugursal, 2008). These engineering methods can be divided into (Kavgic et al., 2010):

Archetype method: this method is based on the aggregation of dwellings in representative building classes clustered according to key characteristics (e.g., construction period and surface to volume ratio) (Corgnati et al., 2013). This method has been broadly widespread as it allows to achieve much more disaggregated results. The characterization of archetypes to be representative of a broad set of buildings is the main difficulty of this method. The identification of archetypes implies the association of thermos-physical characteristics to each building and consequently to use building simulation software for assessing current and future energy consumption (Ballarini et al., 2014); (Wan and Yik, 2004).

Shimoda et al. (2004) have described the simulation model which predicts the end-use residential buildings energy consumption, considering the occupant presences, energy efficiencies of appliances, and weather data for Osaka City. They classified the household types into 23 archetypes. In 2010, the sample of 500 houses using the questionnaire is performed in Cyprus (Panayiotou et al., 2010). Later they selected a smaller sample of 20 houses for which in situ measurements and asset rating using SBEM Cy software is used for assessing the energy performance of buildings (Panayiotou et al., 2010)

Sample method: sample methods consider the data collected from surveys and monitoring campaign used to model the actual behaviour of the building stock. The Domestic Energy and Carbon Model (DECM) has been developed to improve the occupancy patterns details (Cheng and Steemers, 2011). This model has also been applied at the regional level using census data on dwelling types and socioeconomic data with good performances. Limited applications of sample method have been found at local level (Cheng and Steemers, 2011).

Population distribution method: this method is an accounting method reflecting energy consumption of household appliances regarding the ownership saturation rate of appliances. Accordingly, it can be suitable for building up the electric distribution load of an area or for estimating the energy consumption of household appliances (Kadian et al., 2007); (Saidur et al., 2007).

To conclude this section, although it might be possible to use the sample and population distribution models at the urban level. The more applicable widespread method for urban spatial analyses is the archetype one. This approach allows both short and long-term analysis and the possibility to create energy retrofit scenarios).

2.5.1.3 Hybrid models

Generally, hybrid models combine different methods to merge their strengths and compensate their weaknesses. These methods are also useful when the thermal parameters are unattainable (Chalal et al., 2016).

2.5.2 GIS-based building energy consumption modelling

This section reviews the integration of statistical and engineering models with GIS methods by focusing on spatial applications of urban energy modelling techniques (Torabi Moghadam et al., 2017a). These methods are appropriate for short-term planning based on large data requirement and to create energy retrofit scenarios. The use of energy and environmental energy models based on GIS methodologies has been progressively increased in the last ten years in order to help urban energy planning, for instance (La Gennusa et al., 2011); (Cheng and Steemers, 2011); (Grassi et al., 2012); (Iowerth et al., 2013); (Li et al., 2015); (Yang and Yan, 2016); (Carozza et al., 2017).

2.5.2.1 GIS-based-statistical models

Recently, Dall'O' et al. (2012) introduced a statistical GIS-based methodology for creating the comprehensive framework of the energy performance in buildings and applied to five municipalities in the province of Milan. The study is largely based on available information and data of building stock (e.g. thematic maps, cartographic documentation, geometric data, energy data). Especially, the energy data derived from energy audits of sample buildings (Dall'O' et al., 2012). This model used to specify primary energy for space heating data to construct regression lines based on shape factor ratio during different construction periods. At the same year, Howard et al. (2012) built a statistical bottom-up GIS-based model for New

York City. They estimated the energy end-use intensity for domestic hot water, space heating, and electricity consumption of the building sector. Their result was spatially explicit that energy consumption can be a significant factor in determining energy efficiency policies and renewable energy strategies (Howard et al., 2012). In this study, the model has been performed by robust multivariate linear regression. Interestingly, building age factor was not considered as a predictor to estimate the energy consumption.

Moreover, Mutani and Vicentini (2013) conducted a GIS-based regression analysis to correlate building energy consumption to building compactness and construction period. Yeo et al. (2013) developed an urban demand forecasting system, with hourly resolution, based on a GIS database (E-GIS DB) with 2D/3D visualization. Furthermore, a bottom-up statistical methodology considering dwelling type, a period of construction, floor surface and some occupants has been developed by Mastrucci (2014). The Ordinary Least Squares (OLS) method was used to fit this model. Another GIS integrated data mining methodology for assessing the energy use intensity of buildings in city scale is proposed by Ma and Cheng (2016). This model is based on 216 prepared features for a case study of 3640 multi-family residential buildings in New York City. The model then is tested and cross-validated in order to have more robust results. Recently, Braulio-Gonzalo et al. (2016) modelled energy performance of existing residential building stocks based on five parameters using simulation software. Several some example, which highlight methodologies for evaluating the energy performances of building stock using GIS with regression methods are (Yeo et al., 2013); (Torabi Moghadam et al., 2016b); (Torabi Moghadam et al., 2016c); (Torabi Moghadam et al., 2017b); (Torabi Moghadam et al., 2016a).

From the literature emerged that among the above mentioned statistical approaches, the regression methods have been coupled with GIS more than the other methods. These methods are appropriate for short-term planning based on large data requirement (Torabi Moghadam et al., 2017a).

2.5.2.2 GIS-based-engineering models

In this section the integration of engineering models with GIS methods in order to focus on spatial applications reconsidered. In particular, the impact of heritage buildings on the overall energy demand of Ferrara (Italy) has been investigated by Fabbri et al. (2012). This study considered the influence of the number and energy incidence and their characteristics in accordance with geometry, thermo-physics and using GIS maps as a strong platform for linking a different data. Moreover, an interesting "post-processed" map is provided. As the energy information is already available, the calculation approaches are not described (Fabbri et al., 2012). In 2007, a new clustering modelling approach has been proposed to define CO_2 reduction scenarios in the commercial sector (Yamaguchi et al., 2007). In this study, a capable simulation model was developed by considering various parameters, which affect energy use and management Jones and Williams (2001) developed the Energy and Environmental Prediction (EEP) model based on a technique that augmented archetypes with additional information based on a "*drive-pass*" survey using GIS. They described the level of data that was needed, the survey technique and the operation of the model to predict building energy consumption over the whole of the city or local authority area.

GIS-based calculation and visualization approach for energy use and greenhouse gas emissions for the residential stock is another archetype bottom-up approach that conducted by Mattinen et al. (2014). Moreover in 2016, a methodology to describe the building-stock regarding the energy efficiency measures has been proposed (Österbring et al., 2016). This methodology integrates building characteristics from energy performance certificates, measured energy use and envelope areas from a GIS model. Recently, a GIS-based simulation model has been developed by Li et al. (2016) to evaluate how building typology and urban morphology influences on building energy consumption and CO2 emissions. Moreover, Delmastro et al. (2016a) have developed several long-term scenarios assessing the energy saving potential and the relative cost. They spatially analysed the socio-economic feasibility of renovation measures. Yamaguchi et al . (2007) suggested a new clustering modelling approach for energy use in the commercial sector to define CO_2 reduction scenarios. Initially, they classified the districts into several sets according to the spatial building stock pattern, or urban form. Afterward, the energy consumption per unit floor area of the building is evaluated concerning each district typology using a simulation of energy consumption in buildings in a representative district. Finally, a proper simulation model is developed by taking into account different parameters which are affect energy usage and management. This model is applied in the commercial sector of Osaka city in order to support urban energy policy.

Additionally, Ascione et al. (2013) suggested a new method for calculating the space heating demand for buildings. This model aimed at characterizing both winter and summer energy performance of new and existing building stocks at the urban contest, geo-referencing all the data. Their target was to promote efficient refurbishment solutions for existing buildings and efficient design for new buildings. Both Caputo et al. (2013) and Costa (2012) proposed a methodology to evaluate the energy performance of the built environment at the city level. The method suggested by Costa (2012) took the information from the National Buildings Census statistical database, and it is an applicable methodology to all the Italian cities. It is implemented in GIS to evaluate how energy performance scenarios effect on the built environment at city/district level. This study developed by Caputo et al. (2013) introduced a methodology that can determine the built environment energy performances in a city/neighborhood level.

2.5.2.3 GIS-based-hybrid model

More recently, Mutani and Vicentini (2013)have conducted hybrid analysis where they used the energy demand of some sample buildings to adapt them to estimate the energy consumption of a city (bottom-up). The achieved results were calibrated through top-down level data. Again in 2014, Mutani and Pairona (2014). have also submitted an approach for calculating the energy consumption of residential building stock by starting from census data information and real energy consumption data. The model is based on actual heating energy consumption data of Turin residential construction sector. Thermal analysis of typical buildings allowed the assessment of the energy savings on renovated buildings. These considerations can be extended on an urban scale to European cities, calculating the overall energy savings obtained by different energy policies

In 2015, Nouvel et al. (2015) developed an interesting combined methodology, as a multi-framework for urban scale applications, based on Ordinary Least Squares (OLS) multiple linear-GIS and an engineering model making use of 3D city models. This multiple linear-GIS was previously proposed by Mastrucci et al. (2014). In this study, both statistical and engineering methods are combined in a multi-scale framework to improve the heat demand predictions for the case study of Bospolder-Rotterdam counting about 1000 buildings. They first performed the statistical equations to predict city building energy consumption. Later, they selected relevant neighborhood for retrofitting scenarios utilizing the engineering model. Into this, this study individualized energy savings potentials based on a good agreement with measured gas consumption data at the neighborhood level (5-25% deviation) (Nouvel et al., 2015).

Similarly, towards sustainable management of building stocks, a model conducted by Tornberg and Thuvander (2005) developed a hybrid energy model of building a stock of Goteborg. The model is based on GIS technique to support the evaluation of the consumption levels of specific energy sources. The outcomes illustrated as maps are useful to have a global overview of the energy performances of cities. In this study, a top-down approach is combined with a bottom-up approach to compensate lack of data and evolve each other. These methods have been widely integrated with GIS in the literature.

A framework, so-called EnerGIS has been proposed by Girardin et al. (2010) to support qualitative long-term scenario analysis involving building renovation. EnerGIS is based on the pinch and statistical analysis. A new method has been suggested by Ascione et al. (2013) to evaluate the energy demand for buildings with the aim of characterizing both cooling and heating performances. The target was to promote efficient refurbishment solutions for existing buildings and efficient design for new ones.

2.6 Phase III: prioritization and decisional process

The main purpose of this section is to give an overview of SDSS and MC-SDSS existing tools, which are potential can be used for energy saving scenarios purposes.

2.6.1 Spatial Decision Support System (SDSS) and Multi Criteria Analysis (MCA)

The concept of sustainable development dates back to 1970s, and since then it has been widely the subject of several sectors concerns, being the main effort of national and international economic, social and environmental agendas (Doukas et al., 2007); (Alam et al., 2007); (Pereira and Duckstein, 2007); (Bilgen et al., 2008); (Omer, 2008); (Hoffman and Jorgenson, 2016); (Tsai, 2010); (Iddrisu and Bhattacharyya, 2015); (Cosmi et al., 2015); (Brandon et al., 2016). Previous studies have discussed a broad consensus on the concept of sustainable development and their application in the field of energy planning.

According to Brandon and Lombardi (2011) " *sustainable development is a process which aims to provide physical, social and psychological environment in which the behaviour of human beings is harmoniously adjusted to address the integration with, and dependence upon, nature in order to improve, and not to impact adversely, on present or future generations*". This continuous process makes a balance between the environmental, economic and social aspects related to the living environment and their systematic (Rad, 2010).

In this context, a sustainable energy development sector means at balancing energy production and consumption, along with having the minimum impact on the environment and giving the opportunity to employ the social and economic activities (Hofman and Li, 2009). To comply a future sustainable energy development, prioritization and decision process should be integrated into the procedure of energy planning sustainable development of cities and regions due to technology diversity, uncertainties and different conflicting objectives and preferences of planning participants (Mirakyan and De Guio, 2013). Traditionally, energy and environmental planning are considered a single measurement criterion, as costs benefit maximization, to make their decisions (Greening and Bernow, 2004). However, the complexity, conflicting and multidimensionality concept of long/medium-term sustainable development of urban energy planning matters cannot rely upon just one criterion alternatives. Moreover, an urban and regional planning should be sustained by collaborative and participative processes since cities are dynamic living organisms that are continuously evolving (Lombardi and Ferretti, 2015). In this regard, the use of adequate tools and methods for addressing complex interactions of energy system planning problems is significantly needed. They should able to perform different data type, multi-objective and preferences, and conflicting objectives (Lombardi et al., 2017).

Multi-Criteria Decision Analysis (MCDA) is an integrated form of a sustainability evaluation. It provides well-established decision support tools for sustainable energy development because of the multi-dimensionality of the sustainability goal and the complexity of socio-economic aspects (Wang et al., 2009). However, MCDA approach cannot make the actual decisions by themselves, but, it should aid DMs in making better decisions.

Reported from a comprehensive study of Belton and Stewart (2002), "*One of the principal aims of MCDA approaches is to help DMs organize and synthesize such information in a way which leads them to feel comfortable and confident about making a decision, minimizing the potential for post-decision regret by being satisfied that all criteria or factors have properly been taken into account*."

A huge number of multi-criteria models and approaches are available in the literature. However, the general MCDA process in sustainable energy decision-making is shown in Figure 6 according to Wang et al. (2009); Ustinovichius et al. (2007); Pohekar and Ramachandran (2004). Generally, the first phase in MCDA is to formulate the problem and alternatives for sustainable energy decision-making problem, setting the sustainable evaluation criteria and normalizing both quantitative and qualitative criteria data. Afterward, weights of each criterion should be defined to show their impact performance. Then, it is necessary to structure the model and the evaluation matrix (acceptable criteria and alternatives matrix). Finally, after selecting the appropriate method, it can assess and evaluate the alternatives to rank/sort/choice/descript them. If the performed sensitivity analysis shows the constancy of the obtained result the decision-making process will be ended (Wang et al., 2009); (Torabi Moghadam et al., 2017a). Otherwise, the results are analysed again, and the best one is selected.

So far, there are a number of the MCDA review methods in the literature regarding the sustainable energy planning. The most comprehensive review of decision analysis in energy and environment modelling was presented by Huang et al. (1995). They classified suggested studies with regard to the decision analysis application area and techniques. They found out that the most widespread application of MCDA is in energy planning and policy analysis. Furthermore, they highlighted that the most important application techniques include decision making under uncertainty. Greening and Bernow (2004) focused on the application of multi-criteria decision-making methods to analyse and formulate the energy and environment policies. Pohekar and Ramachandran (2004) reviewed the application areas of MCDA in energy planning such as energy resource allocation, renewable energy planning, planning for energy projects, building energy management, and electric utility planning. This study reported that the most widespread MCDA methods are a multi-objective optimization, AHP, PROMETHEE, ELECTRE, MAUT, fuzzy methods and Decision Support Systems (DSS).

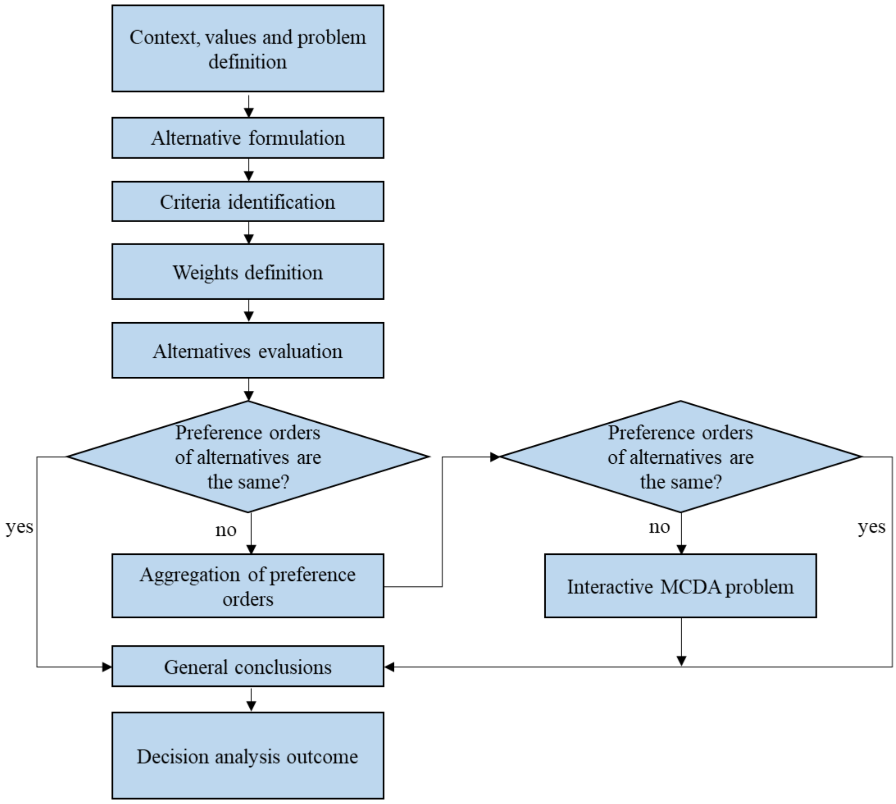


Figure 6: MCDA process in sustainable energy decision-making, elaborated from (Wang et al., 2009); (Ustinovichius et al., 2007); (Pohekar and Ramachandran, 2004); (Cajot et al., 2017).

Moreover, Zhou et al. (2006) underlined again a high importance of MCDA methods and energy-related environmental studies. In this study, more than 250 studies have been reviewed to classify the MCDA methods according to the application type and methods. They have classified MCDA applications for energy planning into the three main categories: Single Objective Decision Making (SODM) methods, MCDM methods, DSS. The literature review conducted by Løken (2007a) has emphasized that energy planning is a very suitable field for the use of MCDA. Recently, Cajot et al. (2017) updated the state of the art of the given context. They have systematically reviewed MCDA problems and methods in the context of UIEP. This survey synthesized the data and insights obtained, which support potential users identifying suitable decision analysis methods based on given problem context.

In the context of integrated energy planning, although the MCDA aims at presenting the most appropriate plan, it should fulfil the understanding of the multi-criteria complex situation recommendation (Mirakyan and De Guio, 2013). This fact realizes by supporting the interactive planning and learning, helping people to express and exert their value judgments, and documenting the values and the alternatives of each recommendation (Mirakyan and De Guio, 2013). However, since the energy consumption at the built environment influenced by different features, urban energy planners need proper MCDA tools. These tools should support their urban energy planning decision-making with regards to identify potential areas that need improvement (Chalal et al., 2016). They have to implement the most effective strategy for each scenario and analyse the energy consumption saved after certain measures in related areas (Chalal et al., 2016).

This fact needs data on the geographical locations of alternatives with GIS. McHarg (1969) was the first who used maps to make decisions; this concept has been later developed in GIS (Charlton and Ellis, 1991a). Using of maps in decision-making processes has been defined by Charlton and Ellis (1991b). GIS is a strong and useful system that integrates, captures, manages and visualizes all big data, which are spatially geo-referenced into different levels (Azzena, 1995). GIS produces thematic maps and performs spatial operations, while Multi-criteria methods translate these maps into value maps, optimal or compromise maps and rankings (Arciniegas et al., 2011). Due to this reason, in the last two decades, a lot of geospatial data processing is done to gain information for decision making, and many spatial decision problems give the rise to the GIS-based multicriteria decision analysis (GIS-MCDA) (Malczewski, 2006). Interestingly, these two tools take advantage of each other (Chakhar and Martel, 2006). Integrating GIS and MCDA has been highlighted in the late 1980s and early 1990s with the aims at developing the long-term perspectives SDSS. This fact is devoted to helping DMs in spatial problems highlighted by different previous studies (Carver, 1991); (Densham, 1991); (Sharifi et al., 2002); (Chakhar and Martel, 2006) (Malczewski, 2006);(Pereira and Duckstein, 2007); (Arciniegas et al., 2011); (Lombardi and Ferretti, 2015); (Demetriou et al., 2017).

From a methodological point of view, the process to build a model can be described in three following phases (Malczewski, 1999), involving both GIS and MCA (Malczewski, 1999). Figure 7 shows the framework of MC-SDSS process, illustrating the involvement of both GIS and MCA method for each 3 macro-phases: intelligence (process model), design (planning model), choice (evaluation model) (Wang et al., 2009); (Ustinovichius et al., 2007); (Sharifi et al., 2002); (Herbert Alexander Simon, 1977); (Pohekar and Ramachandran, 2004).

1. Process Model (Intelligence phase): the decisional context analysis for structuring and identifying the decision problem to be evaluated should be provided in this phase and also the relevant evaluation criteria should be established and identified, assigning them later the proper weights of alternative options.
2. Planning Model (Design phase): once the alternative options have been determined, it is necessary to structure the model and the evaluation matrix (criteria and alternatives matrix). This step involves the selection of the MCDA method.
3. Evaluation Model (Choice): after choosing the appropriate method, it can assess and evaluate the alternatives to rank/sort/choice/descript them (Roy, 1985). Finally, a sensitivity analysis is suggested with a view to examine the constancy of the obtained outcomes and the robustness of the model.

SDSS can be considered as an interactive computer system for assisting the user/s (i.e., single or group) to perform decision processes efficiently (Malczewski, 2006). In this sense, the SDSS can visually support the stakeholders during different focus groups and workshops to understand how the criterion trade-offs evolve when one or several decision parameters changed. (Chakhar, 2003). Its main advantage is that the DMs can express and exert their preferences concerning evaluation criteria and/or alternatives (value judgments) into GIS-based decision-making procedures, and consequently, get back feedback to increase the DMs trust in the results (Chakhar, 2003). The SDSS acquires, manages and stores the geo-referenced data performing the analysis of spatial problems. Moreover, it provides an interactive environment for performing effective visual activities thanks to the visual interface, which enables a dynamically interactive session in a real-time exchange of information between the user and the system to support the stakeholders through all decision phases (Malczewski, 1999).

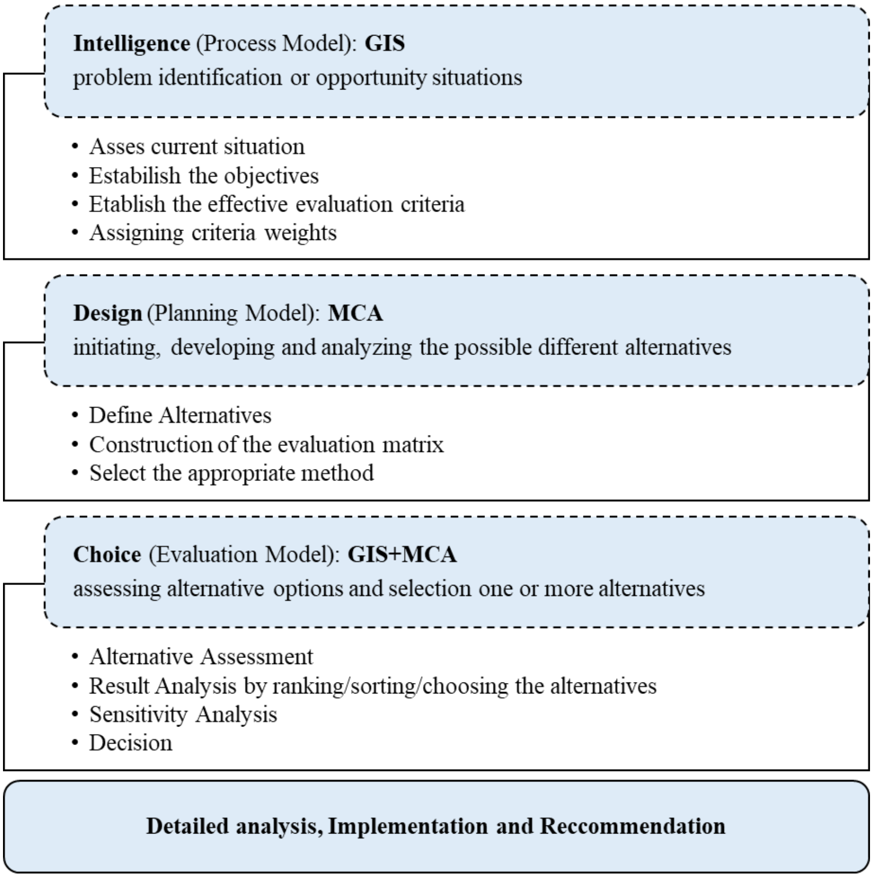


Figure 7: Schematic spatial multi-criteria analysis process, sources: (Wang et al., 2009); (Ustinovichius et al., 2007); (Sharifi et al., 2002); (Herbert Alexander Simon, 1977); (Pohekar and Ramachandran, 2004).

Particularly, SDSSs include nine general features: (i) solve ill-structured problems; (ii) user friendly interface; (iii) analytical models with data integration; (iv) able to find spatial solution through building alternatives; (v) support a variety of decision-making techniques; (vi) interactive and recursive problem solving; (vii) spatial data input; (viii) application of spatial analysis; (ix) produce geographic outputs according to different spatial forms including maps, graphs (Aydin, 2014); (Malczewski, 1999); (Densham, 1991). The MC-SDSS are part of a larger field of SDSS (Ferretti, 2011). In the framework of MC-SDSS, two interrelated instruments existed. On one hand, GIS supports in data storage, management, visualization of maps and analyses the decision problems. On the other hand, MCA provides a full range of methods for structuring decision problems and for designing, evaluating and prioritizing alternative decisions (Malczewski, 2006). Moreover, they are strong visualization tool through which maps become a "visual index" to provide solutions to the planners to optimize the conditions (Janssen and Herwijnen, 2007);

(Lotov et al., 1997); (Andrienko and Andrienko, 1999); (Jankowski et al., 2001). In other words, digital maps are meant for communication among workshop participants and an interactive mapping device (Arciniegas et al., 2011).

2.6.2 Available tools for UIEP-an overview

This section illustrates some SDSS/MC-SDSS tools, which support (or can potentially support) the energy saving scenarios in UIEP approaches towards a more sustainable development of cities (Torabi Moghadam et al., 2017a). Some of the existing SDSS/MC-SDSS tools related to sustainable energy planning are presented as follows from the study conducted by Torabi Moghadam et. al (2017a):

- **MEU (Urban Energy Management)** (Rager et al., 2013) is a web-based platform as a decision support which integrates with CitySim (Robinson et al., 2009) to develop different energy demand and supply scenarios, including GIS-based visualization of the results. This tool can quantitatively analyse different scenarios. It permits to continuously monitor annual energy flows, consumptions and related actions (Puerto et al., 2015). UrbanSim (Waddell, 2007) is an open source SDSS tool for scenario development and simulation for the city scale. It is an integrated platform to share data, design alternative plans, simulates the impacts of those plans over time, and visualize outcomes in 3D. This platform analyses of impacts of alternative scenarios, adopt UrbanCanvas for interactive design, UrbanSim Commons for sharing data on the cloud. This tool is not specifically produced for the building sector; however, they are used to evaluate alternative transportation and land use plans taking into account the building stock evolution.
- **DIMMER (District Information Modelling and Management for Energy Reduction) Dashboard"** (Lombardi et al., 2014) is an open SDSS platform for existing and real-time data processing and visualization at the district/urban level to support decision making by energy managers and public authorities, monitoring district energy data as well as simulating and implementing energy management policies. DIMMER can integrate Building Information Model (BIM), System Information Model (SIM) and GIS to visualize real-time energy-related information in the built. One of the examples of the application of MCA method using the DIMMER Dashboard, as an integrated participative SDSS, is the study conducted by Abastante et al. (2017). In this study they have evaluated three scenarios

regarding heating supply system options in a district using the MACBETH method.

- **InViTo (Interactive Visualisation Tool)** (Pensa et al., 2016) is an interactive SDSS web interface for supporting users in the exploration of spatial data. The tool purposes to provide a structured framework for aiding users in accessing and interrogating a geo-referenced spatial thematic database. InViTo works with GIS database and relies upon on the free and open web technologies such as Google Maps and Google Fusion Tables, for visually managing and exploring geo-referenced data
- **INDICATE** (Melia et al., 2015) is an ongoing project to support DMs and other stakeholders towards Smart City context. The concept of smart cities will be achieved through the development of a SDSS interactive cloud-based tool, which will provide a dynamic assessment of the interactions between buildings, the electricity grid, renewable technologies and Information Communication Technologies (ICT). It integrates new technologies in the city to better manage supply and demand by dynamic simulation modelling, GIS, and 3D urban modelling.

The integration of SDSS tools with MCDA (MC-SDSS) has been widely applied in the field of urban energy planning, especially in the siting of renewable energy technologies in the land use. Few tools have been developed for energy analysis in the built environment but potentially can be adapted for this context. In this section, both are considered.

- **CommunityVIZ** (Kwartler and Bernard, 2001) is an ArcGIS-based decision support system for community planning and design applications, which allows obtaining different interactive visualization and understand their potential impacts (Lieske and Hamerlinck, 2013). It encompasses two components: (i). Scenario 360 for communication, analysis, and engagement; (ii). Scenario 3D for three-dimensional visualization. It could be integrated into energy analysis and planning (Novak et al., 2012)
- **FASUDIR-IDST (Friendly and Affordable Sustainable Urban District Retrofitting-Development of Decision Support Tool)** (Barbano et al., 2015) is a comprehensive interactive and user-friendly decision support tool to analyse the outcome of the building retrofitting strategies on the sustainability of the urban district. The Integrated Decision Support Tool (IDST) features a 3D graphical user interface, to facilitate the interaction between the multiple stakeholders involved in the decision-making process.

- **AHP in ArcGIS** is a powerful ArcGIS extension that determines criteria weight considering the well-known Analytic Hierarchy Process (AHP) (Saaty, 1980).

Table 5 and Table 6 summarize the most important characteristics of the explained tools of (section 2.6.2) to facilitate the readers to choose the most appropriate one for their research and applications, reported from Torabi Moghadam et al. (2017a).

Table 5: SDSS tools characteristics, source (Torabi Moghadam et al., 2017a).

			SDSS		
Name	DIMMER Dashboard	InViTo	INDICATE	MEU	UrbanSim
Developer	DIMMER project team	SiTI Istituto	INDICATE project team	LESO-PB	Urban Analytics Lab
Open Source	Yes	Yes	No	Yes	Yes
Objective	district energy saving	guide users in building their spatial knowledge by dynamic maps	support stakeholders in the transition towards smart cities	urban energy management	community planning tool
Visualization	2D/3D	2D	2D/3D	2D/3D	3D
Approach	participative collaboration	open collaborative web tools	participative collaboration	direct collaborative framework	simulation, visualization and shared open data
Method	dynamic monitoring, management of energy consumption	interactive visualization tool	interactive decision support and information exchange platform	link to citysim	scenario development and simulation
Spatial Coverage	building and district	cities and regions	city and neighborhood	urban district	community/urban
Type of tool	WebGIS dashboard	web platform	platform	ArcGIS based web platform	software based on python data
Time resolution	real-time	_	_	hourly	short/long-term

Table 6: MC-SDSS tools characteristics, adopted from (Torabi Moghadam et al., 2017a).

MC-SDSS			
Name of the tool	CommunityVIZ	FASUDIR-IDST	ArcGIS with AHP

Developer	Orton Family Foundation	Fasudir project Team	Saaty
Open Source	No	No	No
Objective	visualize, analyse and communicate about planning decisions	define different retrofitting scenarios with regards to sustainable KPI	spatial analysis
Visualization	2D/3D	2D/3D	2D/3D
Approach	collaborative decision-making	collaborative stakeholders	data integration and collaborative
Method	dynamic scenario tool	retrofitting scenarios tool	pairwise-comparison
Spatial Coverage	cities and regions (large and small)	district and neighborhood	user-dependent
Type of tool	ArcGIS extension	Web-based software	ArcGIS extension
Time resolution	time-scope	long-term	user-dependent

In the Tables 5 and 6, CommunityViz and UrbanSim can be named also Planning Support System (PSS), offering planners the ability to reflect different alternative for possible future spatial scenarios (Li and Jiao, 2013). According to recent literature, these tools include geographically-oriented websites and interactive communication-oriented map-based touch tables that provide groups of stakeholders a mutual workbench to discuss and evaluate sketches of future layouts, e.g. (Vonk et al., 2005); (Geertman and Stillwell, 2004); (Pelzer and Geertman, 2014); (Campagna et al., 2015); (Arciniegas et al., 2013); (Geertman et al., 2015).

2.7 Results

This section illustrates the results of a meta-analysis of 80 analysed papers by Torabi Moghadam et al. (2017a). Moreover, this study provided the SWOT analysis for providing information and insights on how the various UIEP approaches can be integrated to handle the entire planning procedure.

2.7.1 Meta-analysis of previous literature

Eighty papers on the UIEP application have been identified by Torabi Moghadam et al. (2017a). These papers have been classified based on three criteria for the purpose of presenting results effectively: the year of publication, the level of integration of UIEP phases and the types of combination of methodology. In Figure 8, the results of the meta-analysis are shown.

- The level of integration. Phase I is always integrated with the other UIEP phases since it is the necessary basis of the entire planning procedure. Phase II is the most widely used phase, involving a total of 70 papers out of 80, accounting for 87,5% (27 papers integrate Phase I with Phase II, 36 papers belong to Phase II only and only 7 papers include all the Phases). Since Phase III is the prioritization and decisional process, complementary to the other Phases, it is required to be integrated. The Figure shows that 17 papers (21,25%) are referred to Phase I, of which 10 papers integrate Phase I and III while 7 papers integrate all the Phases. The most important finding, relevant to be highlighted, is that the full integration of the different Phases is reported by only 8,75% of the papers (7 papers).

- Methods (shape of the bullets in Figure 8). According to the previous studies, the possible combinations of methodologies have been classified in: (i) Methodology isolationism: one method for one paradigm; (ii) Methodology enhancement: enhancing a methodology by exploiting other methodologies; (iii) Methodology combination: combining methodologies in a unique intervention; (iv) Multi-methodology: combining parts of different methodologies (Mirakyan and De Guio, 2013); (Mingers and Brocklesby, 1997). A total of 36 papers (45%), which are classified in Phase II by a circle shape (○), perform the methodology isolationism by proposing urban energy modelling approach without integration. 35 of reviewed papers (43,75%), shaped as a triangle (Δ), belong to Methodology enhancement classification since they enhanced the proposed approach by using GIS tools. Further, regarding the Methodology combination shaped as a square (□), 6 papers (7,5%) have combined their approaches in a unique intervention. Finally, the remaining 3 papers (3,75%) shaped as (⁎), have combined different parts of different methodologies in a Multi-methodology.
- Year of publication (colour of the bullets in Figure 8). The most important output from this analysis is that the UIEP is a very recent research topic. In fact, 78 papers (97,5%) have been published after 2000, red and blue bullets. Two other papers are older, but still relevant for the survey field.

In comparing the reviewed papers based on the three aforementioned criteria, this meta-analysis first recognizes that in urban energy planning the number of papers that fully integrate the UIEP Phases is very few and very recent. Finally, one can say that although there are several examples of urban energy planning approaches there is still not a well-recognized procedure and an integrated method to face the UIEP (Torabi Moghadam et al., 2017a).

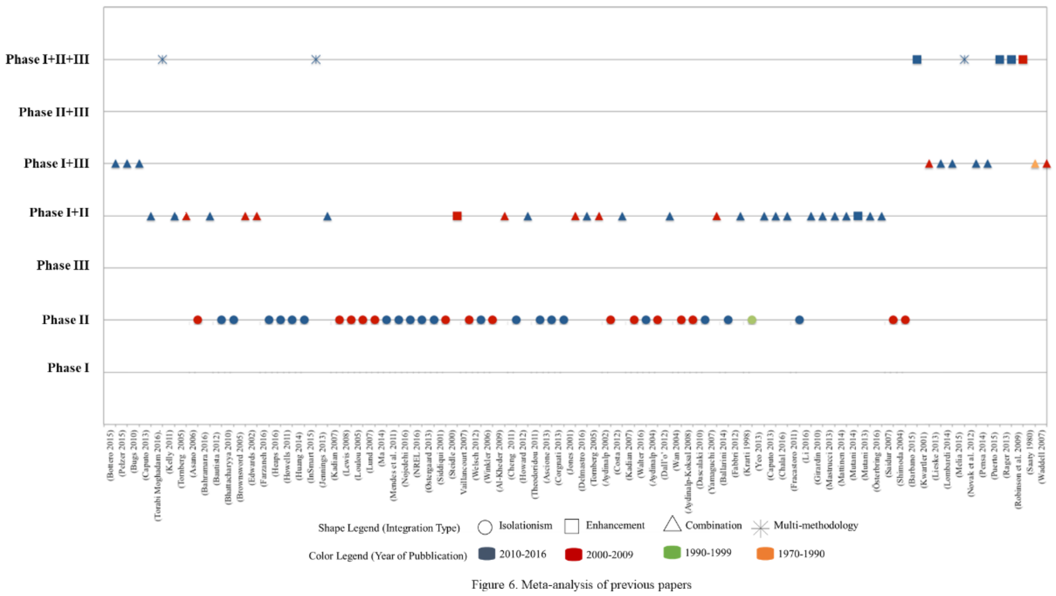


Figure 8: Meta-analysis of previous papers, source (Torabi Moghadam et al., 2017a).

2.7.2 SWOT analysis of the reviewed methodologies

From this survey on integrated UIEP emerged a broad range of available individual approaches for existed sustainable urban energy planning. A SWOT analysis is presented in Figure 9 to discuss the main strengths, weaknesses, opportunities, and threats of each available spatial approach described in previous sections (Torabi Moghadam et al., 2017a).

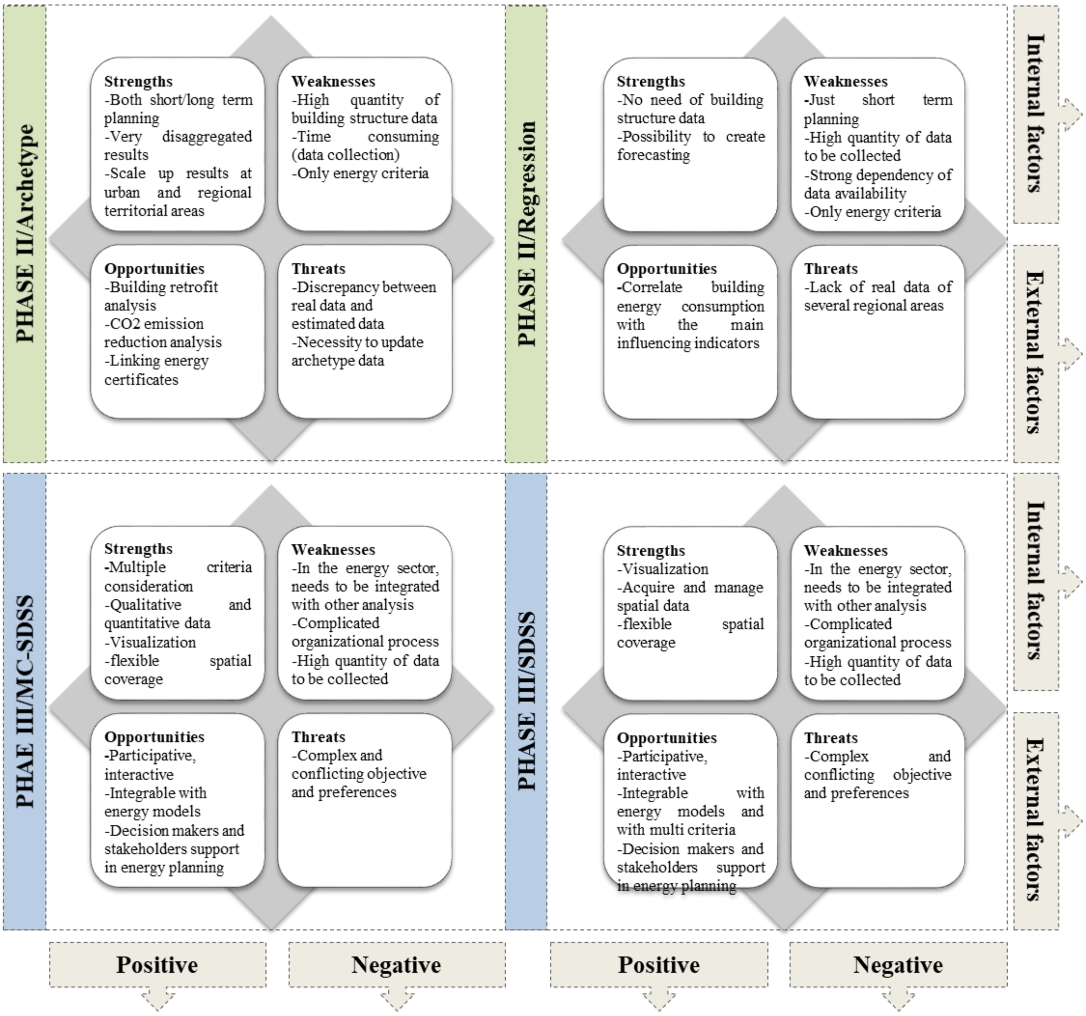


Figure 9: SWOT analysis related to the presented approaches in Section 2, elaborated from (Torabi Moghadam et al., 2017a).

From Figure 9 the following considerations are derived (Torabi Moghadam et al., 2017a):

- Phase I-spatial database creation: since built environment data and information at the local level are significantly scattered among several entities, and there is a lack of interoperability among the data sources, one of the most challenging barriers in developing a robust and detailed analysis is data collection (Caputo and Pasetti, 2015). In this regard, a huge effort is required in order to provide a supportive and comprehensive accessible building stock database, at the local level for different goals and different stakeholders, gathering all the necessary data from various sources (Cajot et al., 2017);(Caputo and Pasetti, 2015). In Italy, information about building stock and their energy performances are derived from different regional and local authorities and often are not homogeneous (e.g., ISTAT, Italian National Institute of Statistics, ARPA, Regional Agency for Environmental Protection, Regional register of energy performance certificates and AEEG Regulatory Authority for Electricity and Gas) (Caputo et al., 2013b). Therefore, in order to set up an effective energy planning at the local scale, it is crucial to improve data availability and management. Data availability about buildings energy consumption will be increasingly improved in the future, thanks to smart metering and real-time data monitoring, following recent open data policies (COM n.882 final, 2011). In this context, GIS helps to identify and visualize buildings data and their distribution, supporting decision-making, at urban and regional scale. This approach can manage location-based information, linking alfa-numerical information databases to spatial maps to create dynamic displays. Moreover, GIS highlights the high energy use hotspots that need requalification (Chalal et al., 2016). Although GIS is principally used for buildings geometrical data, it can significantly assist the energy performance of buildings. The procedure of data collection and geo-referencing procedure is very time-consuming. Moreover, the quality of data is a very big faced challenge in this phase. However, in order to create MC-SDSS for urban energy planning, this phase is non-negligible. The geospatial database includes several attributes that are associated with each building. Some of the information derives from the bulging level. When the single building level information is not available the data come from the census level.

- Phase II-spatial building energy modelling: this phase provides a detailed information on the building stock and its retrofit potential. Here it is possible to understand also relevant purposes for design. Among aforementioned models, the choice between archetype and regression methods strongly depends on data availability and the willingness to explore retrofit retrofitting solutions (i.e. archetype) or to forecast energy consumption (i.e. regression).
- Phase III-spatial decision support systems: a tool to build alternative actions, to express different and conflicting objectives, and to explore the various aspects that can influence final decisions. Also, these tools can take into account both quantitative and qualitative aspects, considering all sustainability pillars. In this regard, a huge amount of data is required to compute all different aspects (i.e. social, environmental and economic). In

some of these tools the MC methods are integrated into their application (MC-SDSS), and for the other, the MC analysis should be incorporated exogenously (SDSS). This means that, once the scenarios are defined in the SDSS, the MC analysis will be performed separately.

From the SWOT analysis (Figure 9), urban energy planners can recognize how the strengths of others can rectify the weaknesses of the different approaches. Accordingly, the urban actors can realize which approach could be proper for their planning purposes. Therefore, the presented SWOT analysis may guide and support urban players in the choices among the summarized individual approaches by highlighting the key features. Furthermore, the SWOT analysis is beneficial to urban energy planners and DMs since models become useful when the users are aware of the models advantages and limitations to make effective decisions (Cheng and Steemers, 2011).

2.7.3 Major findings

The major findings are summarized in this section to give new insights for future research and extend existing research. Taking into account the aforementioned considerations emerging from meta-analysis and SWOT analysis, Figure 9 shows which approaches are suitable for creating the different scenarios explained (Torabi Moghadam et al., 2017a). Moreover, this figure illustrates the possible integration of different methods to help the urban actors in performing the whole UIEP procedure. As shown in Figure 10, Phase I must be integrated with all other phases in a spatial framework due to the necessity of handling a large volume of data (i.e. the building energy demands and the relative retrofit potential) to improve significantly the quality of planning and decision-making processes. In Phase II, it is possible to interlink more than one method when it is necessary. For instance, the output of the archetype models could be used as the input of comprehensive energy system models (e.g. energy requirement of a building typology and retrofit solutions). Phase III should be integrated with all the methodologies of Phase I and II to support a collaborative process, to better visualize the structure of group decision problems, and organize communication among participants. Therefore, in order to obtain an effective UIEP, decision making process for sustainable development should be broadened to including the stakeholders' presence. In this context, collaborative SDSS and MC-SDSS based on spatial information sharing and on expert systems are more proper to tackle the problem (Lombardi and Ferretti, 2015). Existing tools are very effective in modelling energy consumption but not very efficient in structuring urban planning problems.

Scenarios Type — **Integration Possibility**

SUITABILITY FOR CREATING FUTURE SCENARIOS	Approaches	Phase I	Phase II	Phase III
PREDICTIVE , EXPLORATIVE, NORMATIVE	PREPARATION			
PREDICTIVE	REGRESSION			
PREDICTIVE , EXPLORATIVE, NORMATIVE	ARCHETYPE			
PREDICTIVE , EXPLORATIVE, NORMATIVE	MC-SDSS/SDSS			

Figure 10: Approaches suitability for creating future scenarios and integrating with other phases. The barred bullets mean the possible integration methods in Phase II in order to improve one of them, source (Torabi Moghadam et al., 2017a).

Here, pointed out some of the most relevant findings of the review and some insights for future research developments are pointed out. The major findings cover two following main points:

- Urban energy planning has to take into consideration an integrated approach: considering that energy planning is complex and multi-disciplinary, from the in-depth analysis of the state of the art, the main challenge for future research is to integrate the existing different methodologies in an agreed structure in order to enhance the quality and robustness of the planning results. In fact, although the research field of energy planning has become progressively important at urban and regional scales, performing the entire energy planning process by integrating different approaches is still not a common practice. The discussion so far underlines that the advantage of integrating different approaches is due to their complementarity in fulfilling different tasks of the process. Indeed, the preparation of the GIS supportive database allows to manage and visualize the territorial and socio-economic spatial peculiarities (Phase I); energy modelling tools allow to quantitatively analyse the current and future sustainable built environment evolution (Phase II); while MC-SDSS allows to involve the different actors in the decision process and to analyse and choose between the different strategies obtained from the energy modelling parts (Phase III).

- An integrated urban and regional energy planning is an opportunity through which it is possible to contribute towards a greater sustainability. The whole process is essential to guarantee a future sustainable urban transformation by: investing responsibly in alternative consumption patterns and greener strategies; speeding the decision-making process through participation and intuitive visualization; strengthening the collaboration and relationship between research and private and public local authorities; leading to various new commercial consequences for the environment, economy and society at the national level down to the city level; offering the opportunities of engaging stakeholders in the planning process by establishing a shared framework between them.

2.8 Concluding remarks

From the review of an existing literature is emerged that there is still not an integrated method to face the UIEP. Therefore, in this Ph.D. work, a new integrated MC-SDSS is proposed to evaluate and visualize the results of different UIEP scenarios taking into account the DMs involvement from the early stage of planning.

Concluding, the approaches described in this chapter represent the necessary base for creating the future urban energy consumption paths for scenarios analysis. Particularly, the importance of using GIS tools for calculating, managing, storing and visualizing data at the urban scale is highlighted. From the overview, the top-down models are rarely adopted at the urban scale.

While, the bottom-up models are appropriate to characterize the energy consumption of the existing building stock. Among the mentioned statistical methods, the regression ones have been the most widespread coupled with GIS. These statistical methods are suitable for short-term planning based on large data requirement. Regarding engineering methods, although it might be possible to use the sample and population distribution models at the urban level, the most well-known and applicable method for urban spatial analyses is the archetype method. Archetype methods allow both short and long-term analysis and the possibility to create future energy retrofit scenarios.

Part of the work described in this chapter was also previously published in the following publications. Minor grammatical changes have been made to integrate the articles within this dissertation.

Paper 2. S. Torabi Moghadam, G. Mutani, P. Lombardi. (2017). A mixed methodology for defining a new spatial decision analysis towards low carbon cities. Procedia Engineering, vol. 198, pp. 375–385. doi: 10.1016/j.proeng.2017.07.093.

Paper 3. S. Torabi Moghadam, J. Toniolo, G. Mutani, P. Lombardi. (2018). A GIS-Statistical Approach for Assessing Built Environment Energy Use at Urban Scale. Journal of Sustainable Cities and Society, vol. 37, pp. 70-84. doi: 10.1016/j.scs.2017.10.002.

Paper 4. P. Lombardi, F. Abastante, S. Torabi Moghadam, J. Toniolo. (2017). Multicriteria Spatial Decision Support Systems for Future Urban Energy Retrofitting Scenarios. Sustainability, vol. 9, n. 7. pp. 1-13. ISSN 2071. doi: 1050, 10.3390/su9071252.

Paper 6. S. Torabi Moghadam, P. Lombardi, F.M. Ugliotti, A. Osello, G. Mutani. (2016). BIM-GIS Modelling for Sustainable Urban Development. NEWDIST, vol. Special Issue n. July 2, pp. 339-350. ISSN 2283-8791.

Chapter 3

Research Design and Method

3.1 Introduction

This chapter will discuss in detail the design and the methodological set-up of the Ph.D. research. The idea is to solve the problems that stated in chapter 1 by combining the methodologies and approaches discussed in chapter 2. In fact, the aim of this chapter is to offer an interdisciplinary integrated methodological framework which is able to support decision-making processes. This will help in defining and evaluating energy-saving scenarios taking into account the participation of stakeholders in an interactive way. The meaning of integrating different tools and methods in this framework is due to their complementarity in fulfilling various tasks in the UIEP process. The research approach and framework are explained in section 3.2 and 3.3. Moreover, section 3.4 illustrates the study area as a demonstrator of the Ph.D. project. Furthermore, some concluding remarks of this chapter are given in the last part of the chapter (section 3.5). To understand the outcomes, it is essential that the reader is aware of the methodological choices made in all the phases.

3.2 An interdisciplinary integrated approach

To address a complex challenge of urban and regional energy planning, there is a need for an interdisciplinary and integrated spectrum (Brömmelstroet et al., 2014). In fact, the planning processes in urban energy problems may be not specifically innovative approach; however, its management by means of integrated, cross-sector, multi criteria and multi actors approaches is absolutely a novel approach to be resolved (Cajot et al., 2017). In this vein, many cities should struggle to develop innovative methods to successfully reinforce the collaboration among different research disciplines dealing with energy issues (Zanon and Verones, 2013).

On one hand, considering the existing research gaps and methodological directions, this Ph.D. study follows an interdisciplinary path. Both technical (e.g., energy modelling) and societal (e.g., an active engagement of relevant actors and interest groups) elements help to perform a proper UIEP; especially, from the stakeholders' perspective (Dantsiou, 2017). On the other hand, this study is fundamentally based on "Multi-Methodology Integration" defined by Mirakyan and De Guio (2013), in which parts of different methodologies are combined (e.g., statistical, engineering, focus groups and etc.).

In structuring the UIEP, it is important to select different appropriate approaches and to choose them considering the decision context and the type of planning project. The SWOT analysis presented in chapter 2 (Figure 9) can significantly aid. Furthermore, it is crucial to analyse how it is possible to implement the interaction among the different stakeholders. As a result, the developed MC-SDSS for UIEP in the built environment uses techniques at the crossroads of three domains (see Figure 11):

1. Spatial database, which constitutes the GIS platform including all the relative information and data and enables the use of analytical process and outcomes such as the maps, graphs, and tables;
2. Spatial building energy modelling, which develops a bottom-up modelling to evaluate the current and future energy consumption at the city scale concluding a sufficient level of detail;
3. Spatial decision support system, which is the fact that the DMs can express and exert their preferences with respect to multiple evaluation criteria and/or alternatives, and consequently, get back feedback in a real-time to increase the DMs trust in the outcomes.

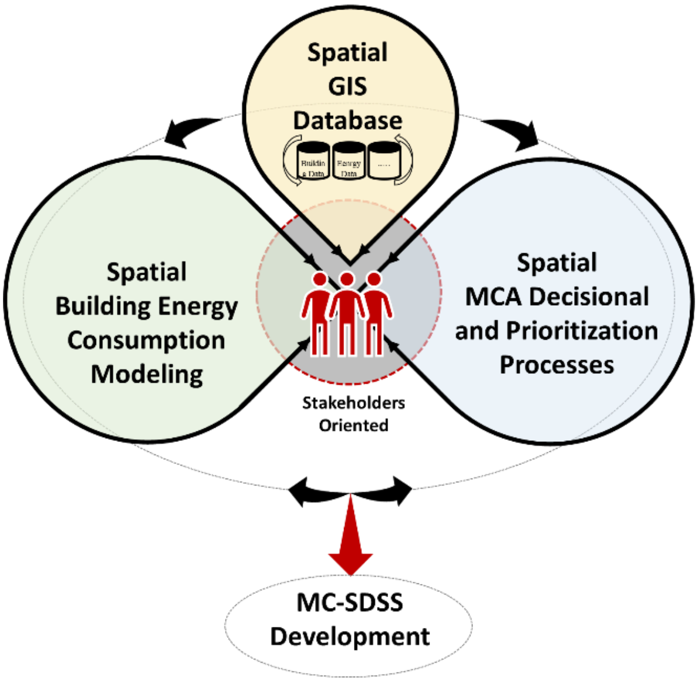


Figure 11: Schematic overview of the three main components of this research.

The integration of this technical know-how allows providing maps of energy, economic, environmental, social and technical indicators resulting from the evaluation of energy saving scenarios. This provides a supportive tool for the urban actors in the participatory planning processes allowing several stakeholders with different backgrounds and interests to gather and discuss the issues of several urban and regional energy saving scenarios (Girardin, 2012). In the following section, the integration of theoretical proposed framework and how it is supposed to be applied to the study practice is shown.

3.3 The research framework

A new MC-SDSS, which is an interactive plug-in of GIS environment is developed in this three-year research. The plug-in will help to dynamically analyse the energy retrofitting scenarios based on the stakeholders' preferences within an urban scale. The methodological framework of this study consists of several phases involved in the framework of an integrated urban energy planning according to (Mirakyan and De Guio, 2013). Hence, it is helpful to break it down into the main elements that frame it to understand the research process steps employed in this study. To this end, in Figure 12 a schematic flowchart of the methodological approaches of the thesis is shown.

During the early stage, the research questions were defined (Table 1). Afterward, a critical systematic review of each phase of urban energy planning from the literature has been conducted [Paper 1]. This step provides a statistical analysis of the 80 reviewed papers through a Meta-analysis (Figure 8) to figure out current research trends and to identify the main gap of the given context that needs to be filled. It also provides a SWOT (Figure 9) analysis of the different approaches to discuss the main strengths and weaknesses of each available spatial approach that are described in chapter 2. The review allowed to identify the lacks in the UIEP research filed, emphasizing the need for well-organized interdisciplinary integrated frameworks.

Phase I

Accordingly, the fieldwork thesis is started starting from the quantitative data collection to characterize the building stock and to create a supportive geodatabase. This phase (Phase I), entitled "preparation and preliminary analysis". Phase I is the foundation of all processes and modelling approaches in the next Phases, II and III. Of course, the GIS database can be always updated, and more data can be joint into the framework. In this step, the information characterizes by geo-referenced and non-georeferenced data. Therefore, the geo-referencing procedure should be performed for those non-geo-referenced ones in order to create a strong geospatial database. All the collected data have been then overlapped and integrated into the GIS platform. In this regard, each building polygon has been associated with its available and necessary information. The goal of this Phase was to create a 2D-GIS-database platform for the city including the various factors, which may influence the building energy issues. The use of GIS was crucial since it offers the opportunity to characterize the building stocks and to visualize the spatial distribution of a large number of data through its location-based feature and its multiple layers representation (see the section 4.3.1 of chapter 4).

Phase II

Consequently, Phase II has been performed to model the energy consumption of building stock a detailed way. First, in chapter 4, a bottom-up statistical model has been developed to estimate the energy consumption for the built environment space heating at the city level. This model is based on the integration of statistical analysis (considering several variables reported in Table 10) with 2D-GIS to map the current energy consumption of the city [Papers 2, 3 and 10]. The novelty of the proposed statistical model lies on its simplicity and applicability and the high level of their robustness in the literature (see chapter 2). However, these statistical methods rely strongly upon monitored real data. It should be noted that fortunately, the author succeeded to collect a sample of information of energy billings as a data source for modelling purpose and for analysing the link between energy consumption and a wide range of different variables. Moreover, the statistical models are also able to take into account socio-economic effects in the equations (Mastrucci et al., 2014). They perform reliable consumption information about the present condition of buildings and for the calibration process of engineering-based models. However, due to the strong dependency of statistical methods on available historical consumption data, these methods are limited to predict the impact of innovative technology options and energy saving potential after applying renewal solutions.

In counterpart, engineering methods are very detailed models based on traditional thermodynamic relationships and heat transfer calculations (Nouvel et al., 2015). Although the historical data can be used for making a comparison against measured consumption data, these methods can assess energy consumption without any historical information. However, the engineering modelling approaches require a high quantity of information about building structure and parametric input to calculate the energy consumption of a set of reference buildings of the stock based on a numerical model. Into this, 3D city models can significantly help (Nouvel et al., 2015). One the main benefits of engineering-based methods, which is used this thesis is their ability to predict energy saving quantity for buildings after renovating solutions application (Mangold et al., 2015). In this phase, the study proposed to simulate the energy consumption of urban areas after applying retrofitting actions. Although the engineering methods are able to predict future conditions, simulating whole cities using energy demand software can be very extensive in terms of computer resources and data collection. The reduction of these time-consuming methods thus still remains to be resolved. Therefore, a new methodology, using city archetypes is proposed, in chapter 5, to simulate the energy consumption of urban areas including urban energy planning scenarios. The objective of this chapter is to present an innovative solution for the simulating of the energy demand of cities by using a simplified 3D-GIS model, designed as a function of the city urban characteristics.

In fact, the chapter 5 of the dissertation combines both the statistical and engineering approaches to obtain a more robust prediction of the urban energy consumption. The framework is performed in order to reduce time-consuming processes of energy demand simulation, assessment and for designing urban energy saving scenarios [Paper 13]. A spatial distribution of urban building energy consumption in 2D/3D visualization provides SDSS tool in order to identify where the energy consumption is mostly concentrated to make the better decisions.

Phase III

Phase III of the study follows "a mixed methodology" that combines qualitative and quantitative approaches (Dantsiou, 2017). Qualitative research refers to semi-structured focus groups formed in which the qualitative data such as stakeholders' opinion are collected through discussions and questionnaires. Particularly, the use of focus groups by stakeholders in this study has the following implications: (i) it answers the research question 3 reported in section 1.2. (ii) it reflects the "mixed methodology" choice for Phase III with the use of qualitative (semi-structured focus groups, questionnaires, playing card) and quantitative (building stock energy data, costs, etc.) data collection and analysis methods.

To define evaluation criteria, several methods exist in the literature (Wang et al., 2009). In this thesis, the evaluation criteria are defined through the first workshop including semi-structured focus group organized on 30th November 2016 involving relevant stakeholders [Paper 4]. The definition of evaluation criteria side-by-side the real local stakeholders leads to have trustable results that grantee the robustness of planning process. Given a vast number of available MCDA approaches, makes it necessary to carefully select the most appropriate method for each specific decision context (Lombardi et al., 2017). In this thesis, the "Playing Cards" was chosen (Simos, 1990) due to some reasons. First, it is a simple and intuitive method and easy to be understood, even by non-experts in the field of decision processes (Figueira et al., 2005); (Lombardi et al., 2017). Second, they can help DMs in managing values that cannot be quantified without difficulty, involving qualitative judgments. Finally, the technical parameters involved in the playing card methodology can be interpreted easily, allowing a simplification of the problem (Lombardi et al., 2017). Chapter 6 describe the main the procedure of "Playing Cards" method and its results.

Subsequently, each of the selected criteria from the first workshop was analysed and assessed to be implemented in a new MC-SDSS tool (see chapter 7). Two main instruments, Interactive Impact Assessment and Suitability Analysis, are modelled and adapted in order to develop a new MC-SDSS. Several dynamic attributes and indicators were modelled and coded using CommunityViz as a Planning Support System (PSS) tool (Kwartler and Bernard, 2001). This PSS tool is selected as a base for further modelling processes due to its several strengths. It helps in analysing and understanding the potential alternatives and their impacts through visual investigation and scenario analysis. Moreover, this tool is interactive and provide dynamic feedbacks on changing the assumptions and viewing the influences of changes on the future scenarios on-the-fly. Furthermore, it engages stakeholders in participative and collaborative decision-making processes through visualization in real-time approach. All the above strengths lead to stronger consensus and better decisions in resolving complex problems. The detailed methodological procedure developed for supporting this phase of research is presented in chapter 7 (section 7.3).

This Ph.D. work provides a significant innovative progress in the research field, that is developing an interactive plug-in tool for UIEP in the GIS environment. In this regard, finally, the second workshop is organized on 12th July 2017 to test the usability and validate the tool from the real stakeholder point of view (section 7.5). For evaluation purposes, this workshop included in two semi-structured focus groups. This step attempts to understand the weaknesses and strengths of the mentioned framework. In this workshop, the questionnaires also were designed for analysing the stakeholders' feedbacks about the developed tool. Within the use of this GIS extension, public administrative users, such as urban energy planners, policymakers and built environment stakeholders can plan, design and manage low-carbon cities. This plug-in will provide the stakeholders with the ability to visualize interactively and explore a range of possible futures saving scenarios.

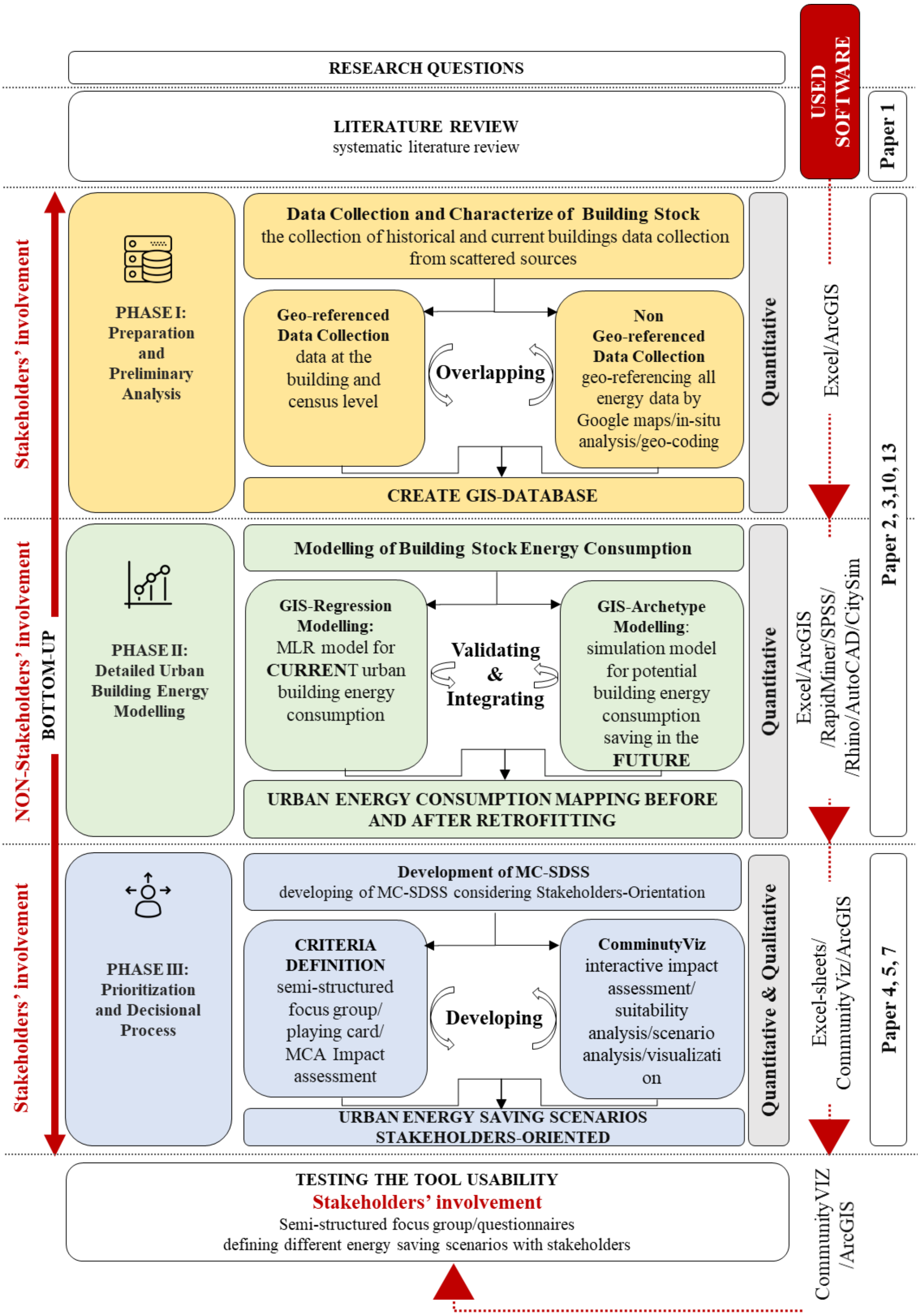


Figure 12: A schematic overview of the methodological approach.

3.4 Study area

Research design links the collected data of the case study to the research questions (Dantsiou, 2017). The case study includes numerous levels of analysis with the aim of illustrating the application of the proposed methodology.

The application of the methodology in the urban area will be performed by a significant selection of buildings belonging to the "beating heart" of the Italian city of Turin (Piedmont), named Settimo Torinese. The residential building stock of this city is located in North-West of Italy in the continental temperature climatic zone. This municipality represents a proper demonstrator due to the presence of a various buildings typology, size and age of construction. Settimo Torinese (45º8' North, 7º46' East, 207 m asl) is a medium-sized city. The choice of this medium-sized city is significantly important since these cities have not been at the centre of attention of sustainable developments (Rosenzweig et al., 2010). The city is composed of 300 census sections and about 3600 residential buildings with 47,831 inhabitants, and it occupies an area of 33 km^2, as visible in Figure 13, showing aerial views of the city of Settimo Torinese. Moreover, the total heated volume of the residential buildings is equal to 8.55 Mm^3.

Interestingly, the city can be divided into three main zones based on their geometrical and urban characterizations: (i) Fiat Village (semi-suburban area), (ii) Campidoglio Square (transformation area) and (iii) Historical Centre (consolidate area). Table 7 summarizes the generic information and characterization of Settimo Torinese. The study area presented here, will be used as a demonstrator during the rest of dissertation for applying the proposed methodology. The municipality of Settimo Torinese will assume the role of DM.

Figure 13: Aerial and 3D view of the city of Settimo Torinese, source Google maps.

Table 7: General information about the case study, source Municipality of Settimo Torinese.

Municipality	Settimo Torinese
Province	Turin
Region	Piedmont
State	Italy
Coordinates	45°08′21″ N; 7°46′12″ E
Climatic zone	E
HDD	2664
Altitude	207 m above sea level
Surface	32,37 km2
Inhabitants	47 785
Density	1476,21 In/km2

According to energy consumption analyses, reported by the North-East Turin Union of Municipalities (NET) (i.e., Borgaro Torinese, Caselle Torinese, San Benigno Canavese, San Mauro Torinese, Settimo Torinese, Volpiano), the total energy consumption in 2009 was equal to 3,252 GWh for a population density of 535 ab/ km^2 (Figure 14). The highest value is referred to the industrial sector (36% of the total), and it is also significant for residential (27%) and transport sector (26%). The public sector accounted for a share of 1% of total consumption. Compared to 2000, the first available year for historical values, there was an overall consumption decline of about 8.5% (SEAP, 2012). The Municipality of Settimo Torinese is the most energy consumer both in 2000 and 2009 for about half of the total energy consumption respectively 49.93% and 46.68%, amounting for about 40% of the total population in 2009 (SEAP, 2012).

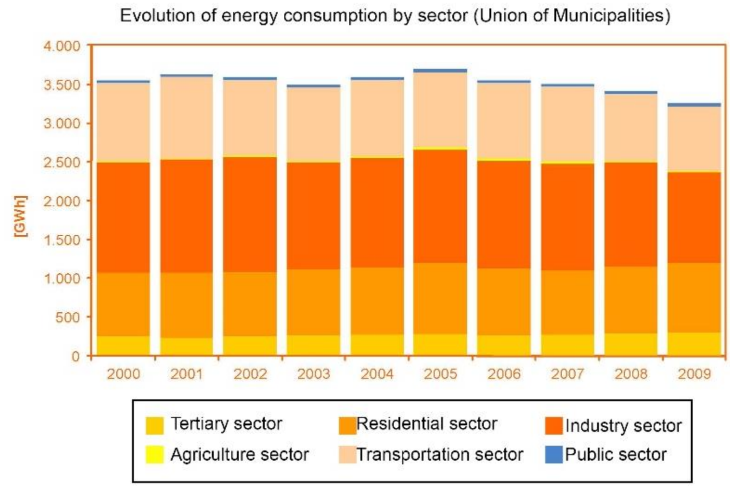


Figure 14: Evolution of energy consumption by sector in the North-East Turin Union of Municipalities, source (SEAP, 2012).

Currently, District Heating (DH) network is extended for about 40 km of network, serving 7000 users for an equivalent of about 350 condominiums. Figure 15 shows the recent map of DH network in Settimo Torinese. The presence of District Heating allows Settimo Torinese network to save on the installation of single point boilers, which overall would have the greater impact than a plant in emitting terms. The plant is equipped with very recent technology, with low NOx emission and CO burners, which allow relatively low mass flows, limiting its environmental impact.

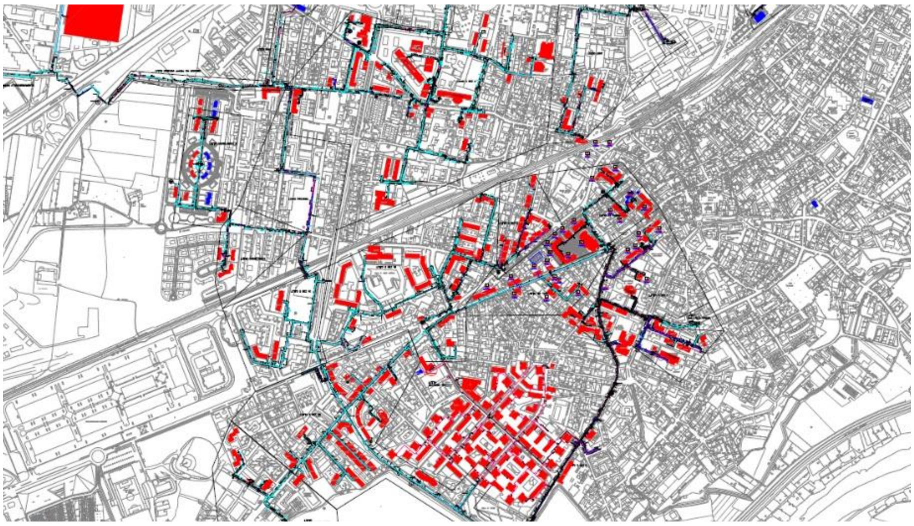


Figure 15: District Heating network in Settimo Torinese, source EEB Project.

In addition, the city is proactive towards initiatives related to technological innovation and smart cities. The city, in fact, provides the opportunity for its citizens to free surfing, using Wi-Fi of active networks over the city squares and major public buildings. However, the existing built environment still needs to overcome a difficulty of integration of intelligent technologies and systems for increasing the energy efficiency and management.

3.5 Concluding remarks

This chapter has illustrated the methodology framework proposed for this Ph.D. research. A methodology is an interdisciplinary integrated approach, where there is a need for both quantitative and qualitative analysis in order to have a comprehensive structure for UIEP. Providing useful information to DMs (urban planners, municipalities or architects) can be a tedious task when designing more sustainable urban areas. On the one hand, statistical methods are often used to understand the driving parameters of energy consumption but rarely used to evaluate future urban renovation scenarios. On the other hand, the simulation of a complete city or urban area can be extensive in terms of computational resources, data acquisition and modelling.

In order to address these shortcomings, this work first proposed a geospatial statistical method to estimate the heating energy consumption at the current state of the city; afterward, it has developed a new methodology to define an archetype urban area that would be representative of a city of the case study. The objective was to decrease the number of buildings that need to be simulated. However, a transition towards a sustainable urban development requires a wider societal consensus building with an active and earnest engagement with all relevant stakeholders. Therefore, in the next step, intuitive approaches such as playing card method are proposed in order to define relevant evaluation criteria through participative approaches. After selecting the evaluation criteria, a new developed MC-SDSS is modelled to define different interactive energy retrofitting scenarios. Finally, a case study is introduced in this chapter, which helps to investigate practices within their real-world setting.

Part of the work described in this chapter was previously published in the following publication. Minor grammatical changes have been made to integrate the articles within this dissertation.

Paper 3. S. Torabi Moghadam, J. Toniolo, G. Mutani, P. Lombardi. (2018). A GIS-Statistical Approach for Assessing Built Environment Energy Use at Urban Scale. Journal of Sustainable Cities and Society, ELSEVIER, vol. 37, pp. 70-84. doi: 10.1016/j.scs.2017.10.002.

Chapter 4

Building Energy Consumption Modelling at Urban Scale: Estimation Using Statistical-Regression Technique

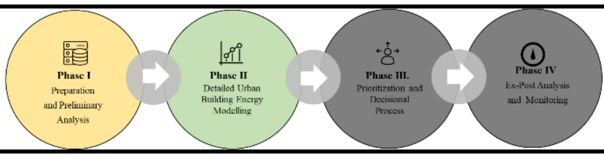
4.1 Introduction

This chapter will illustrate the development of a geospatial bottom-up model for estimating the space heating energy consumption of a vast number of residential building stock, considering a broad range of variables. Section 4.2 presents a general statistical modelling procedure. In section 4.3 first the data collection procedure is detailly illustrated, which is involved in Phase I (i.e. Preparation and Preliminary Analysis). Afterward, this section develops a methodology based on 2D-GIS and Multiple Linear Regression (MLR) providing location-based information for every single dwelling to discover correlations and assess the heating space energy consumption of the current state of the city (Phase II: Detailed Urban Buildings Energy Modelling). This framework is tested for the study area, including around 3600 residential buildings. Section 4.4 and 4.5 provide the required input data for the modelling process and the achieved results, which are validated by residual analysis and cross-validation approach.

It is notable to recall the first models that were previously published in (Torabi Moghadam et al., 2016b) [Paper 2] and (Torabi Moghadam et al., 2017b) [Paper 10]. The reader interested in knowing more about the first models, which were based on two significant predictors, the building age and surface to volume ratio, can refer to indicated publications. These two models were validated through the calibration coefficient that is the ratio between the top-down analysis (e.g. energy balance quote) and bottom-up analysis (the energy consumption estimated for each building) (Delmastro et al., 2016a).

This chapter focuses on illustrating the optimized and final model published in [Paper 3]. Thus, this part of the research represents a primary step for performing the future energy investigations at the urban level. The results from will aid spatial decision-making processes (section 7) in performing energy planning and testing how different scenarios affect energy performance and carbon emissions and its relationship as well as maintaining the dynamic context of the smart city. For schematic summary of this chapter refer to Table 8.

Table 8: Schematic summary of chapter 4 including Phase I and Phase II of UIEP.



Research limitations	**Research questions**	**Addressing questions**	**Related publications**
the difficulty in collecting the scattered data having a different type from various sources and entities; the lack of all real measured data of energy consumption at the current status of the cities.	How to model the energy consumption at urban scale in a spatial way for the current and future scenarios? Which kind of data are needed? How to connect different data type from different and scattered sources?	Spatial-GIS-database creation; Spatial-GIS-statistical method.	[Paper 2] A mixed methodology for defining a new spatial decision analysis towards low carbon cities. [Paper 3] A GIS-Statistical Approach for Assessing Built Environment Energy Use at Urban Scale. [Paper 10] GIS-Based Energy. Consumption Model

at the Urban Scale for the Building Stock.

4.2 GIS-statistical model

Chapter 2 discussed and reviewed comprehensively the advantages of the use of GIS-based statistical methods. Although many studies mentioned in section 2.5.2.1 focused on the development of statistical building stock models, the number of studies which adopted a GIS-statistical methodology is quite limited. Moreover, in the most of previous studies, the real monitored data was not available but only the simulated values were used. The main difference between the Urban Energy Modelling (UEM) proposed in this work and the previously mentioned studies is that this model considers various real measured data and also a considerable number of predictors. The proposed model is greatly useful to diminish time-consuming energy demand estimation processes and to support urban energy planning. Moreover, the spatial results of this study are a valuable tool to help DMs in the urban planning process to create future energy transition strategies, implementing energy efficiency and renewable energy technologies in the context of sustainable cities. Additionally, the proposed methodology can be simply applied to all cities worldwide. As section 4.3 will illustrate better, this work developed a UEM, which describes the current situation of urban energy consumption to support decisional process in evaluating future scenarios. The specific goal is to create an energy map of the entire city, integrating MLR statistical techniques and 2D-GIS-based methodologies.

The data used in this research work is derived from a sample of 290 residential buildings, built in different construction periods[2]. Relationships were searched among the various variables that were appropriately combined to discover statistical relations. The estimated energy demand was validated by splitting the data-set into training and testing subsets. Moreover, the cross-validation was also applied for selecting the features more accurately. For the improvement of the GIS database, the input data were composed by: (i) climate (external air temperatures); (ii) geometric data (e.g., surface to volume ratio, floor area, number of floors); (iii) typology of the building envelope (class of thermal transmittance U for opaque surfaces, class of U for transparent surfaces); (iv) period of construction; (v)

[2] This process of data collection is involved in the Phase I, as a preparation. In this phase, all the data were analyzed and elaborated. It is not possible to use the data directly for the modelling approach (Torabi Moghadam et al., 2017b, 2016b).

ground-floor type (commercial, residential and pilotis, which means open space entrance with pillars that support building on the ground floor); (vi) roof type (flat, gable); (vii) building type (residential); (viii) monthly measured data of space heating consumption (two heating seasons).

4.3 Modelling framework

To create a valid and understandable model for urban energy consumption, a methodology is needed to be developed in order to evaluate space heating of residential building stock in an Italian context. The model represents the spatial distribution of urban building energy consumption to ease the decision-making process to simulate various urban transition energy policies according to local conditions. The proposed methodology is mainly based on existing census data and real measurements of DH energy consumption data. Moreover, GIS was used to identify the geometrical characteristics, data, and information of the building stock. The geo-referencing process assists significantly in managing, analysing and visualizing a huge amount of data to support the participative and collaborative workshops for making the better decisions at the urban scale analysis. Based on the available data, a regression methodology was applied to estimate the energy demand of city residential building stock. Figure 16 shows the proposed methodology comprised of three major steps:

Step 1-data collection and data integration: the available information on the existing building stock was collected and analysed. All the collected data were overlapped and integrated at this step. Each building polygon was associated with the relative energy consumption and other data. The building stock was thereby characterized. The goal was to create a city GIS Database framework on the factors influencing building energy consumption.

Step 2-parameter identification, modelling, and validation: firstly, a pre-processing procedure was performed using "missing value replacement" and "outlier detection". Next, a feature selection process was applied to the given dataset to identify the most influencing factors on energy performances. Lastly, a robust MLR was employed to evaluate the energy consumption of building stock. The feature selection process and regression models were tested with the cross-validation and splitting data set process to produce more robust outcomes (Ma and Cheng, 2016).

Step 3-model expansion at urban scale: the model obtained from the Step 2 was expanded to urban scale of a medium-sized city, located in North-West of Italy. At this step, the buildings, which were not accurately estimated, were excluded.

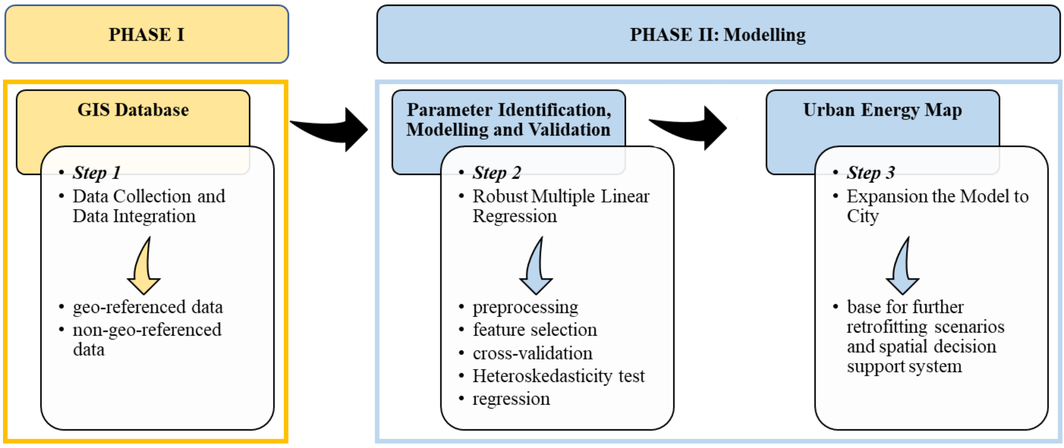


Figure 16: Proposed methodology framework of the GIS-statistical-modelling approach. Yellow part belongs to Phase I and the blue one constitutes to Phase II.

The proposed approach could be used by everyone involved in the formulation and optimization of operation strategy. The methodology is introduced in the sub-sections below.

4.3.1 Data collection and data integration: GIS database

Here the Phase I will be demonstrated, in which the data collection procedure and its main reference sources, (e.g., building stock characterization and distribution) are fundamental to the next phases. Although the data collection procedure can be generalized, data and information availability depend strongly on each specific nation. The research began with the collection and analysis of the available data of building stock, which affects space heating energy consumption. The proposed methodology shown in Figure 16 integrates GIS as a supportive data collection tool, which can join different types of information or datasets by using location as the common feature (Ma and Cheng, 2016). For instance, the Census data sets consist of demographical, and housing information can easily be overlapped to individual buildings which have shape files. Since the target of this research is always the urban and local level, the definition of the buildings database is crucial. Table 9 illustrates the different predictors that principally characterize the heating space energy consumption of buildings with their references. The geometrical data were mostly acquired from the digital cartographic base using the automatic functions of the GIS tool.

Table 9: Structure of the database and the relative description of the variables.

Data	Raw data	unite	Source of information	Reference
Dispersing Surface	Floor area Perimeter Height Contiguity	m^2	Cartography Cartography Derived Derived	(Dall'O' et al., 2012); (Fracastoro and Serraino, 2011)
Net floor Area	Gross floor area Gross/net ratio	m^2	Cartography Normative	(Caputo et al., 2013b); (Fracastoro and Serraino, 2011)
Height	Number of floors Floor height	m	Cartography Literature	(Dall'O' et al., 2012)
Heated Volumes	Net floor area Net floor height	m^3	Derived Derived	(Dall'O' et al., 2012); (Fracastoro and Serraino, 2011)
Number of floors	-	number	Cartography	(Dall'O' et al., 2012)
Perimeter	-	m	Cartography	(Caputo et al., 2013b); (Dall'O' et al., 2012)
Building shape factor	Net floor area Net floor height Gross floor area Gross/net ratio	m^{-1}	Derived	(Penna et al., 2015); (Florio and Teissier, 2015); (Braulio-Gonzalo et al., 2016); (Aksoezen et al., 2015)
Roof type	-	-	Google earth/ In-situ analysis	(Dall'O' et al., 2012)
Period of construction	-	-	ISTAT national census	(Theodoridou et al., 2011); (Aksoezen et al., 2015); (Florio and Teissier, 2015); (Dascalaki et al., 2010)
Temperature	Typical meteorological	C°	ARPA	(Mastrucci et al., 2014)
Building occupation ratio	Occupied buildings Empty buildings	%	ISTAT national census ISTAT national census	(Mutani and Vicentini, 2015)
Ground floor type	-	-	Cartography	(Evans et al., 2015)
Installed power	-	kW	DH Company	-

Collected data consists in:

On one hand, **geo-referenced data**: geometrical information on the building stock derived from the digital cartographic technical map of the municipality (perimeter, number of floors, heated volume, and area). The height of the building (eave height) was computed by multiplying the number of floors per the average height of the floor (Delmastro et al., 2016a). The average of used floor height depends on the age of the building, and consequently, it can be used to calculate gross heated volume. Another interesting approach to determine the height of buildings in which it used in this research validation is to approximate the height of buildings from the LiDAR Data or DSM (Digital Surface Model) subtracting the DTM (Digital Terrain Model) height data (Normalized Digital Surface Model: NDSM=DSM-DTM), source (Berlin Environmental Atlas, 2014).

This is possible when the relative data is available. The prevailing period of construction of a large building stock was extracted from the ISTAT national Census database (ISTAT, 2011), which provides information for each census parcel. This variable suggests the typical envelope characteristics of buildings (e.g., roofs, floors and windows) and heating systems efficiencies. According to the Italian national classification, the period of construction can be divided into nine classes characterized by homogeneous features of buildings as; age_1: before 1919; age_2: 1919-1945; age_3: 1946-1960; age_4:1961-1970; age_5: 1971 1980; age_6: 1981-1990; age_7: 1981-2000; age_8: 2001-2005; age_9: after 2005. This variable considers the building envelope, such as the percentage of the transparent envelope and a class of U-value ($W{\cdot}m^{-2}K^{-1}$) for both opaque and transparent surfaces, and the performance of the heating system.

Mutani and Todeschi (2017) reported that fewer clusters of Italian period of construction can be considered based on an increased energy consumption for buildings built before 1919 to 1960, higher values for the buildings build in economic boom period (1961-1980) and a decreasing energy consumption for buildings age after 1981. This evidently means that Italian building stock is characterized by high energy consumption before the first energy regulation (e.g., Law 373/1976), when the envelope insulation and energy efficient system was not required (Delmastro et al., 2016a). Furthermore, the building's occupation factor can be identified from the percentage of the occupied building, which is derived from ISTAT national census database. Unlike many previous studies, ground-floor typology (R: residential, C: commercial and P: pilotis) was also considered in this study, which is derived from the digital cartographic buildings' map of technical departments of the municipality.

The model to define the space heating consumption of the buildings depends clearly on the surface to volume ratio of the buildings (S/V, dispersing surface/heated volume). This factor represents the non-compactness of the building, and it was determined using GIS excluding the contiguous surfaces between two heated buildings. Figure 17 shows the automatic calculation of the adjacent walls has been permitted to subtract this parameter from the gross dispersant surface in order to obtain the real dispersant surface that was applied according to (Mutani and Vicentini, 2013). The unheated volumes and then the higher dispersant surfaces were considered for typical Italian building archetypes. The surface to volume ratio is classified as Single-Family House (SFH): S/V$\geq$ 0.8 m^{-1}; Terrace House (TH): 0.6 $\leq$S/V$\leq$ 0.8 m^{-1}; Multi-Family House (MFH): 0.4 $\leq$S/V$\leq$ 0.6 m^{-1}; Apartment Block (AB): S/V$\leq$ 0.4 m^{-1} (TABULA, 2012).

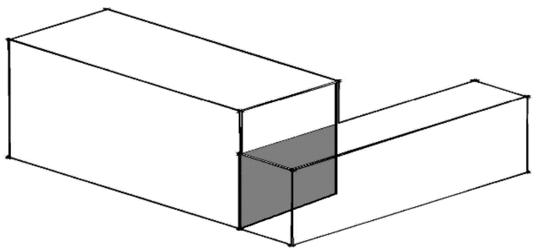


Figure 17: The determination of the common surface of the two contiguous buildings that will be removed from the dispersed surface, source (Mutani and Vicentini, 2013).

On the other hand, the non-georeferenced necessary energy consumption data of buildings were collected such as measured monthly energy consumption for DH with the relative installed power information. In the case that the measured real data is not available (in many nations), other methodologies such as building simulation tools can be used to determine the energy consumption, the database was updated monthly on the two heating seasons 2011-2012 and 2014-2015. The monthly DH energy consumption was given by the district heating company. In this step, these kinds of data should be geo-referenced and associated with each building entity using Google maps and in-situ analyses. First, all the data is analysed in excel-sheets and organized. The GIS volume and the real volume are compared in order to find an error less than 20%. Regarding heating data, which the data is georeferenced automatically based on buildings address and geocoding. Additionally, the roof type (G: gable, F: flat) and the mean daily climate temperature were also added to other information. This parameter emerges from the google earth.

Finally, for creating the supportive and strong GIS database, it is necessary to overlap and integrate all the data collected at two levels: (a) the individual building level (e.g. the base floor area, the perimeter, the gross volume and eaves height of the buildings, the external surface, DH data) and (b) the ISTAT census cartography level (e.g. the main construction period and the average building occupation percentage). Figure 18 illustrated the summarized procedure of GIS database framework consists of all data and information describing each building as a basis for estimating the related energy consumption for space heating. It is important to highlight a significance of this stage since it is a basis of all calculation process and other substantial action. In this stage, the stakeholders' involvement should be integrated as well in order to obtain the existing data and determine relevant sustainable objectives for future planning (Pelzer et al., 2015).

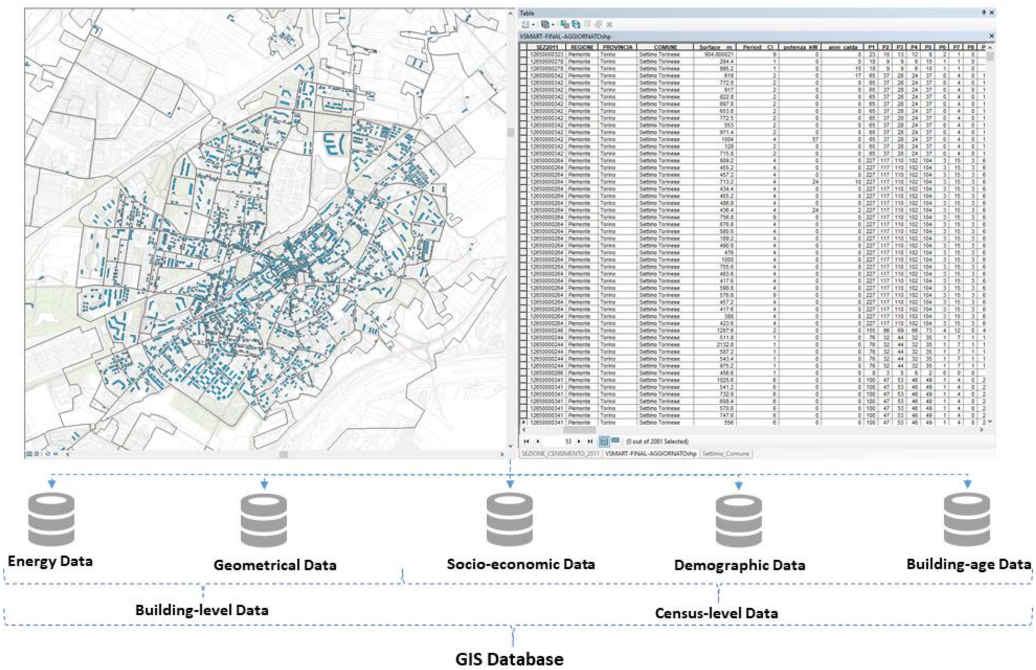


Figure 18: The conceptual scheme of GIS data platform.

4.3.2 Parameter identification, modelling, and validation: modelling process

The statistical methodology is based on a geospatial multiple linear regression model that applied at the urban scale. Many different statistical bottom-up methods exist in the building sector (Torabi Moghadam et al., 2017a). From a comparison of regression analysis, decision tree and neural network emerge, these methods seem to be comparable in predicting energy consumption with a slight difference in accordance with errors (Tso and Yau, 2007). Using regressions help in easing the usage and interpretation of the parameters that introduced in the analysis (Mastrucci et al., 2014); (Arboit et al., 2010). The MLR is one of the most well-known popular regression algorithms. Specifically, numerous researchers have used the MLR method with the aim of predicting energy consumption by using a range of different predictors (see chapter 2). These techniques determine the strength of the relationship between dependent variables that used for numerical prediction. Moreover, the regression models are top-rated due to their simple application (Bassani et al., 2016).

A multiple linear regression model with more than one explanatory variable is described as follows:

$$y = I + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon$$

Where:

- y is the output variable;
- I the general model intercept;
- β_i the regression coefficient (i =1,2, ..., p);
- x_i the input variables (i =1,2, ..., p)
- ε the random effect (to measure the random difference between the y variables for all buildings and the corresponding prediction for a specific building) and remaining errors.

Pre-processing: There are usually features with missing values in data set, which in this study, they were replaced by the mean value of that attribute (Han et al., 2011). Moreover, the outliers' detection procedure was performed, and the presence of outliers was checked.

Feature Selection: Many variables for estimating the energy consumption in statistical models could be irrelevant or redundant; therefore, the key of variables selection is a major step in achieving more accurate predictions (Hsu, 2015). Indeed, those redundant variables led to reduce the model performance. Therefore, an appropriate feature selection process and identification of the correlation is fundamental in order to be measured the degree of association between two attributes. In this study, Akaike Information Criterion (AIC) used to select features for the linear regression (Akaike, 1973) as different approaches used in the computer for the feature selection. This method selects the attribute with the smallest standardized coefficient in each iteration, removing it and performing another regression (Deshpande, 2012). For robustly selecting the feature the removed correlation variables operation was applied in the proposed methodology to eliminate the highly correlated variables. Correlated attributes are usually removed since they behave similarly, and they have the same impact in prediction calculations, therefore, keeping those attributes is redundant and time-space consuming.

Validation: In order to be assured about the accuracy of prediction and the proper model characteristics, assumptions at the basis of the regression model should be attentively verified. Validation of the statistical model can be internally performed, utilizing techniques such as cross-validation. In this study, the performance of the representative regression approach in these two following aspects compared. To verify the estimation of energy demand, the actual energy consumption of the target area was compared with the calculated energy demand. Details are as follows:

First, very high correlated variables were removed before applying the regression model. Then, the dataset is divided into two subsets, as training and testing partitions, for assessing the model performance. In this way, a model is first trained on a 90% of the dataset and then that model is applied to the testing partition to validate and identify the reliability of the methodology. The performance gives the difference between training and testing set estimates regarding fitting (coefficient of determination, R^2) and also prediction error (Mean-Root-Squared-Error, MRSE). (Figure 19)

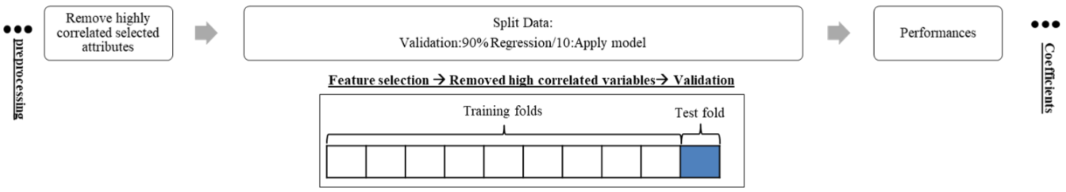


Figure 19: Validation approach (90% training-10 % testing), source (Torabi Moghadam et al., 2018)

Second, the feature selection procedure and regression were validated by cross-validation approach to achieve more steady state results and to avoid the high risk of overfitting (Han et al., 2011). In the cross-validation process, the data set is divided into the ten same size folds. A single fold is considered as the testing data set and the remaining nine subsets are used as training data set. The cross-validation process is then repeated ten times ($k = 10$), with each of the ten subsets used exactly once as the testing data. By applying cross-validation, the model can do a more comparison study on the features selection approaches and the identification of regression equations. The results show (section 4.5) that both approaches have produced similar performances and coefficients (Figure 20).

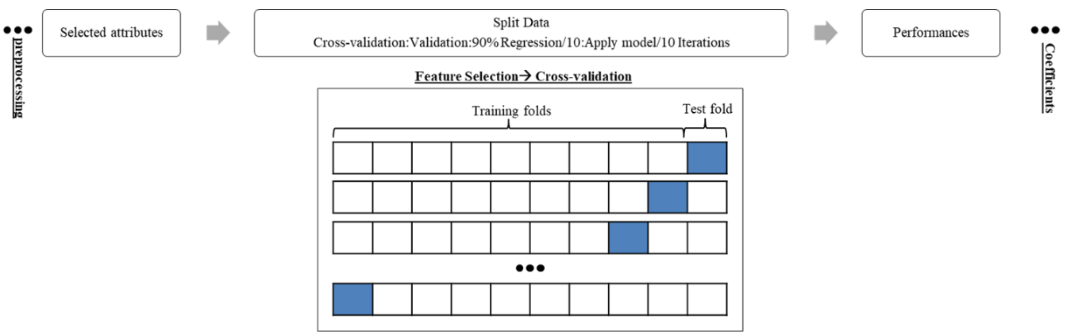


Figure 20: Cross-Validation approach (90% training-10% testing, 10 iteration), source (Torabi Moghadam et al., 2018).

Heteroskedasticity test: Homoscedasticity is a significant assumption in regression analysis (Hayes and Cai, 2007). Therefore, the appropriate diagnostics (e.g., Breusch–Pagan test and White test) were performed to carefully check the multiple linear regression model assumptions to verify the correct specification and accuracy of the model prediction. The homoscedasticity (assumption of homogeneous variance for residuals) was tested through the scatter plot of residuals (or the squared residuals) against predicted values. Into this, the initial presence of heteroscedasticity is reduced thorough heteroskedasticity-consistent standard errors (HCSE) (or robust errors) in the linear regression model (White, 1980), which allowed the fitting of a model that does contain heteroscedastic residuals. The software SPSS was used additionally for this scope. Finally, no significant heteroscedasticity issues were detected being the residuals randomly scattered.

4.3.3 Model expansion at urban scale: urban energy map

As previously stated, the purpose of the study was the evaluation of a simplified energy consumption model for space heating at the urban scale. All the considered variables needed to be extendable and available for the whole city. Once the statistical analysis of using building function was performed, the results are mapped across the city. Since the sample of dataset includes a specific range of heated volume, the buildings that were lower and much higher than this value were excluded. The database information quality accordingly, the geo-referenced model can be continuously improved (Ascione et al., 2013). This methodology is flexible enough to add variables according to the data availability and purpose of the analysis, such as occupants' behaviour or buildings renovation ratio information.

4.4 Required input data

The energy consumption data available consist of monthly records of DH energy consumption for the residential sector, and the heating periods 2011-2012/2014-2015, with respectively 2597 and 2342 HDD at 20°C measured. The data were pre-processed and carefully analysed before being used to put into the model. In this study, the monthly data energy consumption was elaborated first for each month (from the exact first day of the month to the last day), and then it was divided by the number of days of each month in order to have a normalized daily energy consumption. The monthly measured DH energy consumption data of 290 residential buildings were used for the analysis (the local DH Company provided the total number of mixed typology buildings connected to the DH network, which was 350). Almost 50% of the data were excluded before creating the model due to the difficulty of associating the address of the building to its heated volume. Another reason was the presences of some differences between the heated volume calculated by GIS and the heated volume given by the DH Company. Moreover, the GIS data was optimized by comparing the volume of the buildings and the measured volume provided by the DH Company, with an acceptable limit of 15% difference. 165 buildings out of a total number of 290 residential buildings that connected to the DH were successfully associated and geo-referenced with the polygon of each building on the GIS map. This operation was performed manually using the Google Maps platform and in-situ analysis to identify the relative buildings.

In order to create a supportive database and to have enough available data, these 165 residential buildings were considered over 7 months (from October to April) of two heating seasons, taking into account the residential typology; ground floor typology (C: commercial, R: residential, P: pilotis); occupation factor; number of floors; geometrical information of each building (area, perimeter, heated volume, height); the surface to heated volume ratio S/V. Regarding the period of construction, a linear correlation can be hypothesized by dividing the buildings into three clusters, with higher energy consumption for the buildings built from 1961 to 1980 (n. data 1344), lower consumption for the older ones (n. data 678) and for the newer ones (n. data 245). As a complement to the data set provided directly by the city, daily records of the outdoor air temperature of these two years were made available by the Regional Agency for Environmental Protection (ARPA). The acquired input data set is summarized in Table 10.

Table 10: Input sample dataset. with minimum, maximum, average and standard deviation values.

	Sample of data (165 residential buildings)				**Entire Building stock (3608 residential buildings)**			
Numerical Input Variable	Min	Max	SD	Ave.	Min	Max	SD	Ave.
Dispersing Surface (m^2)	802.2	11678.6	1618.3	2822.9	190.0	13910.4	1336.1	1384.7
Area (m^2)	147.4	1688.1	270.62	502.89	6.10	2953.72	221.7	230.97
Height (m)	7.0	27.00	5.51	16.49	3.10	27.20	4.35	8.06
Heated volumes (m^3)	1504.1	40178.4	6205.3	8609.8	20.7	51063.7	3902.0	2370.9
Number of floor (number)	2.0	8.0	1.6	4.0	1.0	8.0	1.2	2.3
Perimeter (m)	49.2	348.8	46.9	107.6	9.9	498.9	41.0	66.2
S/V_{real} (m^{-1})	0.3	0.7	0.0	0.5	0.3	2.3	0.3	0.9
Temperature (C^o)	-0.3	12.8	4.2	6.8	-0.3	12.8	4.2	6.8
Building occupation ratio (%)	0.00	1.0	0.0	0.9	0.0	1.0	0.2	0.8
Installed power (kW)	50.0	1000.0	126.2	196.4	n.d.	n.d.	n.d.	n.d.
Nominal Input Variable	Least	Most	-	-	Least	Most	-	-
Period of construction	>1919 (1)	1961-1970 (84)	-	-	2001-2005 (82)	1946-1960 (1028)	-	-
Ground floor type	P (6)	R (135)	-	-	P (48)	R (2962)	-	-
Roof type	F (5)	G (160)	-	-	n.d.	n.d.	-	-

By using GIS tool, it became possible to represent how these variables distributed in the city of the case study. Figure 21 shows the urban block distribution according to the year of construction, ground floor type, and S/V. Among all the surveyed buildings, 82 % of the buildings characterized by the ground floor as a residential type and just 14% accounts for a commercial ground floor. Regarding the period of construction, 47 buildings were built in the category of age3: 1946-1960, accounting for 29%. While 84 buildings were built in age4: 1961-1970, accounting for 51%. This fact is very well proportionated with the reality of entire building stock and it means that the building stock is mostly characterized by buildings that constructed before the first Italian energy regulation. Figure 21 shows that the MFH typology is the most widely used, accounting for 68%, followed by TH and AB accounting for 16%. This fact shows that the single house as SFH is not connected to the DH network. The results of the multiple regression analysis will strongly depend on the sample of buildings analysed.

4.5 Results

In this section the outcomes of the regression analysis and the spatial distribution of the annual energy consumption discussed. The open source software for data mining, Rapid Miner 7.1, was employed, which has a visual environment for predictive analytics and data mining (RapidMiner Studio, 2016). Having an intuitive graphical user interface and no need for a specific programming language are main reasons that lead to select this tool for this research (D’Oca and Hong, 2015). Moreover, this tool is one the best open sources one in terms of technology and applicability basing on an XML internal process structure.

Additionally, the influence of every single variable on energy consumption was analysed. In Figure 22 the scatter plots for each of the variables concerning the daily space heating energy consumption indicated. As it is shown, there are correlations between the energy-use for space heating and some of the selected variables of buildings as the: perimeter, heated volume, installed power, and area. It must be remembered that in this analysis, not all the variables have been fully taken into account, for example, the level of buildings’ renovations and the adoption of renewable energy technologies; this can impact the dispersion of the results. Moreover, the results of this first analysis are influenced by the number of analysed buildings, for instance, each period of construction and each value of surface to volume ratio (S/V), the number of buildings is not the same; for example, the sample of buildings connected to the DH network mainly consists of big apartment blocks built in 1961-70.

Figure 21: Comparison between Sample of input data (165 buildings) on the left and the entire building stock (3608 buildings) in the right for ground floor and period of construction, and S/V respectively, source (Torabi Moghadam et al., 2018).

In Table 11 the value of the correlation coefficients between the daily heating energy consumption (kWh) and different single variables of the available sample of data is shown. Some correlations appear to be very rational and intuitive such as perimeter, surface, area, height, heated volume, installed power, occupation ratio, and air temperature. An interesting result is that some correlations seem to be controversial, taking into account basic thermophysical of buildings such as S/V ratio. Table 11 reports that the S/V ratio correlation is negatively correlated with space heating energy consumption. This fact is explained by the strong correlation between the variables heated volumes and S/V. Due to buildings geometry, high values of S/V are generally related to small buildings (e.g. semi-detached houses) with low energy consumptions, while small S/V values are related to big condominiums with higher energy consumptions. However, a positive correlation is expected between the S/V and the specific daily energy consumption (kWh/m^2 or kWh/m^3).

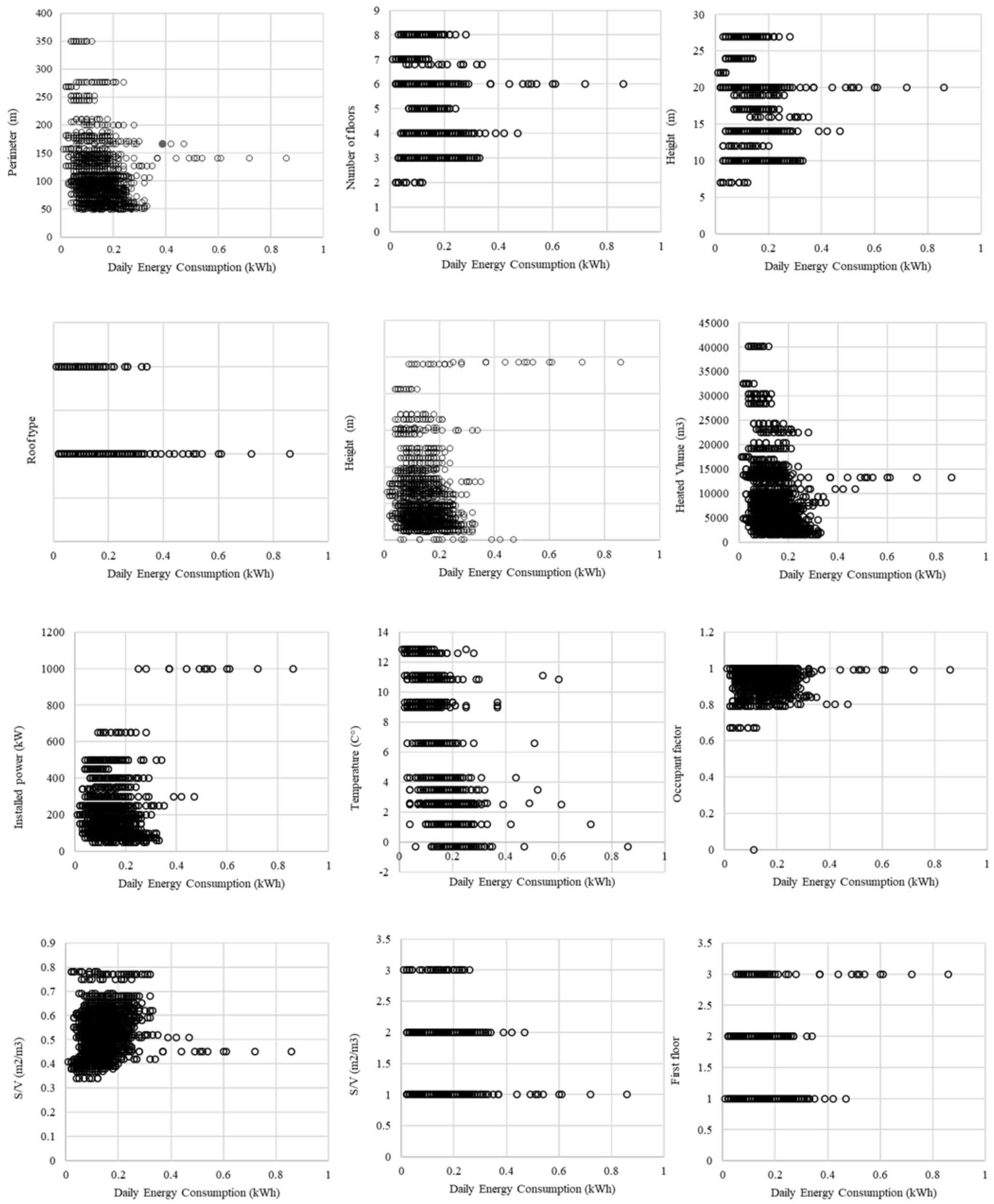


Figure 22: Scatter plot: DH energy consumption and variables, elaborated from (Torabi Moghadam et al., 2018).

Table 11: Correlations of the selected variables with energy consumption (kWh).

Attributes	**Daily Energy Consumption (kWh)**	**Association**
	Numerical Variables	
Installed power (kW)	0.789	Strong positive association
Dispersant Surface (m^2)	0.631	Strong positive association
Heated volumes (GIS) (m^3)	0.619	Strong positive association
Perimeter (m)	0.544	Strong positive association
Area (m^2)	0.541	Strong positive association
S/V_{real} (m^{-1})	- 0.528	Strong negative association
Eaves' height (m)	0.440	Weak positive association
Number of floors (number)	0.434	Weak positive association
Temperature (C°)	-0.383	Weak negative association
Buildings occupation ratio (%)	0.161	Weak positive association
	Non-Numerical Variables	
Ground -floor type R	-0.074	Weak negative association
Ground -floor type C	-0,057	Weak negative association
Ground-floor type P	0.261	Weak positive association
Roof type F	0.045	Little positive or no association
Roof type G	-0.045	Little negative or no association
Period 1:<1960	-0.009	Little negative or no association
Period 2:1961-80	0.003	Little positive or no association
Period 3:>1981	-0.019	Little negative or no association

The correlations of each of these variables on energy-use for space heating were analysed and MLR was modelled identifying the best coefficient of determination (R^2). The estimated coefficients, standard error, and p-values (the probability for a given statistical model) for energy consumption robust linear regression are shown in Table 12 (Model A) and Table 13 (Model B), respectively. All numerical predictors rejected strongly the null hypothesis for a value of ≤ 0.05 in which indicating that the estimated intensities are statistically significant (Howard et al., 2012).

Moreover, the code factor (*) directly is based on p-value; more stars mean the variable is more significant. In the following paragraphs, the predicted values derived from the model will be compared with the real data collected. Analyses of variance, known as the ANOVA, the F-statistic = 1132.478 (p-value < 0.0001), indicating the results of the regression model are satisfactory. The correlation coefficient between the predicted and monitored values, measured by the mean squared error (MSE) and squared correlation (R^2), are shown in Table 12 (Model A) and Table 13 (Model B). In the second model (B), the data about an installed power and the type of roof were excluded due to their unavailability for the entire building stock. As a result, the performance of the second model (B) was slightly diminished with respect to Model A. The coefficients of the regression equation for each variable seem to have the expected trend:

- The highest coefficient for the buildings that constructed in 1961-1980, they consume more energy and lower consumption for the older buildings due to their lower percentage of transparent envelope. and higher thickness of structure for the newer buildings due to their thermally insulated envelopes;
- A positive coefficient with gable roofs, as the dispersant surface and heated volume is greater with higher energy consumption;
- A negative coefficient for the commercial typology of the ground floor, as it is usually heated autonomously;
- A positive coefficient for the pilots, as the floor disperses more heat to the outside environment;
- A positive coefficient for bigger buildings, as the high heated volume, number of floors, and perimeter leads to higher energy consumption;
- A positive coefficient for the installed power of the heat exchanger as it depends on the dimensions and the level of energy efficiency of buildings;
- A negative coefficient for the outdoor air temperature, as with lower air temperatures the energy consumption increases;
- A positive coefficient for the occupation factor as the buildings consume more if they are utilized and occupied.

In Figure 23, it is possible to notice the good correlation of the models and the correspondence between measured and predicted annual energy consumption. The colours of the points indicate the heated volumes of the buildings and it is shown that the model does not work for massive buildings. The coefficients of determination R^2 for the two models are of 0.84 and 0.80, meaning a high-performance correlation even without the installed power and the type of roof variables. The precision of a model depends on the availability and the accuracy of data and, mostly, on the typology of the data sample.

Table 12: Linear regression results considering all the influencing variables, considering installed power and the roof type (Model A).

X-Validation				
Attribute	Coef.	Std.error	t-stat	p-value
Period of construction (< 1960)	-24.32	17.29	-1.41	0.159
Period of construction (1981)	4.87	27.96	0.17	0.861

Roof type F	-203.95	57.04	-3.58	3.58E-04****
Roof type G	-	-	-	-
Ground floor R	-14.57	21.25	-0.69	0.493
Ground floor C	-54.28	22.97	-2.36	0.018**
Ground floor P	68.70	49.14	1.40	0.162
Perimeter (m)	2.29	0.29	7.86	6.11E-15****
Number of floor (Eaves)	54.82	5.78	9.49	0****
Heated volumes-GIS (m^3)	0.04	0.00	13.03	0****
Installed power (kW)	1.77	0.12	14.45	0****
Monthly average temperatures (C°)	-63.61	1.86	-34.15	0****
Occupation factor	812.97	134.05	6.06	1.57E-09****
(Intercept)	-430.42	Infinity	0.00	1
Performances	RMSE: 217.598 +/- 22.885			
	R^2: 0.830 +/- 0.036			
Validation				
Attribute	Coef.	Std.error	t-stat	p-value
Period of construction <1960	-31.39	20.48	-1.53	0.125
Period of construction 1981	9.50	33.09	0.29	0.773
Roof type F	-	-	-	-
Roof type G	226.09	59.66	3.79	1.57E-04 ****
Ground floor type R	-14.26	25.53	-0.56	0.576
Ground floor type C	-55.13	27.28	-2.02	0.043**
Ground floor type P	69.42	62.74	1.11	0.268
Perimeter (m)	3.03	0.36	8.48	0****
Number of floor (Eaves)	76.98	6.95	11.08	0****
Heated volumes-GIS (m^3)	0.03	0.00	7.39	2.28E-13****
Installed power (kW)	1.87	0.15	12.91	0****
Monthly average temperatures (C°)	-63.96	2.20	-29.11	0****
Occupation factor	865.81	154.45	5.61	2.43E-08****
(Intercept)	-790.88	Infinity	0.00	1
Performances	RMSE: 207.798 +/- 0.000			
	R^2: 0.835			

*Signific.code:<0.5; ** Signific.code:<0.01; ***Signific.code:<0.001.

Table 13: Linear regressions considering the influencing variables that are expandable at the urban scale, removing installed power and the roof type (Model B).

X-Validation				
Attribute	Coef.	Std.error	t-stat	p-value
Period of construction (< 1960)	15.86	17.77	0.89	0.372
Period of construction (1961–1980)	17.74	16.81	1.06	0.291
Period of construction (> 1981)	-33.19	28.71	-1.16	0.247
Ground floor type C	-25.88	23.58	-1.10	0.272
Ground floor type P	27.00	50.03	0.54	0.589
Perimeter (m)	5.77	0.29	19.73	00****
Number of floor (Eaves)	108.43	5.85	18.54	0****
Heated volumes-GIS (m^3)	0.03	0.00	9.97	0****
Monthly average temperatures (C°)	-63.34	1.91	-33.11	0****

Occupation factor	885.29	137.48	6.44	1.49E-10****
(Intercept)	-776.06	Infinity	0.00	1
Performances	RMSE: 234.668 +/- 28.713			
	R^2: 0.803 +/- 0.058			
Validation				
Attribute	Coef.	Std.error	t-stat	p-value
Period of construction (< 1960)	10.24	19.23	0.53	0.59
Period of construction (1961–1980)	18.11	18.19	0.99	0.32
Period of construction (> 1981)	-28.38	31.22	-0.90	0.36
Ground floor type C	-28.45	25.28	-1.12	0.26
Ground floor type P	23.4	57.90	0.40	0.68
Perimeter (m)	6.44	0.33	19.25	0****
Number of floor (Eaves)	126.62	6.42	19.69	0****
Heated volumes-GIS (m^3)	0.021	0.00	6.15	9.06E-10****
Monthly average temperatures (C°)	-63.52	2.05	-30.96	0****
Occupation factor	917.00	146.48	6.25	4.79E-10****
(Intercept)	-873.41	Infinity	0.53	1
Performances	RMSE: 216.811 +/- 0.000			
	R^2: 0.826			

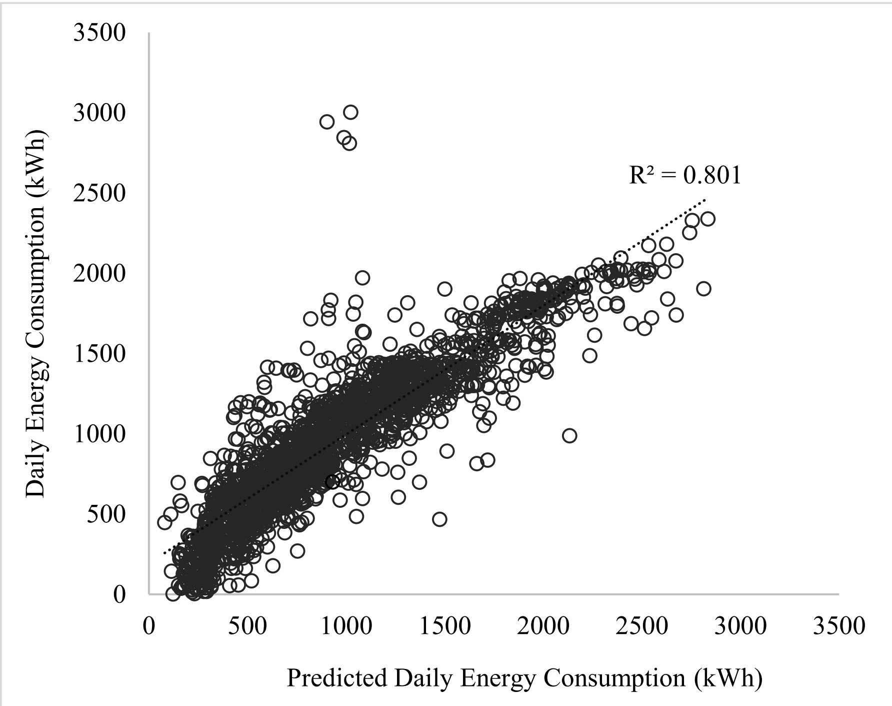


Figure 23: The comparison between the predicted the real energy consumption (kWh), removing installed power and the roof type (Model B).

Finally, applying the energy regression model to the entire building stock area in Settimo Torinese, through the GIS framework, the energy consumption spatial distribution was represented, creating a visual map. The total annual energy consumption (kWh/m^3) for each individual building is shown in Figure 24. Moreover, this fact leads to identify, in which neighbourhoods the energy consumption is mostly concentrated (Caputo et al., 2013a). Since the sample dataset includes the heated volume greater than 1500 m^3 (Table 10), the volumes of the building less than this value were excluded (grey polygons). The results show that the residential buildings constructed before 1980 have a mean annual energy consumption of 27.47 kWh/m^3. Indeed, the buildings located in historical city Centre are one of the largest annual energy consumers as it is shown by the dark colours on the map (about 47.70 kWh/m^3). Those constructed after 2005, show a decrease in the heating energy consumption of 10%.

Figure 24: Urban energy map (2D and 3D); energy consumption for space heating (kWh/m^3/y), source (Torabi Moghadam et al., 2018).

4.6 Concluding remarks

Urban energy efficiency plays a crucial role in the implementation of energy policies in the context of low-carbon cities and smart cities. The research illustrated in this chapter of Ph.D. work demonstrates that urban actors (e.g. energy planners, local and public administrators and other stakeholders) can be supported by an appropriate urban scale energy consumption model in delivering the most effective strategies. The whole procedure was successfully tested at the city level for Settimo Torinese and validated. Given available data, the proposed methodology can be applied to any similar city and also to other kinds of energy usage (e.g., electricity, cooling). Analysis of the available data regarding the existing building stock is vital to understand the solutions needed to increase energy efficiency or decrease gas emissions in the construction sector.

This methodological approach was proposed in order to specify the energy consumption for space heating of a residential building stock at the urban scale. A framework combines statistical analysis with GIS-based techniques to identify the most appropriate variables influencing energy consumption, using detailed measured building data. Moreover, GIS tools were used to support both the geometrical building stock characterization and the energy assessment process. The MLR analysis applied in this study has highlighted the variables most related to energy consumption, as follows: period of construction, heated volume, type of ground floor, occupation factor, air temperature, type of roof and the installed heating power. In case of unavailability of two variables such as the type of roof and the installed power, the model reaches a determination coefficient of 0.8, but only for buildings of a limited heated volume. Since the building stock is constituted mostly by large condominiums, the models have a higher margin of error on low volume buildings; for the same reason, this model should be utilized only for buildings connected to the district heating network. It is important to remember that the level of uncertainty for a model of this type is strongly dependent on the characteristics of the sample. Finally, this model makes it possible to evaluate an average consumption of residential buildings for space heating and it can be used to spatially distribute the energy demand, supply, and emissions at the urban/local scale.

This chapter has been submitted for publication to the journal of "Applied Energy" and is presently under review. Minor grammatical changes have been made to integrate the articles within this dissertation. Moreover, this chapter is conducted as part of the Ph.D. candidate exchange work at LESO-PB Lab at EPFL university.

Paper 13. S. Torabi Moghadam, S. Coccolo, G. Mutani, P. Lombardi, J.L. Scartezzini, D. Mauree. A new clustering and visualization method to evaluate urban energy planning scenarios. Journal of Applied Energy.

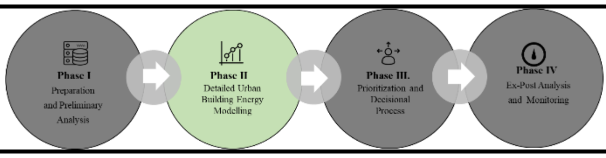
Chapter 5

Building Energy Retrofitting Modelling: Simulation Using Engineering-Archetype Technique

5.1 Introduction

Actually, the simulation of entire buildings of the city is very time-consuming. Therefore, the time-consuming process of the entire process needs to be resolved. Hence, this chapter represents an innovative method to simulate the future energy consumption of urban areas after certain retrofitting by using a simplified 3D model, designed as for function of the city urban characteristics. Into this, an archetype urban area representative of a full city. This chapter belongs to Phase II that was non-negligible step to be integrated into the proposed methodology to perform different future energy saving scenarios at the urban scale regarding different retrofitting solutions. It should be noted that this chapter is conducted to gain the percentages of energy saving affected by various energy retrofitting solutions. These energy percentages will be implemented into the new MC-SDSS tool. The chapter is organized as follows. Section 5.2 presents a general engineering modelling procedure. Section 5.3 is dedicated to illustrating the modelling framework. Section 5.4 describes how the archetype district is constructed and give a detailed overview of the energy model used in the study case. In section 5.5, the results will be discussed in detail to demonstrate the robustness of the solution and decision-support maps are also provided. In conclusion, some concluding remarks are given. For schematic summary of this chapter refer to Table 14.

Table 14: Schematic summary of chapter 4: Phase II.



Research limitation	**Research question**	**Addressing question**	**Related publications**
The difficulty of the entire city simulation due to the time-consuming and the need of very detailed building physics data.	How to model the energy consumption at urban scale in a spatial way for the current and future scenarios? Which kind of data are needed? How to connect different data type from different and scattered sources?	Creating the archetype of a city and applying the GIS-engineering method to create the future scenarios.	[Paper 13] A new clustering and visualization method to evaluate urban energy planning scenarios.

5.2 GIS-engineering model

The development of tools or methodology for the planning of more sustainable cities is necessary if we want to address multiple objectives at the same time. One of the major problems in the evaluation of urban planning scenarios is the computational time. Besides this, construction and geometrical data are needed as input for the models and are very difficult to obtain. As mentioned in section 2, while several statistical and engineering building stock models have already been developed at city scale (Torabi Moghadam et al., 2016c), only a few GIS-statistical-engineering combination models are currently available (Nouvel et al., 2015). This fact compares two methods for obtaining a more robust prediction of the urban energy consumption. Moreover, the integration of these two approaches with GIS raises the opportunity to identify the high energy use hot-spots and make the better decisions. The present chapter combines both the statistical and engineering approaches to obtain a more robust prediction of the urban energy consumption.

Moreover, the integration of these two methods with GIS demonstrates the opportunity to identify the high energy use hot-spots and make the better spatial decisions. The novelty of the proposed methodology lies in its simplicity and applicability. The framework is performed in order to reduce time-consuming processes of energy demand simulation, assessment and for designing urban energy saving scenarios. In this research, a methodology according to Ratti et al. (2003) and Salat (2011) to define a model, of the medium-sized city of Settimo Torinese, that would be representative of the urban form and characteristics is proposed. Then the energy consumption with a deterministic model based on the period of construction and compared the results using monitored data and with energy consumption from a statistical method is evaluated. Finally, two sets of renovation scenarios were assessed, and the energy consumption was also integrated within the GIS database and used for visualization and decision-making processes. It is very important to emphasize that the target of this chapter is to implement the result of these simulations as an input of MC-SDSS tool of the next chapters (6 and 7).

5.3 Modelling framework

As is shown in Figure 25, the proposed framework integrates an engineering simulation model based on 3D city models performed for an archetype of the city to simulate the saving scenarios after retrofitting. In Figure 25 the yellow part belongs to Phase I, which is completely presented in chapter 4. It is recalled to ease the understanding of the integration steps. The blue part of chart belongs to Phase II and it is illustrating how an engineering method is integrated into the proposed methodology. The software of CitySim (Robinson, 2012) was employed to simulate and model the energy consumption of the archetype of residential buildings in Settimo Torinese. The required data consists of physical properties of energy systems according to the buildings period of construction based on (TABULA, 2012).

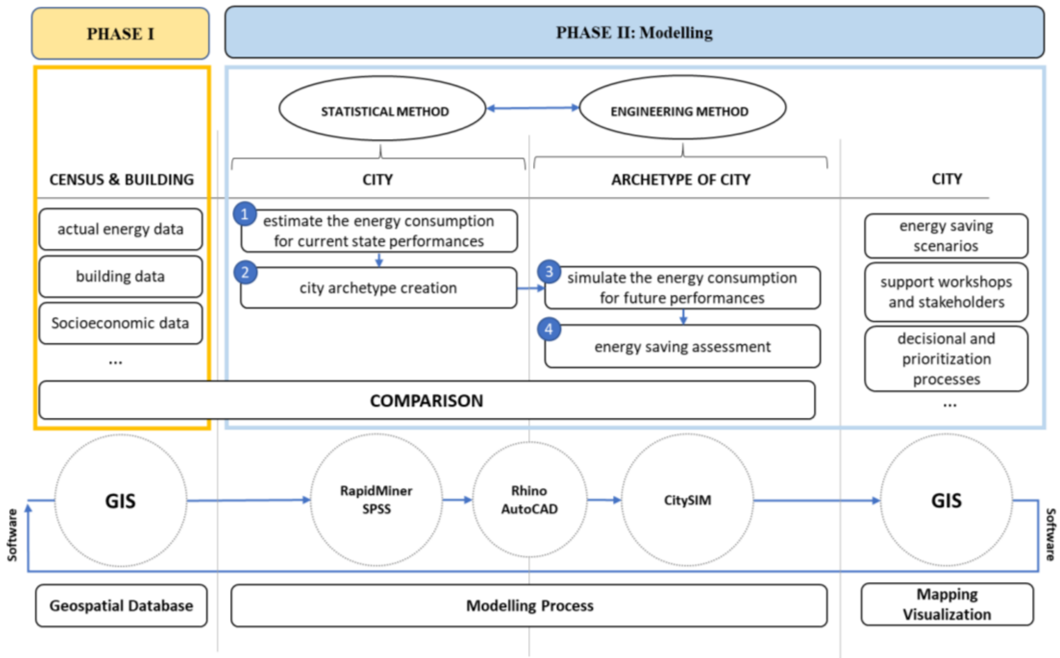


Figure 25: Flowchart of the multi-scale framework to support energy saving scenarios.

5.4 Engineering heating energy consumption modelling

The methodology illustrated in chapter 4 provides the current energy performance of the entire building stock at the city level; however, the methodology should also be able to support decision making about future energy planning (Caputo et al., 2013b). In this context, a further effort was made to perform an analysis of different future scenarios using an engineering method. Figure 26 pictures the methodology that will be used to evaluate the energy consumption and how they will be used to evaluate renovation scenarios. The heating energy consumption modelling method presented in this work is based on 3D-city models. The urban energy modelling tool CitySim was employed to simulate the energy consumption of the proposed archetype, representing the city of Settimo Torinese. Further, the archetype of the city to predict the energy-saving potential of buildings at the city scale, by applying several refurbishment scenarios, as it is explained in the following sections is used.

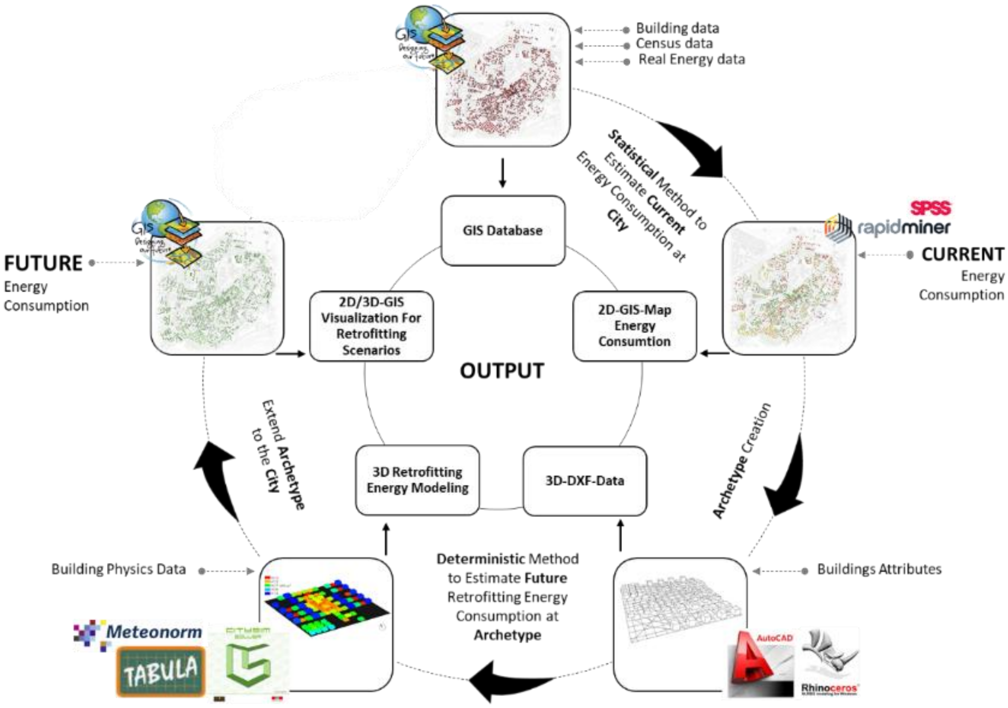


Figure 26: Flowchart describing the methodology used to create and use the archetype for energy demand simulation.

5.4.1 Modelling an archetype city

Defining an archetype urban area representative of a full city is quite a tedious task. To do this, one has to consider the geometrical characteristics of the buildings, the age of the buildings and also their physical properties. In order to create a 3D geometrical model, which is able to scale and fully describe the energy and micro-climatic behaviour of the city of Settimo Torinese, analyses are started from the available archetype, as presented by Ratti (2003). As a first step, the city is divided into its three main zones based on their geometrical and urban characterizations: Fiat Village (semi-suburban area), Campidoglio Square (transformation area) and Historical Centre (consolidate area) (see Figure 27). Moreover, Figure 28 shows the dominant period of construction of the buildings of Settimo Torinese, which latter helps in determining the energy consumption simulations outcomes.

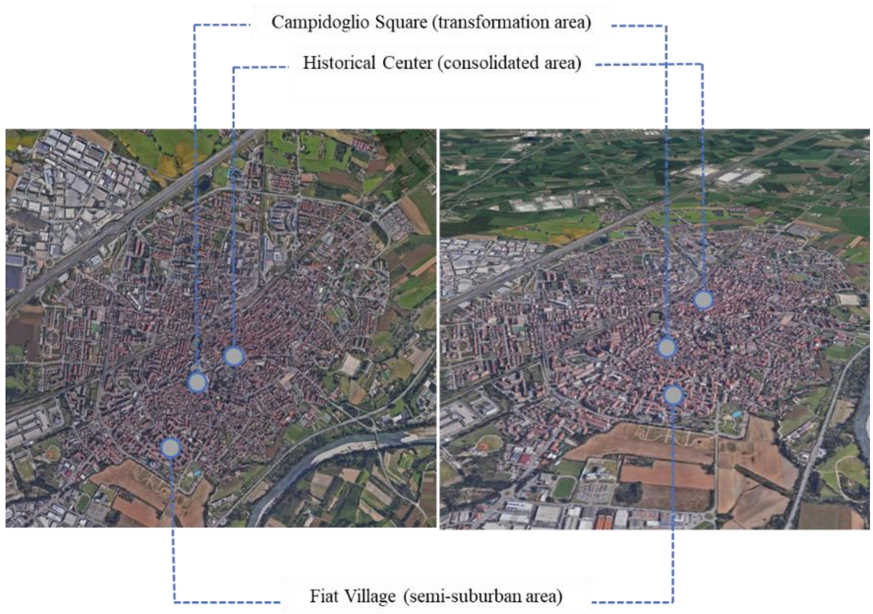


Figure 27: Aerial and 3D view of the city of Settimo Torinese, Source Google maps.

Figure 28: Building age map[3].

[3] According to the Italian national classification, the period of construction is divided into seven classes: C1= 1900-1918; C2= 1919-1945; C3= 1946-1960; C4= 1961-1970; C5= 1971-1990; C6= 1991-2005; C7= 2006-ongoing.

Next, an attempt is made to correlate the archetypes to the city of Settimo Torinese, looking for the “typical” urban form, according to the existing tissue. The second step considers the real city; indeed, the use of archetype was not completely representing the city, as the city is characterized by several urban typologies (e.g. the city centre and the Fiat district). In order to overcome this problem, the typical urban typology for the city of Settimo Torinese is created. By analysing the geometrical characteristics of the city, a new methodology to “prototype” the entire city is provided. In order to do so, the city is subdivided into 22 concentric sections (each 400 m), starting from the city centre (see Figure 29). Each section is then analysed, defining the average height of buildings, their length as well as the width of the street. Based on the data previously calculated, the new urban archetype of the city, as visible is defined in Figure 30.

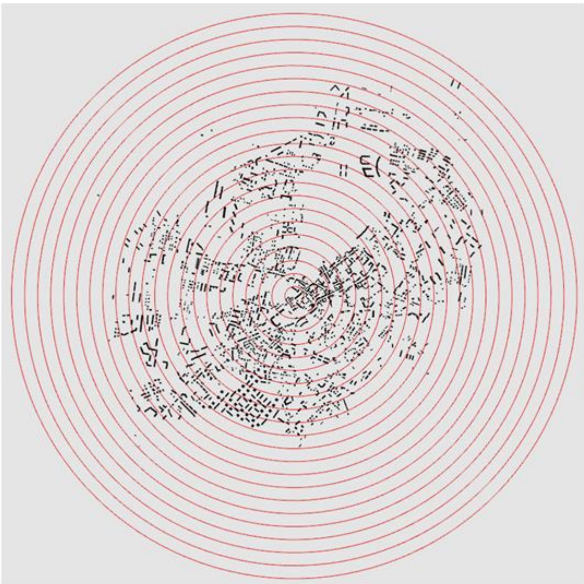


Figure 29: Superposition of the concentric circles, starting from the city centre.

The obtained archetype is composed of 87 buildings (see Figure 30) with their height corresponding to the average height of each concentric layer, as well as the distance between the buildings. With the use of the proposed methodology, the number of buildings from 3600 to 87 were reduced, considerably impacting the time required for the simulations. Table 15 illustrates the surface information of differ components of the defined archetype.

Table 15: Main geometrical characteristics of archetype.

Total Surface	**Floor** m^2	**Roof** m^2	**Windows buildings 1901-1920** m^2	**Windows buildings >1920** m^2	**Wall buildings 1901-1920** m^2	**Wall for buildings >1920** m^2
	2971	2971	16536	37206	66144	45474

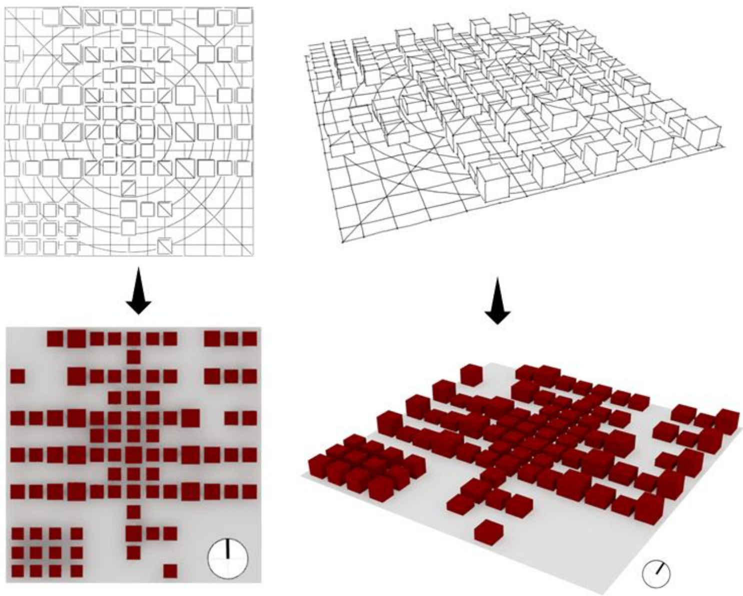


Figure 30: The proposed archetype composed of representative buildings. Plan (left) and 3D view (right).

5.4.2 Required input data

A 3D-city model is extracted from the 2D-ArcGIS database. Afterwards, the file is imported in Rhinoceros to make the 3D model with all associated buildings attributes. Finally, the Rhinoceros model is imported in CitySim. All thermostatic characteristics of the building envelope system are from Tabula (2012), which is an exhaustive dataset of building physics parameters, energy systems, and building use. This helps to refine the urban thermal model and improve the result accuracy. Nevertheless, it is possible to create a model based on a minimum set of building attributes data: building usage and building year (or age class). As reported by Nouvel et al. (2015), these characteristics are necessary to collect realistic building physics parameters from the building libraries Although the renovation ratio is not essential to start the energy analysis, they are valuable data that will be used consequently. These information impact significantly the precision of the heat demand and energy saving scenarios (Nouvel et al., 2015).

5.4.3 Urban energy simulations model

As mentioned before, the energy simulations were performed with the CitySim software (Robinson, 2012), an urban energy modelling tool able to quantify the energy demand and the urban microclimate, from the building to the city scale. Seven models were designed, as a function of the buildings period of construction, as presented in Table 16. All the physical properties of the buildings are based on the Tabula project (2012), assuming a typical construction typology per each period of construction: Single-Family House (SFH), Terraced House (TH), Multi-Family House (MFH) and Apartment Block (AB). Based on the typology, the physical properties are retrieved from the web Tabula tool (2012), and the envelopes are then calculated with Lesosai (2017) based on the available materials and the final U-value of the elements. Table 17 shows, as an example, the physical properties of the walls built during the first phase of construction, as calculated with Lesosai. Each composite of the envelope is defined, assuming its physical properties: thickness (m), conductivity (W $m^{-1} K^{-1}$), density (kg m^{-3}) and specific heat (J $kg^{-1}K^{-1}$).

Table 16: Physical characteristics of buildings per each period of construction, source (Tabula, 2012)

Cluster	Period of construction	Type	Wall (W/m^2K)	Roof (W/m^2K)	Floor (W/m^2K)	Windows (W/m^2K)
1	Before 1919	TH	1.61	1.80	2.00	4.90
2	1919 -1945	SFH	1.48	1.80	2.00	4.90
3	1946-1960	SFH	1.48	2.20	2.00	4.90
4	1961-1970	MFH	1.15	1.10	0.94	4.90
5	1971-1990	MFH	0.8	0.75	0.98	3.70
6	1991-2005	MFH	0.59	0.57	0.77	2.20
7	Since 2006	TH	0.34	0.28	0.33	2.20

Table 17: Composition of the envelope, wall. Period of construction before 1919, Terraced house (according to TABULA)

Element	Conductivity (W/mK)	Density (kg/m^3)	Specific heat (J/ kgK)
Gypsum Plaster	0.21	900	850
Stone and mortar masonry	1.00	800	1045
Gypsum Plaster	0.41	900	850

The windows ratio of each facade is defined as a fluctuation of the period of construction, ranging from 0.20 for buildings constructed between 1901-1920 to 0.45 for the newest ones. The internal temperature is set up at 20° C, as required by the current standards for residential buildings. The internal gains are defined considering both the occupants and the appliances, according to the Swiss normative SIA 2024 (SIA, 2006). Both occupants and appliances are defined, as a function of the liveable surface area in the buildings, as well as the hourly daily profile (SIA, 2006). The infiltration rate of the buildings is defined assuming an average winter Air Change per Hours (ACH) as a function of the tightness of the envelope construction (Younes et al., 2012). A tight envelope has an average ACH of 0.2-0.6, a loose one of 1.0 to 2.0.

In order to compare the results obtained with CitySim with the monitoring data from the city of Settimo Torinese, a new meteorological file including the monitored data of the year 2014-2015 is created (see Figure 31) for the closest ARPA weather station of Brandizzo at the same altitude of Settimo Torinese. The new climatic file is based on the Typical Meteorological Year (TMY), as created by Meteonorm (Younes et al., 2012) by considering the hourly trend of outside air temperature but with the same average, maximum and minimum monitored monthly temperatures. During the heating season from October 15th to April 15th, it is interesting to notice that the monthly average air temperature varies from -1.3 to +10.7 °C on the yearly average of 13.3 °C, consequently impacting the buildings space heating energy consumption. During the winter season, due to the urban microclimate, the average air monthly temperature is 2.6 °C lower during the month of January, with a minimum hourly temperature of -4.9 °C.

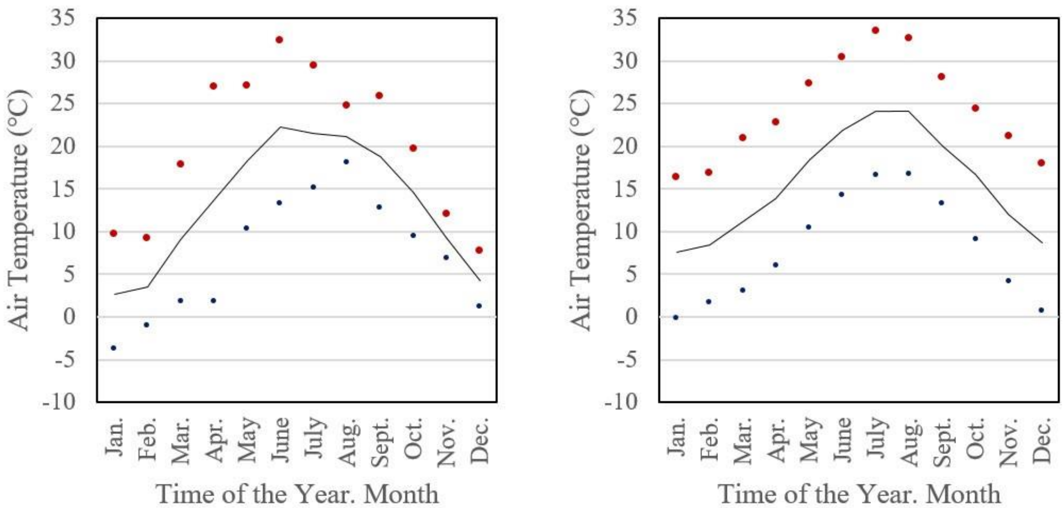


Figure 31: Meteorological data for the city of Settimo Torinese. Typical Meteorological Year from Meteonorm (left) and monitoring data (right).

5.4.4 Urban energy simulations, refurbishment scenarios

In order to understand the impact of the buildings envelope on their energy demand, as a function of the period of construction, ten main refurbishments are proposed, based on the current city and presented in Figure 32.

- **Case study a1**: improvement of the floors thermal insulation, according to the standard refurbishment, as defined by Tabula. This refurbishment varies per each period of construction.
- **Case study a2**: improvement of the roofs thermal insulation, according to the standard refurbishment, as defined by Tabula. This refurbishment varies per each period of construction;
- **Case study a3**: improvement of the walls thermal insulation, according to the standard refurbishment, as defined by Tabula. This refurbishment varies per each period of construction;
- **Case study a4**: improvement of the glazing thermal performance, replacing the current glazing as required by Tabula. This refurbishment varies per each period of construction;
- **Case study global a**: complete refurbishment of the site, by addressing the previous points (case studies from a1 to a4). This refurbishment varies per each period of construction;
- **Case study b1**: improvement of the floors thermal insulation, by adding 0.35 m of EPS insulation;
- **Case study b2**: improvement of the roofs thermal insulation, by adding 0.35 m of EPS insulation;
- **Case study b3**: improvement of the walls thermal insulation, by adding 0.35 m of EPS insulation;
- **Case study b4**: improvement of the glazing thermal performance, replacing the current glazing with triple glazing (U-value equals to 0.7 W $m^{-2}K^{-1}$).
- **Case study global b**: complete refurbishment of the site, by addressing the previous points (case studies from b1 to b4).

All the physical properties of the refurbished envelope, according to Tabula, are expressed in Table 18 and Table 19. More detailed thermo-physical properties of the case studies envelope system are attached in Appendix A.

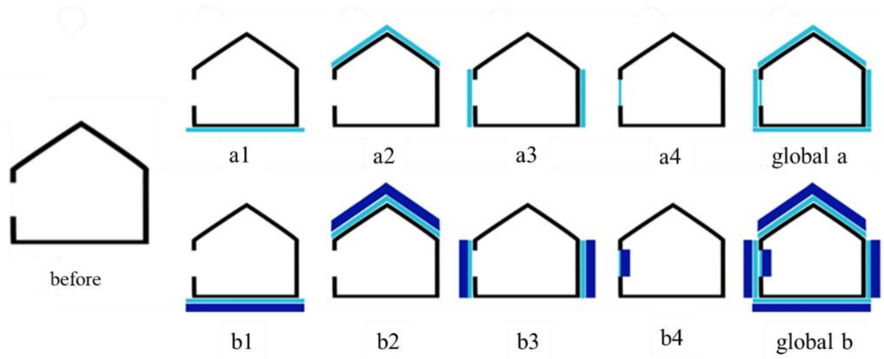


Figure 32: Schematic schemes of the case studies performed.

The thickness of the insulation required in case studies b1 to b4 is 35 cm. It is defined by the Swiss Minergie-P Label and corresponds to a zero-energy building. This value is derived from the characteristic curve of heat loss with respect to the insulation's thickness and which considers that an insulation with a thickness above 35cm does not bring any additional significant protection to the element.

Table 18: Standard refurbishment according to Tabula, per each period of construction. Roof and Wall.

Cluster	Period of construction	Type	Roof. Thickness (m)	Roof. U-value (W/m^{2}K)	Wall. Thickness (m)	Wall. U-value (W/m^{2}K)
1	Before 1919	TH	0.10	0.30	0.11	0.32
2	1919-1945	SFH	0.11	0.30	0.09	0.34
3	1946-1960	SFH	0.12	0.29	0.09	0.34
4	1961-1970	MFH	0.11	0.27	0.09	0.32
5	1971-1990	MFH	0.10	0.26	0.07	0.33
6	1991-2005	MFH	0.08	0.27	0.06	0.31
7	Since 2006	TH	-	0.22	-	0.27

Table 19: Standard refurbishment according to Tabula, per each period of construction. Floor and windows.

Cluster	Period of construction	Type	Floor. Thickness (m)	Floor. U-value (W/m^{2}K)	Windows. U-value (W/m^{2}K)
1	Before 1919	TH	0.11	0.31	2.00
2	1919-1945	SFH	0.11	0.31	2.00
3	1946-1960	SFH	0.11	0.31	2.00
4	1961-1970	MFH	0.11	0.26	2.00
5	1971-1990	MFH	0.10	0.28	2.00
6	1991-2005	MFH	0.08	0.30	2.00
7	Since 2006	TH	-	0.30	1.80

5.5 Results

Results obtained by the proposed methodology are then implemented into the GIS environment in order to visualize the impact of the refurbishment of the buildings, as well as the energy saving scenarios. The purpose was to produce a strong visualization tool through which maps become a 'visual index' to provide solutions to the urban actors with the aim of optimizing the renovations (Lotov et al., 1997); (Janssen and Herwijnen, 2007). As reported by Ascione et al. (2013). the quality of planning processes can be significantly improved when necessary information is efficiently handled and visualized In this sense, SDSS consisting of a tool devoted to support the decision processes in spatial urban energy problems is created (Chakhar and Martel, 2006); (Arciniegas et al., 2011). Moreover, it provides an interactive environment for performing effective visual activities (Chakhar, 2003) thanks to the visual interface, which enables exchanging of information between the user and the system to support the stakeholders through all decision phases (Malczewski, 1999). The proposed SDSS is able to visually support the stakeholders and DMs during different focus groups and workshops (Chakhar, 2003). Using GIS-based procedures helps to the stakeholders to express their preferences by visualizing their alternative scenarios, increasing trust in the results.

5.5.1 Urban energy simulations

The energy model was set up, and the results obtained with CitySim were compared to both with the monitoring data (realized during the years 2014-2015) and the Tabula database. results are compared for the periods 1946-1960, 1961-1970, 1971-1990 and 2005-2016 since they had a sufficiently large representation of monitored buildings. Indeed, the results were compared with more than 210 monitored buildings. Figure 33 summarizes the comparison of the data.

The relative difference was calculated as the difference between the results obtained with CitySim, and the averaged data from the monitoring and TABULA webtool. Indeed, as defined in the methodology, the input data required for the energy model are both defined based on the TABULA database (building characteristics) and on the monitored data (meteorological data). It can be highlighted that all the simulations stay below a 10% of the difference, showing the strength and consistency of the proposed archetype model. It can be noted that for the 1946-1960 period the modelling approach overestimates the energy consumption (by 6%) while with for the other periods there is a slight underestimation (-3% for 1961-1970, -8% for 1971-1990 and -4% for 2005-2016).

It can also be seen in Figure 33 and Table 20 that the deterministic model generally gave better results as compared to the statistical model.

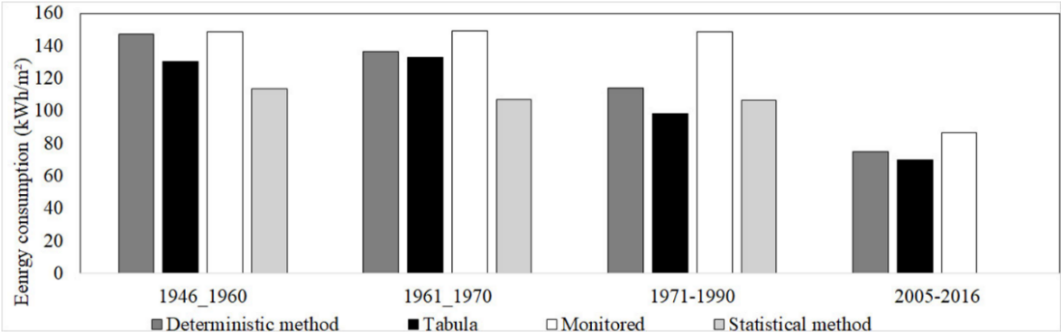
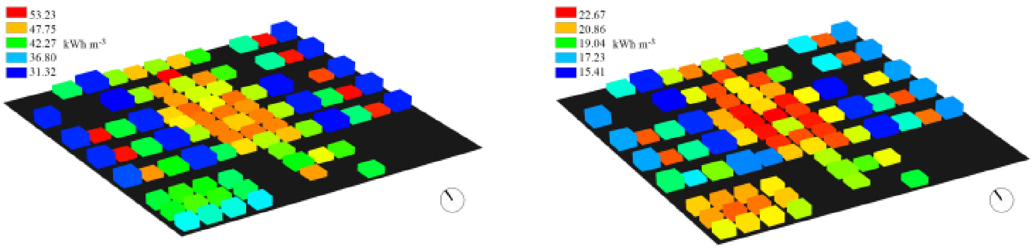


Figure 33: Comparison of the total consumption from measurements, Tabula and engineering models.

Table 20: Comparison between the heating demand computed by the proposed energy model, the monitoring data for the city of Settimo and the results from TABULA.

Period of Construction	CitySim (kWh/m^3)	TABULA (kWh/m)	Monitored (kWh/m^3)	Difference (%)
1946-1960	36.7	32.5	37.1	6
1961-1970	34.0	33.2	37.3	3
1971-1990	28.5	24.6	37.1	8
2005-2016	18.7	17.4	21.6	4

The annual energy demand required for heating, as defined by CitySim for each case study can be analysed for each period of construction. The maximal energy demand is required for buildings built before 1919, with an average demand of 158 kWh m^{-2}. The lower demand is for the ones built between 2005 and 2016, showing a reduction by 53% compared to the building of the first period of construction, with an average demand of 74 kWh m^{-2}. It is quite interesting to notice that the energy demand of the first two periods of construction is quite similar (difference by 1%), and it increases between the next periods of construction, with an average reduction by 7% between the periods 1919-1945, 1946-1960 and 1961-1970. The difference doubles during the next periods of construction (1971-1990, 1991-2005 and 2006-2016) by 14%, 15% and 23%, respectively. Finally, it is quite interesting to see the connection between the urban environment, the physical properties of the buildings, and their energy demand. Figure 34 shows the annual heating demand of the site, by assuming that all buildings are built during the first phase of construction (before 1919) and during the last one (2005-2016). Buildings realized during the last phase of construction present a lower energy demand compared to the previous phase, but their thermal behaviour is also directly related to the solar exposure: the higher is the sun exposition, the lower is their energy demand. By contrast, buildings built during the first phase are more impacted by their surface to volume ratio, consequently, the buildings with the higher demand are the ones that are less compact.



(a) Before 1919 (b) 2005-2016

Figure 34: Annual heating demand of the first period of construction (please note the difference in scale

Additionally, the results of the statistical method and with the deterministic model for the whole of the city were compared. The results are shown in Figure 35 As demonstrated previously with the comparison with the monitored and Tabula data, the deterministic model showed a better correspondence. The fact that the older buildings (and the less well insulated) are located in the city centre typically means that they have higher energy consumption. This can then be visualized with the map and distribution of buildings in the city.

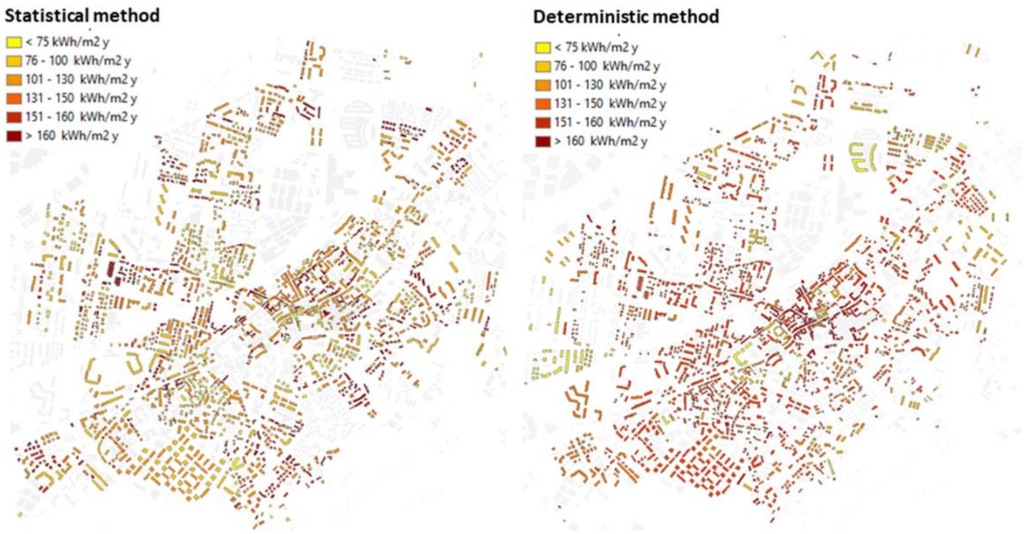


Figure 35: Statistical and deterministic method energy consumption maps.

5.5.2 Standard refurbishment scenarios

The simulations performed with CitySim underline the impact of the period of construction on the energy demand of buildings. Based on the previous results, two main refurbishments are proposed using the archetype presented in the methodology part. Firstly, a refurbishment according to the standard refurbishment presented by the Tabula and secondly according to the Minergie-P certification (advanced). Figure 36 shows that the energy demand of buildings is reduced following the renovation based on the Tabula recommendations. The refurbishment of vertical surfaces (walls and windows) are the elements that have the most impact on the demand. Naturally, the energy demand is lightly reduced thanks to the normal refurbishment, showing an average reduction of 60% for the entire site, and a lower one for the new buildings (by 30% on average for the site).

When looking at the impact of the single elements on the demand, it is quite interesting to notice that a similar refurbishment has a different impact according to the period of construction. As an example, replacing the existing windows with the new ones (with a U-value of 2.0 W $m^{-2}K^{-1}$) reduces significantly the demand (-19%) in buildings built before 1919 while it will only decrease the demand by 5% in buildings built between 1991 and 2005. This again highlights the importance of targeting the appropriate buildings and of tailoring the best possible renovation scenarios according to their specificities.

Table 21 demonstrates the percentages of each energy saving reduction and new clusters. Considering the very low variability in some period of constructions, buildings in C1 (built from 1900-1919) have been grouped together with C2 (1919–1945) and C3 (1946–1960). Thus, the total number of clusters has been reduced to 5.

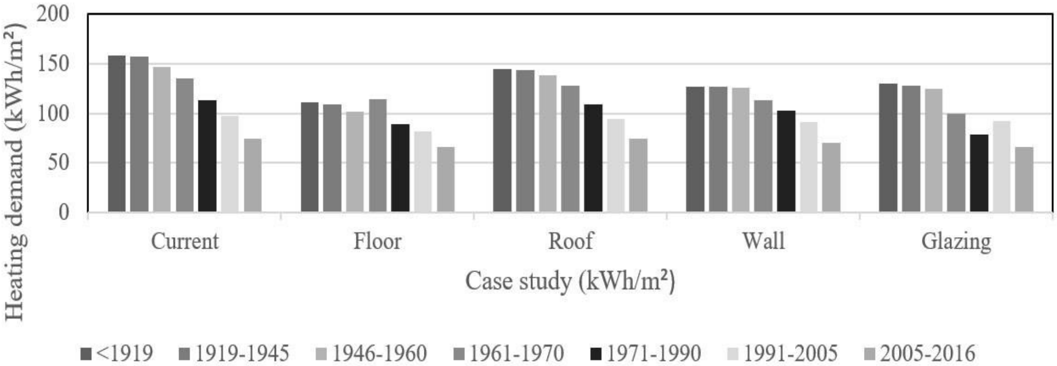


Figure 36: Heating demand following the TABULA standard renovation.

Table 21: Difference between the base and the refurbished case for each scenario.

Final Cluster	Refurbishment strategy	Heating demand (GWh)	Difference (%)
1	<1919	15.42	
	a1	10.78	30.09
	a2	14.11	8.50
	a3	12.37	19.78
	a4	12.61	18.22
	Complete refurbishment	3.7	76.01
	1919-1945	15.28	
	a1	10.64	30.37
	a2	13.96	8.64
	a3	12.37	19.04
	a4	12.47	18.39
	Complete refurbishment	3.7	75.79
	1946-1960	14.24	
	a1	9.92	30.34
	a2	13.42	5.76
	a3	12.24	14.04
	a4	12.11	14.96
	Complete refurbishment	3.75	73.67
2	1961-1970	13.18	
	a1	11.08	15.93
	a2	12.39	5.99
	a3	11.01	16.46
	a4	9.67	26.63
	Complete refurbishment	4.71	64.26

3	1971-1980/ 1981-1990	11.05	
	a1	8.65	21.72
	a2	10.64	3.71
	a3	10.03	9.23
	a4	7.6	31.22
	Complete refurbishment	3.95	64.25
4	1991-2000/ 2001-2005	9.46	
	a1	7.94	16.07
	a2	9.17	3.07
	a3	8.86	6.34
	a4	9.02	4.65
	Complete refurbishment	6.63	29.92
5	>2005	7.25	
	a1	6.43	11.31
	a2	7.24	0.14
	a3	6.83	5.79
	a4	6.37	12.14
	Complete refurbishment	5.14	29.10

The second refurbishment follows the Minergie-P label. It is quite noteworthy to highlight that the refurbishment proposed are not linearly expressed (see Figure 37). As an example, the refurbishment of the floors according to the advanced Minergie-P label (adding 35cm of EPS insulation), implies a reduction of the heating demand by circa 35% during the first three periods of construction, but just by 20% in the period of construction 1961-1970. This is related to the physical properties of the envelope, which was more energy efficient compared to the other ones (with a U-value of 0.94 W $m^{-2}K^{-1}$), as well as its impact on the thermal behaviour of the buildings.

Additionally, it is important to notice that the maximal energy savings are obtained when refurbishing the walls (including opaque and transparent parts), reaching a reduction of around 60% in the periods 1961-1970 and 1971-1990. Indeed, it is during this period, due to the economic growth, that the constructions were built faster, with cheaper materials and without using the thermal mass as passive energy component in the thermal behaviour of buildings. Consequently, buildings of this period, are less energy efficient compared to the older ones. Although, this is the best refurbishment available on the market, but due to the physical characteristics of buildings, their historical value, as well as the economic impact, it is not always possible to apply this kind of renovation. Also, Table 22 shows the percentages value reduction for new clusters of buildings in terms of buildings age.

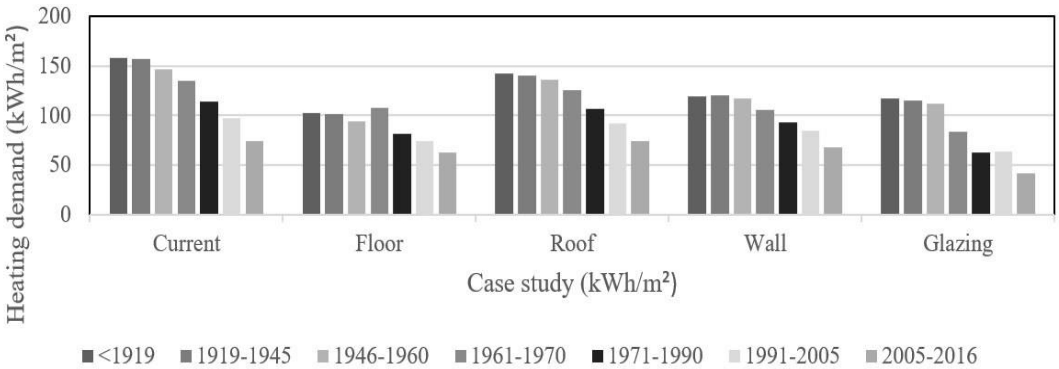


Figure 37: Heating demand following the Minergie-P renovation.

Table 22: Difference between the base and the refurbished case for each scenario.

Final Cluster	Refurbishment strategy	Heating demand (GWh)	Difference (%)
1	<1919	15.42	
	b1	10.02	35.02
	b2	13.84	10.25
	b3	11.66	24.38
	b4	11.37	26.26
	Complete refurbishment	1.18	92.35
	1919-1945	15.28	
	b1	9.89	35.27
	b2	13.69	10.41
	b3	11.66	23.69
	b4	11.22	26.57
	Complete refurbishment	1.18	92.28
	1946-1960	14.24	
	b1	9.14	35.81
	b2	13.2	7.30
	b3	11.37	20.15
	b4	10.87	23.67
	Complete refurbishment	1.15	91.92
2	1961-1970	13.18	
	b1	10.45	20.71
	b2	12.18	7.59
	b3	10.24	22.31
	b4	8.13	38.32
	Complete refurbishment	1.88	85.74
3	1971-1980/ 1981-1990	11.05	
	b1	7.95	28.05
	b2	10.43	5.61
	b3	9.01	18.46
	b4	6.09	44.89
	Complete refurbishment	1.19	89.23
4	1991-2000/ 2001-2005	9.46	
	b1	7.18	24.10

	b2	8.97	5.18
	b3	8.29	12.37
	b4	6.2	34.46
	Complete refurbishment	2.45	74.10
5	>2005	7.25	
	b1	6.11	15.72
	b2	7.24	0.14
	b3	6.64	8.41
	b4	4.01	44.69
	Complete refurbishment	2.41	66.76

5.6 Spatial distribution of building energy consumption through GIS visualization tool

Applying the energy consumption of archetypes to all of the building areas in Settimo Torinese produced the spatial distribution of building energy consumption this City. In this view, the output from the sets of archetypes simulation was used as inputs for the visualization of the data, updating GIS tool with the new building energy consumption values. The energy reduction, from the renovation of each building from a particular period of construction, was mapped back in the GIS environment, providing a complete dataset with the renovation scenarios. The results are visible by maps in which the energy consumption values are displayed with a colourful ramp to illustrate the main differences in the magnitude of consumption and its spatial variation (Figure 38 and Figure 39). The effects of the selected refurbishment solutions, improvement of the opaque and the transparent surfaces, were evaluated both separately and combined with the archetype carrying out 70 simulations (considering buildings age).

A spatial distribution of urban building energy consumption in 2D visualization provides a useful SDSS tool to facilitate the decision-making process and managing aspects. Additionally, Figure 40 illustrates an example of the 3D visualization that can be also available, where the stakeholders and DMs need to visualize the urban form in an intuitive way. Indeed, through the urban energy maps, it is instantly possible to visualize the impacts of both refurbishment solutions, Tabula and Minergie-P, on the energy consumption of each individual building. This fact eases the identification of the high energy consumption districts.

Figure 38: Heating demand Map following the Tabula renovation.

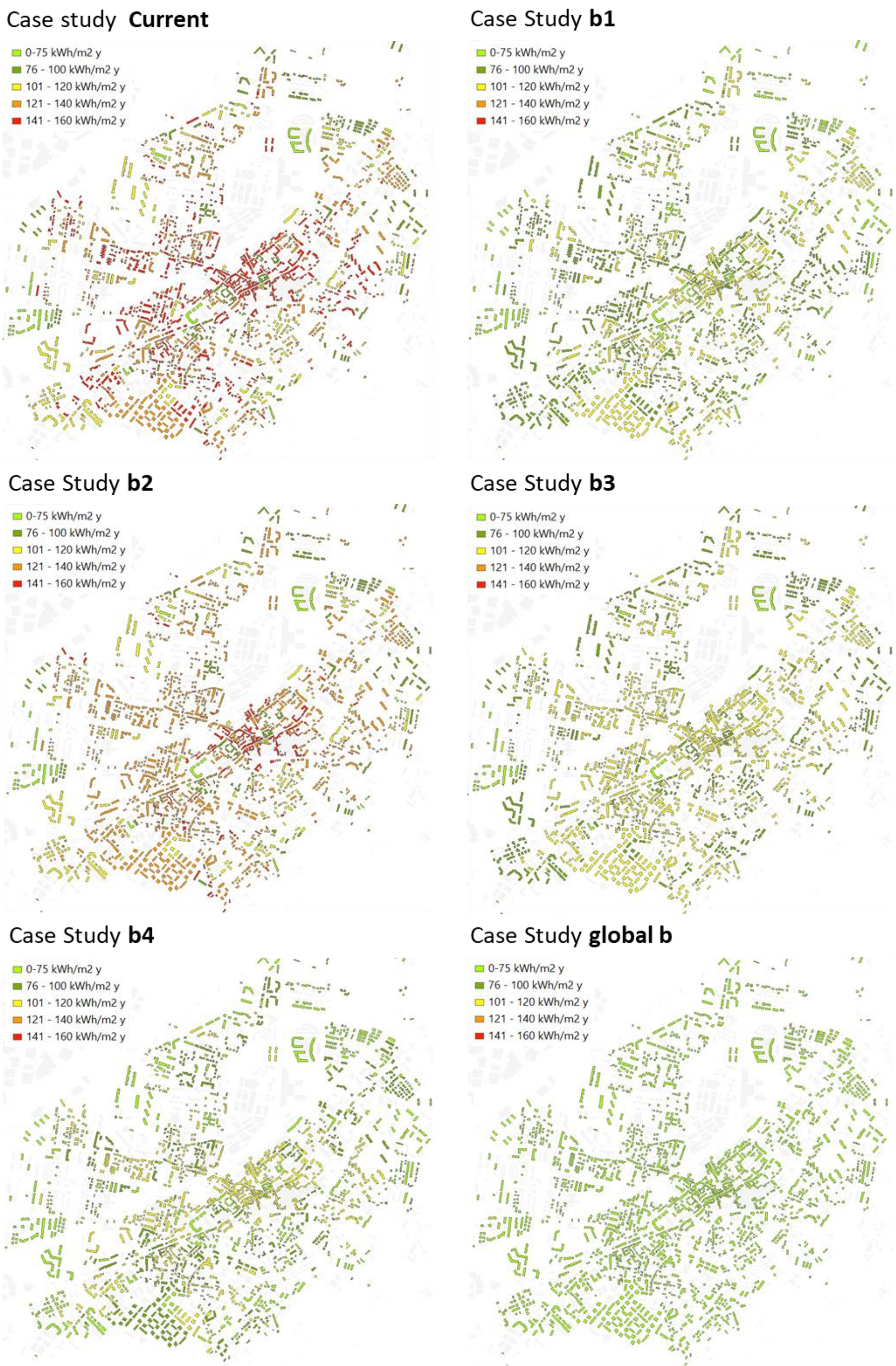


Figure 39: Heating demand Map following the Minergie-P renovation.

The principal concentration of space heating energy consumption is situated in the old city centre district. This difference is explained by the high presence of the buildings built before 1919 to 1960 in this area. From the visualization maps emerge that both case studies a2 and b2 in which the roofs are isolated are not effective enough; they just reduce energy consumption between 7% and 9%.

Contrary, case studies a1 and global (from Tabula), b1, b3, b4 and global (from Minergie-P) are very effective solutions to improve the energy performances. Comparing two performed solutions, Minegie-P solutions are more impressive while the Tabula renovations (e.g. case studies a3 and a4) cannot have an effective impact on the current energy consumption for these old buildings. These two case studies are still shown by red and orange coloured buildings that means the energy consumption is more than 120 kWh^{-2}. Moreover, maps show that the new buildings (after 2005) with lowest energy consumption at the current state of the city are mostly located in the Campidoglio Square neighborhood (transformation area) and suburban area. In the consequence, almost all the retrofitting solutions have no significant impacts on energy consumption reduction. Same as the old buildings, roof insulation is the worth scenarios for reducing the energy consumption of these buildings in the city of Settimo Torinese. This solution might be combined with other ones.

Fiat village is another main area in the city of the case study, which is characterized mostly by the buildings age from 1960 to 1970. Various solutions impact very differently on these buildings. Case studies a1, a3, b1 and b3 behave almost in the same way in terms of energy performances. Regarding the glazing replacement (case studies a4 and b4), the energy consumption reduced from the range of 120-140 kWh/m^2 (orange colour) to the range of 75-100 kWh/m^2 (green colour). Again, roof insulation (case studies a2 and b2) shows the minimum reduction for Fiat village buildings coloured orange. Intuitively, both global retrofitting energy solutions have the maximum energy reduction in all the maps. In the entire city, the total energy consumption diminishes rapidly.

Generally, regarding the standard Tabula renovation solutions, results demonstrate that case study a1 (floor insulation) lead to the most heating reduction of approximately 30% slightly behind the case study global refurbishment. Similar to the Tabula renovation, the results from the advanced Minergie-P scenarios, also showed that the floor insulation (case study b1) was the best energy saving scenario, reducing around 35%. The wall insulation and the windows substitution (case studies a3, a4, b3, and b4) are also one of the effective energy saving solutions as well as economic aspects. Especially Minergie-P solution shift the most of buildings to green colour. On the other hand, the worth scenarios are a2 and b2.

Figure 40: Example of the 3D maps of renovation solutions. (left) Glazing replacement solution from Tabula (right) Glazing replacement solution from Minergie-P.

5.7 Concluding remarks

Providing useful information to DMs (urban planners, municipalities or architects) can be a tedious task when designing more sustainable urban areas. On the one hand, statistical methods are often used to understand the driving parameters of energy consumption but rarely used to evaluate future urban renovation scenarios. On the other hand, the simulation of a complete city or urban area can be extensive in terms of computational resources, data acquisition and modelling.

In order to address these shortcomings, in the current chapter, a new methodology for defining an archetype urban area that would be representative of a medium-sized city has been proposed. The objective was to decrease the number of buildings that need to be simulated while at the same time keeping the same average geometrical and physical characteristics of these buildings. Simulations were performed for a full year using the CitySim software. It was demonstrated that the energy demand obtained using such a methodology was very close to the monitored energy consumption and using data from the TABULA database. Moreover, the simulations results obtained from this chapter (see section 5.5) were also compared using the results emerged from chapter 4 (see section 4.5), the statistical one.

After defining the archetype, multiple renovation scenarios according to TABULA and to the Minergie-P standard were developed. Both these simulation sets for the refurbishment was done with the CitySim software. The values obtained were also compared with previous studies and databases. Finally, the simulated scenarios were integrated into a GIS to provide a powerful visualization tool for the renovation of a medium-sized city. As shown in this chapter there were some differences between the engineering methods result and the statistical ones in chapter 4.

It should nevertheless be highlighted that the method that has been proposed here can be generalized very easily as limited geometrical information was needed to perform the simulation. These types of tools could be used at an early design stage or during the evaluation of urban planning scenarios. Further research will be illustrated in the next chapters (6 and 7) for improving this framework by taking into account additional criteria (e.g., socio-economic, environmental) in order to create a MC-SDSS. This will allow the development of future low-carbon cities scenarios.

Part of the work described in this chapter was previously published in the following publication. Minor grammatical changes have been made to integrate the articles within this dissertation.

Paper 4. P. Lombardi, F. Abastante, S. Torabi Moghadam, J. Toniolo. (2017). Multicriteria Spatial Decision Support Systems for Future Urban Energy Retrofitting Scenarios. Sustainability, vol. 9, n. 7. pp. 1-13. ISSN 2071. doi: 1050, 10.3390/su9071252.

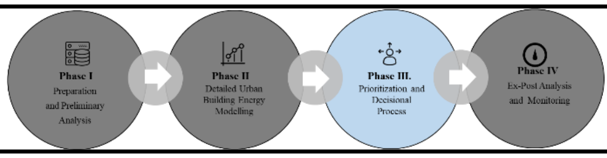
Chapter 6

Identification of Evaluation Criteria for Multi Criteria Spatial Decision Support System (MC-SDSS)

6.1 Introduction

This chapter aims at defining the evaluation criteria based on the real stakeholders' preferences and their conflicting objectives. Section 6.2 introduces, therefore, the selection process starting from the pre-selection of the criteria set and how these criteria will be then definitively selected and implemented into the MC-SDSS tool. The set of evaluation criteria for this work are chosen based on the specific case study and its needs. However, it can be generalized the methodology at other similar case studies considering their particularities. Section 6.3 shows the results of the first organized workshop in which the selection procedure is applied and the evaluation criteria are selected by using "Playing Card" (Simos, 1990) due to its intuitive nature. Afterward, the impact assessment is performed in section 6.4 for the selected criteria. Finally, the chapter will end by highlighting its concluding remarks (see section 6.5). For a schematic summary of this chapter refer to Table 23.

Table 23: Schematic summary of chapter 6: Phase III.



Research limitation	Research question	Addressing question	Related publications
The absence of participative approach starting from early phase of decision-making process for complex problems	How useful are interactive MC-SDSS in supporting the stakeholders in urban energy planning decisions? and how can their usability be improved?	Identification the evaluation criteria based on stakeholders' preferences through an intuitive approach to a playing card in a semi-structured focus group	[Paper 4] Multicriteria Spatial Decision Support Systems for Future Urban Energy Retrofitting Scenarios.

6.2 Selection process for evaluation criteria

The selection process of criteria has been carried out in the following order as shown in Figure 41.

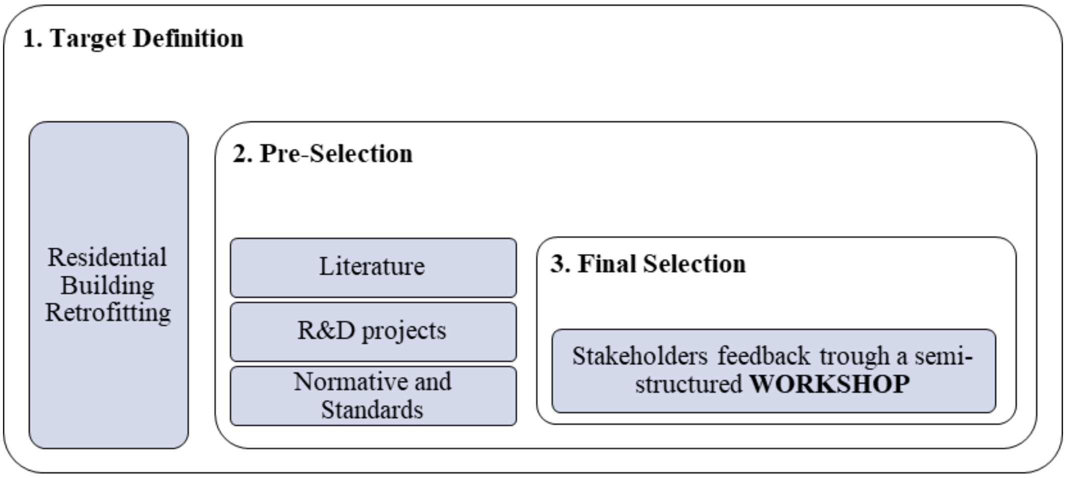


Figure 41: Overview of section process of evaluation criteria

After having collected and elaborated all the needed information and data, the decision criteria need to be carefully identified and selected in order to resolve an urban energy saving problem. According to Wang et al. (2009), multiple decision matrix for sustainable energy problems generally comprises in m alternatives evaluated on n criteria, involving thus alternatives, criteria, criteria weights and the evaluating results as it is shown as follows.

$$Criteria\ C_1\ C_2 \dots C_n$$

$$(Weights\ w_1\ w_2 \dots w_n)$$

$$Alternatives - - - - - - - - - - - - - -$$

$$X = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_3 \end{matrix} \qquad \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}$$

Where:

- $x_{ij}$is the performance of j-th f criteria of i-th alternative;
- w_j is the weight of criteria j;
- n is the number of criteria;
- m is the number of alternatives.

Although a vast number of criteria exist to be assessed to show the energy saving scenarios performances, it is not absolutely helpful having more and more criteria (Wang et al., 2009). Contrary, fewer criteria may sometimes be more advantageous for evaluating the energy issues. Generally, the definition of "Major" criteria requires a consideration of many different parameters such as (Jin and Wei, 2008); (Wang et al., 2009):

- "*Systemic principle*": the selected criteria should completely reflect the important characteristic and the whole performance of the energy systems;
- "*Consistency principle*": the criteria system should be consistent with the objectives of DMs;
- "*Independency principle*": the criteria should not be redundant, and they should reflect the performance of alternatives from different aspects;
- "*Measurability principle*": the criteria should be measurable in quantitative or qualitatively scale;
- "*Comparability principle*": The criteria should be comparable in order to have a more rational Decision-Making result.

Naturally, the different weights of criteria could directly affect the outputs and the definition of different scenarios.

6.2.1 Project needs and target definition

The aim of this research is to define the scenarios regarding the mix of the energy retrofit measures that improve the energy efficiency of the building (e.g., windows replacement, insulation of the opaque envelope) and the plants system efficiency (e.g., heating boiler replacement). The comprehensive retrofitting scenarios and their evaluation are previously illustrated in chapter 5. The key role of evaluation criteria is to aid the DMs to take the best energy retrofit decision by providing quantitative or qualitative data. The criteria assess the project within its social, environmental, economic and technical performance for 5 retrofitting measures in Table 24, which are emerged from chapter 5. This Ph.D. work intends to implement the retrofitting measure in Table 24 in order to create the basic model of MC-SDSS. Naturally, thanks to the fact that the MC-SDSS can be updated, more solutions can be implemented in the future.

Table 24: Considered retrofitting measures following the Minergie-P renovation.

Code	Retrofit Measures	Considered Measure	Note
b1	floor	thermal insulation	0.35 cm of EPS insulation
b2	roof	thermal insulation	0.35 cm of EPS insulation
b3	walls	thermal insulation	0.35 cm of EPS insulation
b4	window	triple glazing replacement	U-value = 0.7 ($W\ m{-}2K{-}1$)
*b5	boiler	condensation	_

*the b5= boiler is added as an example to evaluate also the plant system.

6.2.2 Pre-Selection

Reported by Pohekar and Ramachandran (2004); Strantzali and Aravossis (2016); Cajot et al. (2017), MCDA has been previously applied in energy planning with regard to different issues such as “energy policy and management, environmental impact analysis, renewable energy planning, energy resource allocation, building energy management, transportation energy management, planning for energy projects, electric utility planning, regional planning for coverage of energy demand and other miscellaneous areas”. Especially, Wang et al. (2009) conducted a comprehensive literature review based on 229 articles related to MCDA techniques for the sustainable energy decision-making issues. This study showed that the efficiency, investment cost, operation and maintenance cost, NOx emission, CO_2 emission, land use, social acceptability, and job creation were the most widely used evaluation criteria in energy planning, energy management, and resource allocation studies (Table 25).

Table 25: List of evaluation criteria used in MCDA studies conducted on energy issue, source (Wang et al., 2009).

Technical Criteria	Num. Literature
Efficiency	15
Exergy efficiency	3
Primary energy ratio	4
Safety	9
Reliability	9
Maturity	3
Others	8
Economic Criteria	Num. Literature
Investment cost	24
Operation and maintenance cost Fuel cost	13
Electric cost	9
Net present value (NPV)	7
Payback period	5
Service life	4
Equivalent annual cost (EAC)	4
Others	5
Environmental Criteria	Num. Literature
NOx emission	12
CO2 emission	21
CO emission	3
SO2 emission	8
Particles emission	5
Non-methane volatile organic compounds (NMVOCs)	3
Land use	10
Noise	6
Others	7
Social Criteria	Num. Literature
Social acceptability	4
Job creation	9
Social benefits	5
Others	10

More recently in 2016, Strantzali and Aravossis (2016) has classified the most used criteria with a special focus on decision support methods applied to renewable and sustainable energy. They have shown that the investment cost and CO_2 emissions by 52% locate the first place in all evaluation criteria. Job creation follows them strictly by 46% due to its attention to on social aspects (Table 26).

Table 26: Classification of criteria by (Strantzali and Aravossis, 2016).

Technical Criteria	%. Literature
Efficiency	31%
Reliability	20%
Resource availability	18%
Nominal power/Installed capacity (kW)	17%
Maturity	16%

Safety	10%
Energy production	9%
Demand	9%
Primary Energy Ratio (PER)	8%
Lifespan	8%
Continuity	5%
Stability	3%
Economic Criteria	%
Investment Cost	52%
Operation and Maintenance Cost	34%
Energy cost	23%
Payback period	16%
Internal Rate of Return (IRR)	9%
Life Cycle Cost (LCC)	6%
Net Present Value (NPV)	5%
Service life	5%
Equivalent Annual Cost (EAC)	2%
Environmental Criteria	%
CO2 emissions	52%
Land use	33%
Impacts on ecosystems	31%
NOx emissions	22%
SO2 emissions	17%
Emissions (generally)	17%
Noise	14%
Particles emissions	2%
Social Criteria	%
Job creation	46%
Social acceptability	28%
Social benefits	15%
Visual impact	14%
Local development	13%
Impacts on health	10%
Income from jobs	8%

As it can clearly see in the literature, the evaluation criteria can be classified into four main categories: technical, economic, environmental, and social (Kaya and Kahraman, 2010). Therefore, the first repository of criteria reviewed for this work is built up by considering the mentioned high frequency used evaluation criteria in the energy filed literature (Wang et al., 2009), and especially, the criteria which should be affected by energy retrofitting measures. Moreover, some other existing literatures, projects, tools, and standards are reviewed and analysed. Especially , energy planning and selection (Jovanović et al., 2009); (Doukas et al., 2007); renewable energy problems (Cavallaro and Ciraolo, 2005) ; (Beccali et al., 2003); (Marinakis et al., 2016); (Ertay et al., 2013); (Daim et al., 2013); (Theodorou et al., 2010); (Kaya and Kahraman, 2010); building and building stock energy management (Wang et al., 2008); (Dall’O’ et al., 2013); (Giaccone et al., 2016);

(Lizana et al., 2016); (Volvačiovas et al., 2013); (Roulet et al., 2002); (Hong et al., 2014). However, the fact of high-frequency evaluation criteria in the literature is not enough to take them into consideration. There is a need to understand and analyse all the criteria and a selection form according to the particularities and the goals of the given context (Strantzali and Aravossis, 2016).

The three relative R&D projects, SuPerBuildings (2012), FASUDIR (2014) and INSMART (2016), have been particularly taken into account in order to preselect the evaluation criteria. These projects by themselves consider many international and European initiatives, standardization activities and national building evaluation tools such as CEN TC 350, ISO TC59 SC17, UNEP SBCI, LEnSE, Perfection, and the National building evaluation tools such as BREEAM and LEED. The goal of the pre-selection process is to reduce them to be a practical but still significant amount of criteria that are sufficient for conducting a concrete sustainability assessment of urban built environment energy saving projects (Brandon and Lombardi, 2011). In order to decrease the number of potential criteria to analyse different alternatives, it is necessary to pre-select the most suitable evaluation criteria from the repository built-up (Lombardi et al., 2017).

Table 27: Description of the considered pre-selected criteria for EEB project.

	Criteria	Literature	Description	Unit
Environmental	Global emissions CO_2	(Jovanović et al., 2009); (Beccali et al., 2003); (Marinakis et al., 2016); (Ertay et al., 2013); (Giaccone et al., 2016); (Cavallaro and Ciraolo, 2005)	measure the equivalent emission of CO_2, which is avoided by the examined action.	Tons/ year
	Local emissions NO_X, PM_{10}	(Jovanović et al., 2009)	direct impact on the health of the community and an indirect impact on the social state of the community.	Tons/ year
Economic	Payback period (PBP)	(Doukas et al., 2007); (Volvačiovas et al., 2013)	performance measure used to evaluate the efficiency of an investment or to compare the efficiency of a number of different investments.	Years
	Investment cost	(Jovanović et al., 2009); (Doukas et al., 2007); (Georgopoulou et al., 1997); (Marinakis et al., 2016); (Ertay et al., 2013), (Theodorou et al.,	investment costs related to refurbishment of the building (efficiency investment) and/or new heating system	Euro

		2010);(Wang et al., 2008); Giaccone et al. 2016);(Lizana et al., 2016);(Cavallaro and Ciraolo, 2005); (Becchio et al., 2016)	(infrastructure investment).	
	Socio-economic feasibility	(Mutani and Vicentini, 2015)	the economic capability and willingness of the people.	Number
	Maintenance and operational costs	(Cavallaro and Ciraolo, 2005)	running fixed and variable costs due to the maintenance of the heating system (does not take into account fuel costs).	Euro
Technical	Reliability	(Beccali et al., 2003); (Ertay et al., 2013); (Wang et al., 2008); (Dall'O' et al., 2013)	efficiency of the technology and the requalification result.	Ordinal scale
	Technical life	(Dall'O' et al., 2013); (Giaccone et al. 2016)	durability of the whole strategy in relation to the service life of each retrofit measure.	Years
Social	Social acceptability	(Ertay et al., 2013); (Theodorou et al., 2010); (Cavallaro and Ciraolo, 2005); (Lizana et al., 2016); (Volvačiovas et al., 2013)	the perception of the people related to specific impacts due to the refurbishments.	Ordinal scale
	Local job creation	(Doukas et al., 2007); (Georgopoulou et al., 1997); (Beccali et al., 2003); (Marinakis et al., 2016), (Ertay et al., 2013);(FASUDIR, 2014)	potentiality of creating job and better regularity of the employee.	Man-day/ ordinal scale
	Architectural impact	(Dall'O' et al., 2013); (Cavallaro and Ciraolo, 2005)	the visual and architectural impact of refurbishments in the existing built environment.	ordinal scale

6.2.3 Final Selection

The final list of the criteria was established through a workshop including stakeholders. In this workshop, the author played a role of analyst who aids DMs in making their decision without expressing any personal preferences (Løken, 2007b). The formed workshop was related to the rank and feasibility of the different evaluation criteria to be calculated by the MC-SDSS software tool. The selection process is applied to the practice and the results of the first workshop are shown in 6.3.

Stakeholder involvement: UIEP as a very complex problem needs a comprehensive vision of urban sustainable energy policies and a significant co-operation between national and local governments (Wang et al., 2009). It involves multiple actors and different sectors, being a multidisciplinary and complex problem (Albeverio et al., 2008). There are multiple stakeholders in the procedure of an urban energy planning, where the identification of the stakeholders who can affect or can be affected by the recognition of objectives is required (Dente, 2014); (Liu and Du, 2014). As reported by Løken (2007a) stakeholders can be referred to "everybody that has a just interest in the system", "those who have a right to impose requirements on a solution", or "who have demonstrated their need or willingness to be involved in seeking a solution". Moreover, stakeholders can be categorized into different actors such as political actors, bureaucratic actors, special interests, general interests and experts having a different role such as a promoter, director, ally, mediator, and gatekeeper (Dente, 2014); (Ferretti, 2016).

Particularly, in the public decision problem, the stakeholder's involvement and their identification are significantly important since key representatives can then be invited to participate in brainstorming sessions (Ferretti, 2016). Several innovative methods exist in order to involve multiple stakeholders and experts in the planning procedure that have been developed and tested in practice in recent decades. It is necessary to organize the collaborative events such as a small group of stakeholders (e.g. focus groups, moderated round tables) or larger groups (e.g. future search conferences, world café) (Weisbord, 2012); (Brown et al., 2005). Indeed, in this initial part of the process, the accurate and proper stakeholder grouping is needed to a better image of how relationships and communication between stakeholders can affect the project outcome and its final application (Ferretti, 2016). Furthermore, stakeholder's involvement is an ongoing and iterative procedure in the entire process of UEP and its decision-making part. The serious involvement of the stakeholders from an early phase of planning is significantly necessary. This fact helps to obtain the available existing data, determine relevant sustainable objectives and propose a common strategic vision (Torabi Moghadam et al., 2017a).

Although the relevant actors are commonly involved in the planning process, some stakeholders who are even affected by the decisions are not always invited to take a direct decisional role in the process (Diakoulaki et al., 2005). The objectives of these stakeholders should be then considered in the analysis (Løken, 2007a). This research foresees the organization of different focus group involving real stakeholders in order to take into account the stakeholders' presence. The significant stakeholders in the case study are the local authorities, the local energy provider company, environmental groups, other non-profit organizations and academic and private experts in the given context.

6.3 Results of the evaluation criteria selection: through the 1st Workshop design

Setting the workshop

The first half day workshop was set up on 30th November 2016 at Politecnico di Torino, Turin (Italy) (Figure 42 and Figure 43). As said above, the purpose of the focus group was to select and rank the most important criteria to be further implemented in the MC-SDSS tool in section 7. Initially, the telephone preliminary conversation with the stakeholders has been done. During this first contact, the aims of the workshop were explained to each individual stakeholder. This fact helped in collecting the necessary information regarding their background and their familiarity with UEP (Brömmelstroet et al., 2014). After the stakeholders had agreed to participate in the focus group, an official email has been sent to them, introducing them the material and the structure of focus group and their role. An attempt was made as much as possible to invite participants with different backgrounds involving a number of disciplines. In view of this fact, a variety of point of view on the selection and rank the evaluation criteria has been ensured. Consequently, the invited stakeholders included an architect, representatives of the public administrations (i.e., energy and environment), an expert in SDSS development, an expert in visualization tool, an expert in implant system building administrators and academic experts (i.e., energy, economic evaluations and urban planning).

Figure 42: First focus group at Politecnico di Torino with the aim at defining the evaluation criteria.

Figure 43: First focus group at Politecnico di Torino with the aim at defining the evaluation criteria.

The work by the focus group has been planned in two major steps according to the following structure.

- In a first step, the analyst (author) gave the stakeholders the list of pre-selected criteria, which was previously chosen in Table 27. The analyst asked them to think about the relative importance of criteria in terms of retrofitting actions in order to select and rank the evaluation criteria.
- In the second step, the main task was to express the level of importance of each ranked criterion.

Describing the workshop

To define the importance of the criteria during this Ph.D. research project, it was decided to apply the "Playing Cards" method, which is a semi-structured participative procedure proposed by (Simos, 1990). The "Playing Cards" method is suitable to support group discussions. It allows the stakeholders involved to think and express about the way in which they wish to hierarchize the different criteria in a specific context. One of the major advantages of the "Playing Cards" method is the ease of application. This method, in fact, consists in associating a "card" with each criterion. Moreover, the stakeholders have a set of "white cards" available, the use of which depends on specific needs. The application of the procedure is very simple: (i) the stakeholders are asked to order the "cards" according to the importance of the criteria (from the last importance to the most important one) providing a complete pre-order. If some criteria have the same importance, the stakeholders should build a subset of cards holding them together; (ii) according to the fact that the importance of two successive criteria in the ranking can be more or less close, the stakeholders are asked to insert the "white cards" between two successive "cards" (the greater the difference between the mentioned weights of the criteria, the greater the number of white cards) providing a final ranking of the importance of criteria; (iii) the final ranking of criteria is converted into weights according to Simos' algorithms (Simos, 1990). The fact that the stakeholders involved have to handle the cards in order to rank them allows a rather intuitive understanding of the aim of this procedure (Maystre et al., 1994).

Few applications of this method are available in the literature (Figueira and Roy, 2002) ; (Bottero et al., 2015); (Wang et al., 2009). For this reason, Lombardi et al. (2017) compared the playing card method used for this Ph.D. research (EEB project) with the Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH) method (Bana e Costa et al., 2010). MACBETH method was used previously for the European project with the same purpose (i.e., urban energy saving) for selecting and ranking the evaluation criteria. The European project refers to the smart urban energy project, named DIMMER project (District Information Modelling and Management for Energy Reduction).

Mention has to be made to the study provided by Bottero et al. (2015), which proposed an innovative application of the “Playing Cards” method in connection with ELECTRE III (Bottero et al., 2015) in order to compare five urban requalification projects. Although the topic is different and is not related to the energy context, this study constituted an interesting reference highlighting a number of benefits of the “Playing Cards” method such as: it is interactive, easy to be understood and accepted by the stakeholders involved. In the application of the “Playing Cards” method, Bottero et al. (2015) promoted an individual discussion with the stakeholders. In the present study, on the contrary, the method is applied directly inside a focus group in order to inform the stakeholders and stimulate the discussion. In the urban energy retrofitting context, the present study constitutes one of the first examples (Lombardi et al., 2017).

The workshop set-up was well-targeted, for instance, the form of the tables and seating were arranged to let separate groups of stakeholders to have an interaction as much as possible. Moreover, in order to capture the workshop proceedings, all discussions and dialogs were documented by vocally recording and writing drafts. After the analyst well introduced the aim of the project and the structure of the focus group to the stakeholders, the procedure of Simos (1990) was applied as follows:

1. The analyst provided to the stakeholders a set of pre-selected criteria of Table 27. The name of each criterion was printed on the front of different coloured cards together with some other complementary information (Figure 44). During the focus group, the stakeholders were divided into three heterogeneous groups of work (Figure 45, Figure 46, Figure 47). Each group of stakeholders was asked to select their preferred “cards” discussing it and to rank the criteria according to their importance. They have ordered the criteria in ascending order according to the importance they wanted to assign to the criteria. They were also asked to build a subset of cards regrouping them together with a clip if those criteria had the same importance (ex-aequo criteria) (Simos, 1990); (Figueira and Roy, 2002).
2. In this stage, the analyst gave to the stakeholders a number of white cards with the same size. The purpose was to make them think about the importance of two consecutive criteria. Therefore, the stakeholders were

asked to insert the “white cards” between two consecutive cards (Figueira and Roy, 2002).

- no white card means that those two criteria do not have the same weights, but there is a minimal difference;
- one white card means two times the minimal difference;
- two blank cards correspond to triple the minimal difference, etc.

3. Finally, the three ranks were showed in a plenary session (Figure 48). In this case, the stakeholders were forced to discuss the rank in order to obtain a consensual rank of criteria (Table 28). according to the Simos’ algorithm, the final ranking of criteria was then converted into weights of criteria.

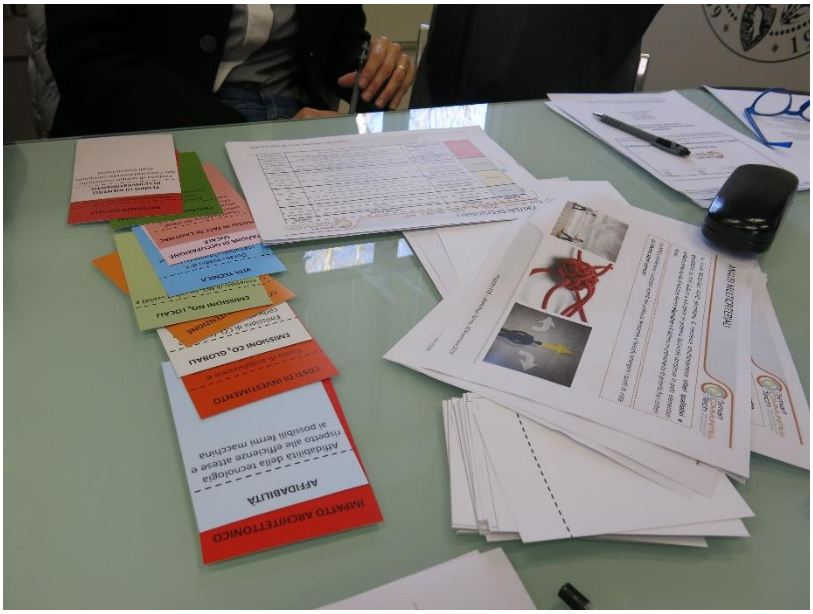


Figure 44: The colourful cards of playing card game.

Figure 45: First focus group at Politecnico di Torino based on Playing Card approach.

Figure 46: First focus group at Politecnico di Torino based on Playing Card approach.

Figure 47: First focus group at Politecnico di Torino based on Playing Card approach, the third group.

Figure 48: First focus group at Politecnico di Torino based on Playing Card approach, final plenary discussion.

Table 28: Final results coming from the Playing Cards method.

Rank	Subset of Ex-Equo	Number of Cards	Positions	Non-Normalize weights	Normalized Weights	Total **
1	Architectural Impact	1	1	1	1,316	1,32
2	White cards	3	(2, 3, 4)	-	-	-
3	Local Job creation	1	5	5	6,579	6,58
4	White cards	1	(6)	-	-	-
5	Reliability	1	7	7	9,211	9,21
6	White cards	2	(8, 9)	-	-	-
7	Socio/economic feasibility + Local emissions	2	10, 11	10,5	13,816	27,63
8	White cards	1	(12)	-	-	0
9	Investment costs	1	13	13	17,105	17,10
10	Payback Period	1	14	14	18,421	18,42
11	Global emissions CO_2	1	15	15	19,737	19,73
SUM			76*			100

*This sum does not include the positions of the white cards (in brackets).

** The total column reports the normalized weights multiplied for the number of cards of each position.

From Table 28 emerges that some of the initially considered criteria (Table 27) have been removed from the stakeholders during the discussion since they were considered not important for the analysis at stake. In details, the aspect "Social acceptability" has not been considered as a decision criterion from the stakeholders involved due to several reasons: 1) the construction phases are usually very short and therefore they do not constitute an inconvenience; 2) the stakeholders believed that the possible inconveniences occurring during a construction phase are unavoidable and uncontrollable. Instead, the criterion "Maintenance costs" has been first considered as a fundamental one. However, the stakeholders decided to be eliminated it and suggest considering it together with the "Payback period" criterion. Finally, following the same reasoning, the criterion "Technical life" has been eliminated and considered in the "Payback period" calculation.

It is interesting to notice that, even if the literature strongly suggests to consider the social criteria as fundamental (Wang et al., 2009), the practice tends to partially deny this evidence. During this exercise, the stakeholders expressed some perplexities related to the calculation methods of the social aspects with particular reference to the "Local job creation". This is probably one of the reasons why the social aspects are partially neglected. Similarly, the "Architectural impact" has been considered not fundamental from the stakeholders involved since this kind of impact is nowadays reduced thanks to International and National norms. On the contrary, the economic and environmental aspects are considered much more important with respect to the technical and social ones. Particularly, the local and global emissions have been generally considered as crucial. The correlation with human health in a specific area will have to take into account the actual concentration of those pollutants in the district environment (air) (Becchio et al., 2016) and to propose risk methodology for the augmented potential risk created.

6.4 Impact assessment

This section illustrates the assessment impact methodology of each selected evaluation criterion regarding the retrofitting measures developed in section 6.3. The impact assessment constitutes the external basis of MC-SDSS and it is then directly integrated into the tool (chapter 7). Impact assessments provide quantitative and qualitative information through different algorithms, which are capable to support the stakeholders' decisions according to "what-if" scenarios they will give some numeric supports for each retrofitting measurements.

6.4.1 Assessment of economic criteria

The economic criteria provided in this research is composed by a group of algorithms developed for the implementation of the MC-SDSS tool. The aim of these criteria was to estimate different costs for the energy retrofitting scenarios. The economic criteria constitute a significant part of this thesis. This category of criterion estimates the following costs:

- Existing buildings: fuel costs, operation and maintenance costs;
- Refurbished buildings: fuel costs, operation and maintenance costs and intervention costs.

6.4.1.1 Investment cost

Investment cost incurs all the costs regarding the purchase of building material, connection to the supplier, technological installation and manpower and set up the cost for each individual element of the renovation project (building envelope and energy systems) (Cavallaro and Ciraolo, 2005); (Becchio et al., 2016). The investors take into account strongly the investment costs and the subsequent benefits (Løken, 2007a). Many studies consider investment costs as the most important criterion to evaluate the energy saving interventions (Jovanović et al., 2009); (Doukas et al., 2007); (Georgopoulou et al., 1997); (Marinakis et al., 2016); (Ertay et al., 2013), (Theodorou et al., 2010);(Wang et al., 2008); (Giaccone et al., 2016). Indeed, Wang et al. (2009) reported that this criterion is the most widespread economic criteria to assess the energy problems.

For applying the investment costs method for energy refurbishment project in buildings, the model evaluates different retrofit strategies including initial investment, operation and maintenance costs during the calculation period. Calculation period (τ) for the analysis were set equal to 30 years for residential buildings, following Regulation N° 244/2012 precepts (EC 2012/C 115/01, 2012).

Generally, these methods pass through the principles of economic, the Net Present Value (NPV) criterion and traditional discounting (Fregonara, 2016). The following steps have been executed, which are shown in Table 29:

- The initial investment cost (C_I) that means all the needed costs in order to deliver the building or the building element to the customer when it is ready to use (EC 2012/C 115/01, 2012). All retrofit measures prices were found by referring to the Italian Regional databases "Pricelist of the Piedmont Region" suggested by (Becchio et al., 2016). Typically from an Italian literature, manpower and setup costs have been assumed 30% of the investment costs (Delmastro et al., 2016a)
- Annual costs (C_a) that means the sum of periodic costs or replacement costs or running costs paid in a determined year (EC 2012/C 115/01, 2012):
    - Running costs (C_r) that take into account annual maintenance costs (C_m), operational costs (C_o) and energy costs (C_e).
      - C_m and C_o are calculated as percentages of the related initial investment cost according to the indicative data given in Annex A of EN15459 (2007). Normally, operation and maintenance costs are considered equal to 0% for envelope components and 2% for energy system components (EN 15459, 2007).
      - (C_e): energy prices were assumed constant during the calculation period including energy taxes. Energy tariffs are considered as: (Natural Gas = 0.072 €/kWh+22% VAT = 0.093 €/kWh) and (District Heating for space heating = 0.076 €/kWh +22% VAT= 0.097 €/kWh)[4].

[4] Data source: (Delmastro et al., 2016b).

- Replacement costs (V_n), were quantified according to the lifespan of the components installed in the buildings that need to be replaced. The lifespan of each component is determined on the basis of values provided by in Annex A of the European standard (EN 15459, 2007).

- It was necessary to specify that the calculation of the maintenance and replacement costs were performed by NPV. NPV refers to the difference between the present value of cash inflows and the present value of cash outflows (Buso, 2017). NPV of costs are referred to the starting year of the calculation period and rely on the discount rate (R_d) for their calculation. R_d was set to 3% in line with the study conducted by Copiello et al. (2017). The NPV factor adapts the future costs to the time when the economic evaluation is performed (OPEN HOUSE, 2013).

Table 29 summarizes investment costs assessment regards to the aforementioned procedure.

Table 29: Investment cost assessment for individual retrofitting measures in geodatabase of MC-SDSS.

Code	Lifespan (year)	Price of measure	Manpower costs	C_m	V_n	C_I*	$C_{f,\tau}(j)$**	Unit
b_1	50	72.56	22	0.00	0.00	94	94	(€/m^2)
b_2	50	48.97	15	0.00	0.00	64	64	(€/m^2)
b_3	50	40.88	12	0.00	0.00	53	53	(€/m^2)
b_4	30	392.23	118	0.00	0.00	510	510	(€/m^2)
b_5	20	1878.82	564	957.47	1312.95	2442	4713	(€/piece)

*C_I (€/m^2) is the initial investment cost at the year τ=0.

**$C_{f,\tau}(j)$(€/m^2/y) is the final value of component j at the end of the calculation period.

6.4.1.2 Pay Back Period (PBP)

Pay Back Period (PBP), simple or discounted, is another popular criterion that gives the number of years it takes to compensate the sum of the investment capitals (Wang et al., 2009). It is based on the amount of the total investment for the retrofitting and the energy saving caused by the retrofitting actions such as windows replacement (Volvačiovas et al., 2013). This criterion gives immediate insights to investors, where the investor clearly prefers the shorter period of payback (Doukas et al., 2007). PBP is assessed by diving the overall investment costs and the annual saving in energy running costs (C_r). For the calculation of PBP, the following steps have been executed (Gupta and Gregg, 2018):

- The total investment costs (C_I) for the energy retrofitting measures will be calculated automatically by MC-SDSS each time the specific scenario will be defined. Basing on the number of buildings to be retrofitted, the amount of C_I will have changed (for example C_I (€/m^2) * transparent retrofitted area (m^2) = total investment for that specific retrofit application €).

- The yearly savings in C_r (€) have been calculated by subtracting the running costs energy of the retrofitted building from the running costs energy of the original building.

$$(C_r)\ \textit{Yearly saving in running costs energy (€)} =$$

$$\textit{Building } C_r \textit{ energy original-Building } C_r \textit{ energy retrofitted}$$

- PBP is calculated based on a static reduction in annual running costs C_r and current cost to install a measure C_I.

$$PBP = CI/Cr$$

6.4.1.3 Socio-economic feasibility

Socio-economic feasibility is a substantial criterion since it evaluates the level of economic willingness and the capacity of the inhabitants to invest in retrofitting solutions (Delmastro et al., 2016a). This criterion is introduced by Mutani and Vicentini (2015), which measures the ability of people to invest; even if the designed retrofitting packages are well-appropriate in terms of energy performances. They reported that the socio-economic feasibility is characterized by different variables as follows:

- f_a: age factor is the percentage of the probable active population of 25-69 years old with respect to the total population. Naturally, this range of population has higher interest in investing energetic renovation. Figure 49 illustrates the spatial distribution of f_a for the study area.

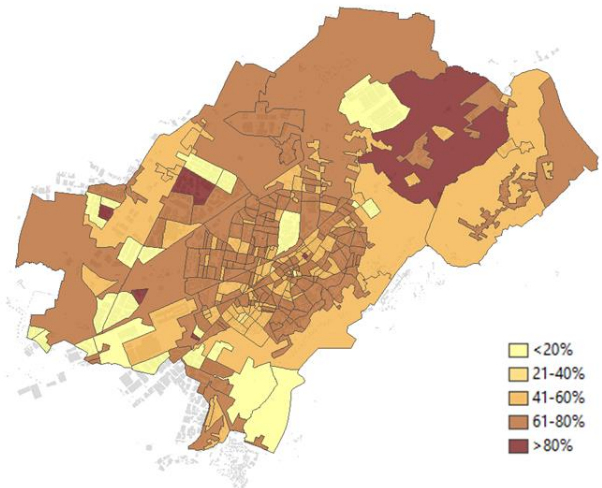


Figure 49: $\boldsymbol{f_a}$ mapping for Settimo Torinese by GIS.

- f_{em}: employment factor is the percentage of the employed population and the total active people of 15-74 years old. This factor can therefore show the initial economic ability of the people to invest as well as their ability to pay their loan funded by the banks. Figure 50 illustrates the spatial distribution of f_{em} for the study area.

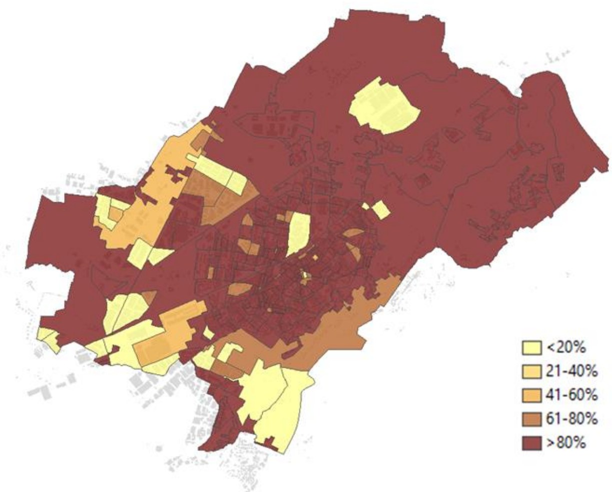


Figure 50: $\boldsymbol{f_{em}}$ mapping for Settimo Torinese by GIS.

- f_p: property factor is the percentage of a number of buildings occupied by the owner families and the total number of buildings (only residential). This factor influences since the owners have more interest to requalify energetically their own buildings rather than tenants. Figure 51 illustrates the spatial distribution of f_p for the study area.

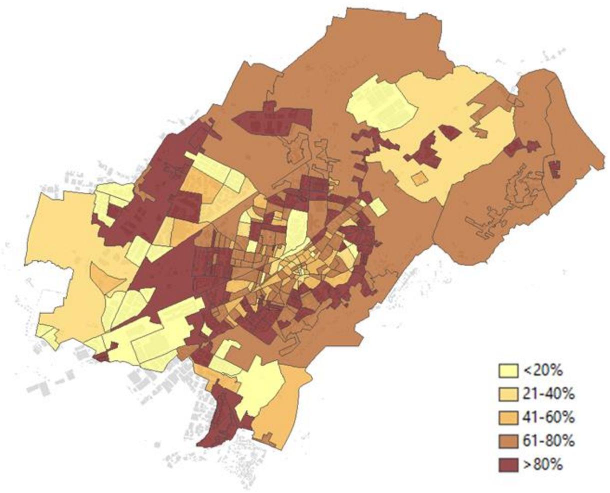


Figure 51: $\boldsymbol{f_p}$ mapping for Settimo Torinese by GIS.

- f_f: family factor is the percentage of 1-2 components families over the total number of families. This factor presents the eventual occupancy presence schedule in dwelling stock. Figure 52 illustrates the spatial distribution of f_f for the study area.

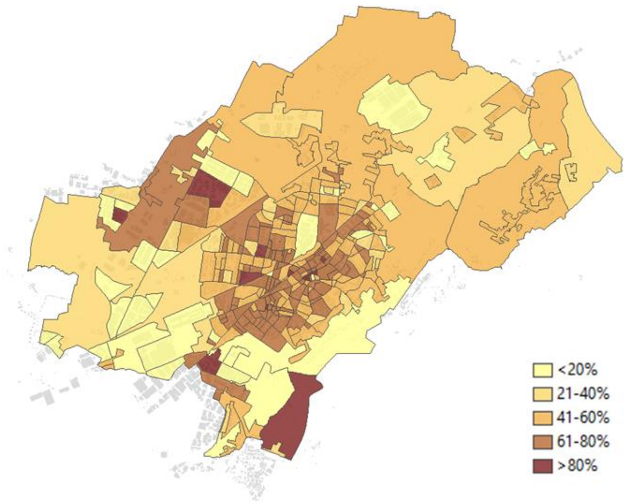


Figure 52: $\boldsymbol{f_f}$ mapping for Settimo Torinese by GIS.

- f_{gm}: gender factor is the percentage of male-gender to the total population. Figure 53 illustrates the spatial distribution of (f_{gm}) for the study area.

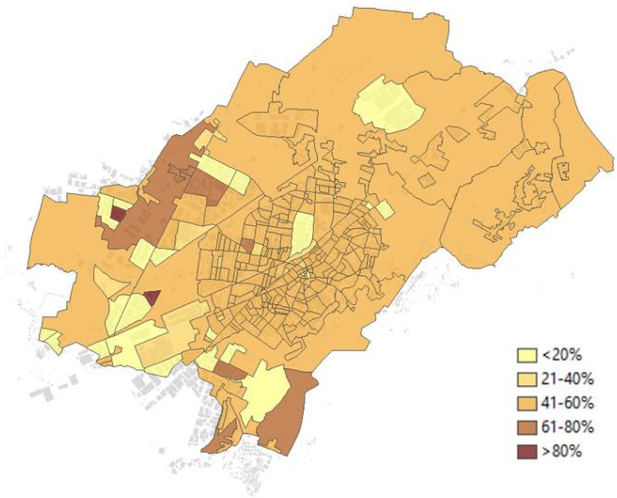


Figure 53: $\boldsymbol{f_{gm}}$ mapping for Settimo Torinese by GIS.

- f_{ed}: education factor is the percentage of graduated people (high school diploma or higher instruction level) with respect to the total population. The educated population may have higher awareness about detrimental environmental impacts and energy technologies. Figure 54 illustrates the spatial distribution of f_{ed} for the study area.

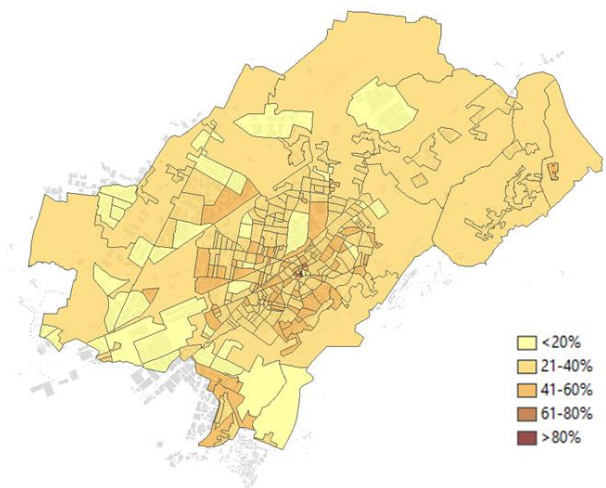


Figure 54: $\boldsymbol{f_{ed}}$ mapping for Settimo Torinese by GIS.

- f_{pc}: period of construction is the percentage of buildings built before 1960 over the total number of buildings. f_{pc} represents the older buildings that need to be energetically requalified. Figure 55 illustrates the spatial distribution of f_{pc} for the study area.

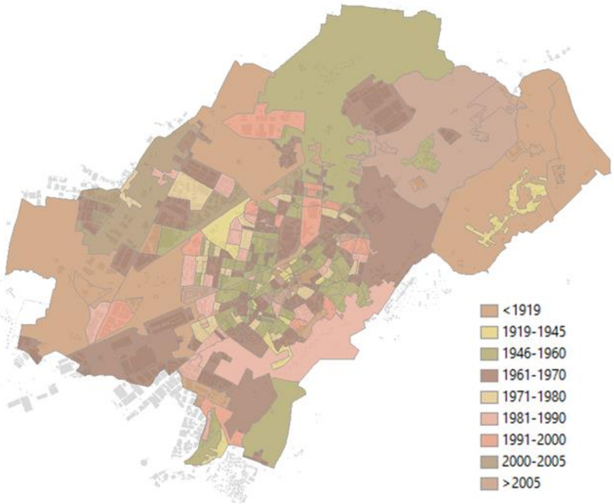


Figure 55: $\boldsymbol{f_{pc}}$ mapping for Settimo Torinese by GIS.

- f_o: buildings occupation factor is the ratio of an occupied building. f_o shows the occupied buildings, consequently, those ones may consume more. Figure 56 illustrates the spatial distribution of f_o for the study area.

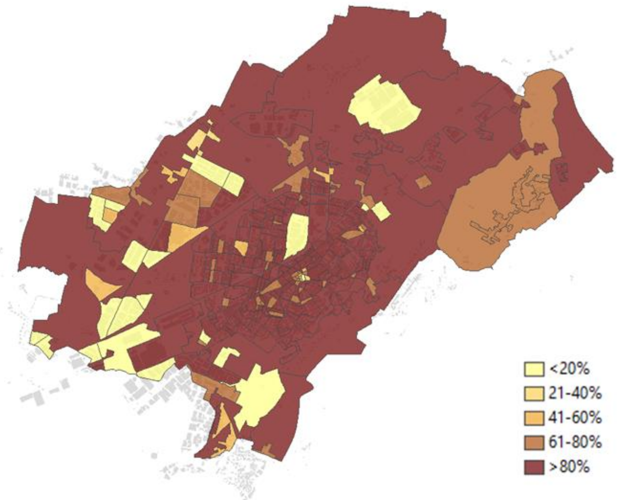


Figure 56: $\boldsymbol{f_o}$ mapping for Settimo Torinese by GIS.

Obviously, when the aforementioned factors are higher the feasibility renovation interventions is more probable (Delmastro et al., 2015). The main objective was to provide a unique global Feasibility Index (F) for the city including all factors though MLR method (Mutani and Vicentini, 2015). Unfortunately, the small number of relative APE data (Energy Performance Certificates) was available. APE data provide the information regarding the people who have renovated their own apartments in each census section. In the consequence, this criterion will not be considered as a “major” criterion, but as visualization criteria. Although this criterion impact on the decisions of DMs, it will not have involved in the calculation phases.

6.4.2 Assessment of environmental criteria

6.4.2.1 Global emissions CO_2

As mentioned before, this criterion was the first rank in the preferred of stakeholders. CO_2 is a kind of gas without colour, smell and taste, which may contribute about 26% to the GHG effect (Kiehl and Trenberth, 1997). The energy systems that are fed by coal, oil and natural gas are the main causes to release CO_2 (Wang et al., 2009). Innovative technologies and retrofitting strategies can help practically in diminishing of CO_2 emissions. Especially, dwelling stock is responsible for about 30%-40% of the total energy demand and must be prioritized to reach a sustainable target within a determined time 2020 horizon (Jeong, 2017). Reported by several researchers such as (Jovanović et al., 2009); (Beccali et al., 2003); (Marinakis et al., 2016); (Ertay et al., 2013); (Giaccone et al., 2016); (Cavallaro and Ciraolo, 2005), CO_2 emission of the energy system is undoubtedly a criterion to be assessed for the sustainable development of cities. The assessment methodology of global emissions was assessed based on the conversion coefficients of (ARPA Lombardia, 2003). The assessments will directly perform internally into the MC-SDSS.

6.4.2.2 Local emissions NO_X

NO_2 and NO are collectively known as a NOx that is mainly formed by mono-nitrogen oxides. They are the most significant causes of harmful air pollution. They easily react with common organic chemicals, volatile organic compounds, ozone, ammonia and moisture (Wang et al., 2009). In the consequence, NOx leads to produce toxic pollution that damage meaningfully the people’s health. Moreover, air pollution can also harm the built environment, climate, vegetations (EEA, 2014). This means also an indirect impact on the social health of communities (Jovanović et al., 2009). The assessment methodology of global emissions was based on the conversion coefficients from the report conducted by ARPA Lombardia (2003). The local emissions assessments will directly perform internally into the MC-SDSS.

6.4.2.3 Local emissions PM_{10}

Particles emissions are the detrimental environmental impact that is caused by coal, oil, and biomass as well as photovoltaic power plants during their cell construction (Wang et al., 2009). PM_{10} are very harmful to the human health, such as lung diseases, heart attacks and arrhythmias, cancer, atherosclerosis, childhood respiratory disease and premature death (EEA, 2014). During a first workshop, stakeholders specifically asked to consider a criterion regarding the health of the local community. Therefore, this criterion has been associated with the geodatabase of MC-SDSS tool and it was calculated based on ARPA Lombardia (2003).

6.4.3 Assessment of technical criteria

6.4.3.1 Reliability

Generally, in the literature, the reliability of retrofitting measures can be assessed by both quantitative and qualitative evaluations manner (Ertay et al., 2013); (Beccali et al., 2003). In fact, the retrofit measures that are considered for this study (see Table 24) are broadly available on the market, and so, they are mostly reliable. However, some of these measures performances depend on the context while others are independents of the context (Dall'O' et al., 2013). For this research, the reliability criterion is determined according to Dall'O' et al. (2013) in qualitative terms: high, medium, low and none. Only the measures b4, b5 present lower performances and the situations of b1, b2 and b3 have almost the same level.

Table 30: Qualitative evaluation of the reduced performance.

Retrofitting Measures	**b1**	**b2**	**b3**	**b4**	**b5**
user interaction	none	none	none	high	low
risk of breaking	none	none	none	none	low
dependence on weather effects	none	none	none	none	none
score	4	4	4	3	3

6.4.4 Assessment of social criteria

6.4.4.1 Local job creation

For stakeholders, an increase in the local job creation was fundamental in order to ensure the community to be socio-economically healthy. Since the focus of this study limits to the local level, the manpower needed for each retrofit solution is considered only based on the installation and maintenance phases. Indeed, job creation criteria do not meet the manpower necessary to produce the building materials or machinery (Dall'O' et al., 2013). Again, this criterion can be assessed in qualitative or quantitative way. As is shown in Table 31, a quantitative approach is performed for each measure based on man-day assessment according to Dall'O' et al. (2013) and a national reference (UNI EN 15459, 2008).

Table 31: Manpower in the installation and maintenance of the measures developed 100% of the potential in thirty years.

Retrofitting Measures	**b1**	**b2**	**b3**	**b4**	**b5**
No. of interventions	1.0	1.0	1.0	1.0	1.0
No. installation in thirty years for installation	1.0	1.0	1.0	1.0	1.0
N. of workman per team	7.0	7.0	7.0	3.0	2.0
Days for installation	3.0	3.0	3.0	3.0	3.0
Man-days for installation MAX	21.0	21.0	21.0	9.0	6.0
man-day euro/m^2	594.3	401.1	334.8	1376.7	4396.4
No. of interventions	1.0	1.0	1.0	1.0	1.0
No. maintenance in thirty years	0.0	0.0	0.0	0.0	1.5
No. Of workmen for maintenance	5.0	5.0	5.0	2.0	2.0
Days for maintenance	4.0	4.0	2.0	1.5	3.0
Man-days for maintenance MAX	20.0	20.0	10.0	3.0	6.0
man-day euro/m2	0.0	0.0	0.0	0.0	87.9
Tot.	41.0	41.0	31.0	12.0	12.0

6.4.4.2 Architectural impact

This criterion evaluates the visual nuisance that may be created by applying of some retrofitting measurements for of a city, which is an important social aspect (Cavallaro and Ciraolo, 2005). When retrofit measures lead to aesthetic improvement of the city, this criterion worth higher. Five scores of impact are presented in Table 32 according to the study conducted by Dall'O' et al. (2013), with the reference to the specific measures. This criterion adopts an ordinal scale to rank the strategies, from the best to the worst. In all cases the considered retrofitting measures achieve positive (b1) or neutral (b2, b3, b5) score since they improve an aesthetic vision of the city. For example, the possible future retrofitting measure like a photovoltaic solution, will be assumed with a negative value since they can have a strong negative architectural and visual impact.

Table 32: Architectural impact criterion.

Positive	great positive impact	b1	1
	positive impact	b4	2
Neutral	no impact	b2, b3, b5	3
Negative	little negative impact	-	4
	negative impact	-	5

6.5 Concluding remarks

Nowadays, there is an increasing concern about sustainable urban energy development considering national priorities of each city. Many cities have started to define future strategies and plan to reduce energy consumption and GHG emissions. One of the main problems, in relation to urban energy retrofitting scenarios, is the lack of appropriate knowledge and relevant evaluation criteria. The latter is crucial for delivering and assessing urban energy scenarios through MC-SDSS tool.

This chapter illustrated how a sensible set of criteria for this thesis were defined and ranked through the "Playing Cards" approach. The main features of this approach can be summarized as (Lombardi et al., 2017):

- Selecting and weighting method: subjective (subjective scale)
- Participation Structure: semi-structured participative based on free discussion
- Approach: participants are asked to rank the cards according to their personal knowledge and background
- Importance ranking: rank importance position by inserting a set of cards "white cards" between coloured cards
- Stakeholders acceptance: intuitive and entertaining

The "Playing Cards" method is stakeholder-based approach and it is based on stakeholders' preferences. This method showed to be flexible with the ability to stimulate the discussion among the stakeholders involved in the focus group. Thanks to its characteristics, the method is useful to support decisions with subjective criteria. Moreover, the stakeholders perceived the "Playing Cards" method as a very intuitive and engaging method, able to support discussion on the criteria involved and useful for ranking them according to their preferences. As shown in Table 28, playing card method highlighted that the most important criteria for the development of energy urban retrofitting scenarios are related to both economic and environmental aspects. On the other hand, the social aspects proved to be difficult to be taken into account.

Finally, it is important to underline that the application of the "Playing Cards" method presented in this study represents a validation step (Landry et al., 1983) aiming at verifying whether the key issues have been appropriately considered in the decision making process (Tsoukiàs, 2008) and testing the model by using experimental or real data. In conclusion, this chapter is one-step toward the goal of developing urban energy scenarios through the development of the MC-SDSS tool in the next and last chapter (7). This will support DMs to deliver retrofitting GIS-based alternative scenarios.

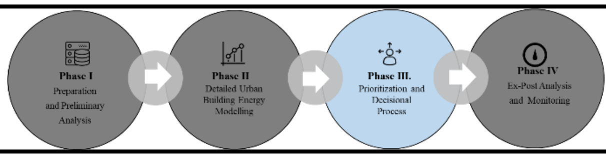
Chapter 7

Development of a New MC-SDSS for Urban Energy Planning

7.1 Introduction

The present chapter will discuss the process of the developing MC-SDSS tool. This tool is an interactive plug-in of GIS environment, which has been adapted from an existing urban planning tool, called CommunityViz. The developed MC-SDSS tool supports the stakeholders in urban energy planning through participatory and collaborative processes. It helps make better decisions by expressing the stakeholders' preferences and their conflicting objectives. Generally, section 7.2 introduces CommunityViz. Section 7.3 presents the architecture design of the new developed MC-SDSS. Section 7.4 describes how the developed tool was tested through the workshop organized for this Ph.D. research side-by-side with relative stakeholders. In the last section 7.6, the concluding remarks are provided. For schematic summary of this chapter refer to Table 33.

Table 33: Schematic summary of chapter 7, Phase III.



Research limitation	Research question	Addressing the question	Related publications
the lack of an interactive and real-time decision support system to help the stakeholders in making their	How useful are interactive MC-SDSS in supporting the stakeholders in urban energy planning decisions? and how can their usability be improved?	development an interactive decision support system and test it through the workshop	[Paper 14] *In preparation* Interactive Multi-Criteria Spatial Planning Support System for Energy Retrofitting Using CommunityViz.

7.2 CommunityViz

CommunityViz is an ArcView modular GIS-based decision support system developed by the Orton Family Foundation (http://www.communityviz.com), which is designed, especially, for regional and local planning processes. The above-said tool is able to integrate different types of data such as scripts, numbers, 2D maps, 3D visualization, raster in a real-time and multidimensional environment (Kwartler and Bernard, 2001). CommunityViz encompasses two main components as extensions to ArcGIS: (i) Scenario 360 to map and analyse, and (ii) Scenario 3D to visualize. Conceptually, Scenario 360 can be described as a spatial spreadsheet allowing for calculations on spatially related data and formulas that call standard GIS functions (Janes and Kwartler, 2007). Since each formula, assumption and dependency is viewable and editable, there is not any "black box" element to a model defined in Scenario 360 (Janes and Kwartler, 2007).

CommunityViz Scenario 360 adds interactive analysis tools and a decision-making framework to the ArcGIS platform with which stakeholders can understand the planning processes easily. Stakeholders can define different decision assumptions and visualize on-the-fly how the changes may affect environmentally, economically, technically, and socially the future scenarios. This dynamic process helps urban actors to negotiate in order to make better decisions (Kwartler and Bernard, 2001). Moreover, it helps facilitate an understanding of the complex problems such as UIEP (Wang et al., 2009). Within this tool, many presentation features are available to assist in sharing information with the users including maps, alerts and charts. In these views, stakeholders can ask "what-if" questions and visualize "if-then" scenarios in a real-time and discuss it very quickly and effectively (Pelzer et al., 2015).

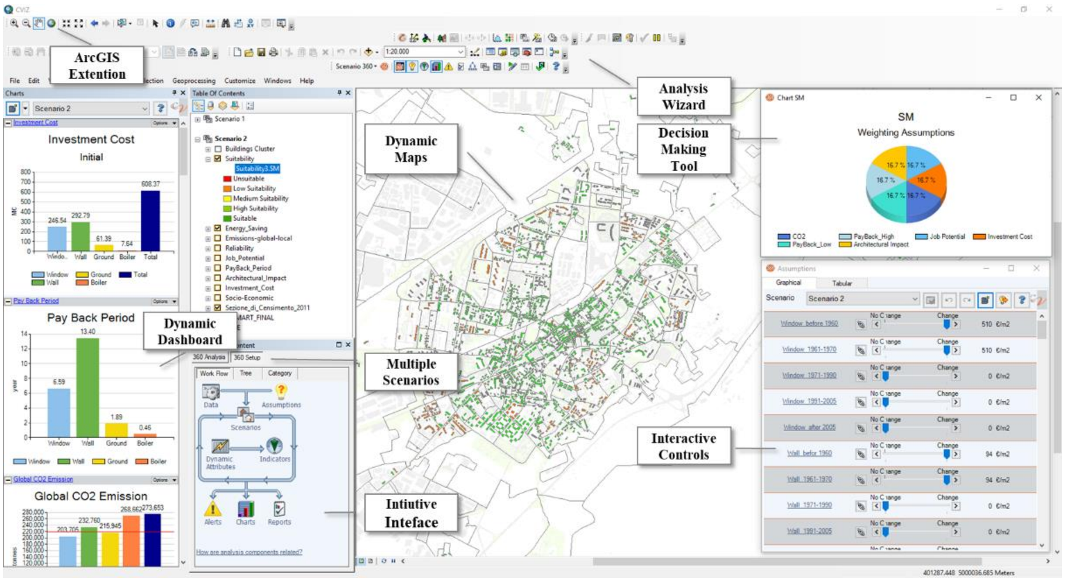


Figure 57: CommunityViz Interface; the case study of Settimo Torinese.

CommunityViz Scenario 360 is selected for this research due to its several strengths (Li and Jiao, 2013). It helps analyse and understand the potential alternatives and their impacts through visual investigation and scenario analysis by a wide range of people. Moreover, it creates a real-time experiment with different scenarios, changing the assumptions quickly, and viewing influences on changes. Furthermore, it engages stakeholders in participative and collaborative decision-making processes through visualization and interactive media (Eikelboom and Janssen, 2017). All aforementioned strengths lead to stronger consensus and better decisions in resolving complex problems. Figure 57 shows the interface of Scenario 360 modelled for the case study of Settimo Torinese.

7.3 Architecture model design of a new MC-SDSS using CommunityViz

As mentioned before, CommunityViz Scenario 360 is broadly used for urban planning containing a wide variety of interactive tools to model, analyse, and visualize geospatial information (Walker and Daniels, 2011); (Pelzer et al., 2015). This section aims at illustrating how CommunityViz Scenario 360 is modelled, coded, and adapted for urban energy retrofitting planning issues. The design and implementation modelling approach were an iterative process. Two main integrated instruments, (i) Interactive impact assessment and (ii) Suitability analysis, of CommunityViz 360 are used in order to build a new MC-SDSS. These two integrated instruments are modelled and adapted through different functions such as Advanced Formula Editors in order to achieve the target of this research. The possibility to edit formulas and to alter assumptions became one of the major strengths of the system developed (Janes and Kwartler, 2007).

(i) The target of interactive impact assessment is to create different dynamic energy saving scenarios considering the five selected retrofitting measurements (i.e., b1, b2, b3, b4, b5) illustrated in Table 24 (chapter 5). Moreover, the building stock is divided into 5 macro-clusters considering the building types and age classes (Table 22). The reason for these choices is completely explained in chapter 5. Moreover, the previous external analysis of the impact assessments for considered criteria (i.e., economic, environmental, social and technical) are performed through Microsoft Excel-sheet in section 6.4. The percentages of energy saving associated with each retrofitting measures for five clusters of buildings are shown in Table 22. These results have previously emerged from chapter 5, where the archetype model is simulated in order to see the short-term future scenarios.

(ii) The target of suitability analysis is to understand the ability of a system to meet the needs of stakeholders. Through this instrument, the stakeholders can understand if their defined scenario would enter into a suitable range or not. In other words, stakeholders can see if their decisions are suitable. They can also associate different weight values to each criterion to analyse the changes the suitability outcomes. Changing the weights help them to evaluate the scenarios within different importance to each criterion.

According to retrofitting assumptions, a series of relative algorithms presented in section 6.4 capable of assessing indicators over a short-time period have been developed. The developed algorithms assess the following indicators at the district level both for each retrofit measure and for the total value considering all the measures: (i) total energy consumption (GWh); (ii) energy saving reduction (%); (iii) initial investment costs (M€); (iv) investment cost (€/m^2), (v) PBP (year), (vi) CO_2 emissions (tonnes); (vii) CO_2 emissions (tonnes/GWh), (viii) local emissions

NO_X (tonnes) (ix) local emissions PM_{10} (kg); (x) job potential (man-day), (xii) architectural impact (rank), and (xiii) reliability of the retrofitting measure (rank).

A conceptual framework is created to model relative instruments and data processing sketching out what would eventually become.

7.3.1 Interactive impact assessment

Figure 58 illustrates the architecture design flowchart of the Interactive Impact Assessment (IIA) function for the new MC-SDSS. The target of this step is to create different energy saving scenarios and visualize the relative impact assessment in real-time.

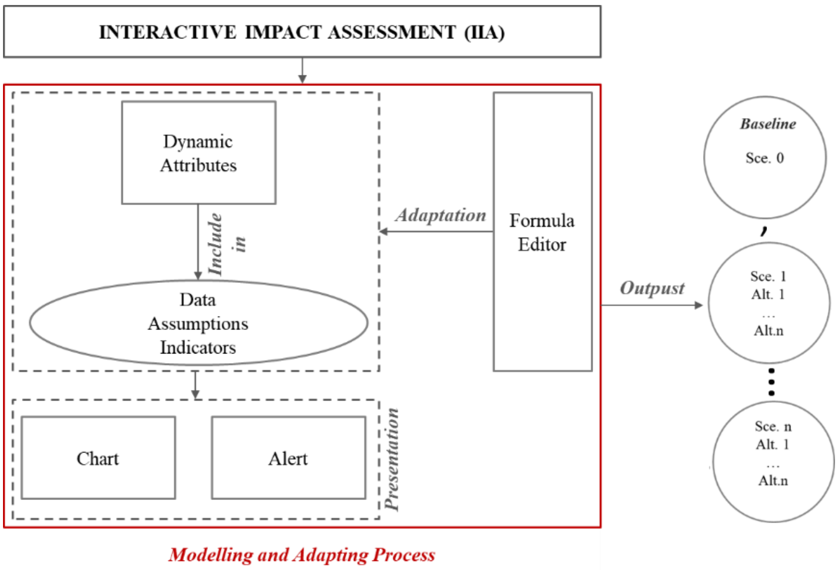


Figure 58: Architecture of MC-SDSS design: modelling and adapting process.

The modelling process starts with a creation of Formula-based GIS dynamic attributes. Dynamic attributes are automatically updated when changes are made in the analysis. In fact, Scenario 360 enlarges the quantitative capabilities of ArcGIS by formula-based spreadsheet-like calculations, which are to be performed on geospatial data (Lieske and Hamerlinck, 2013). Formula-based GIS data attributes create dynamic analysis providing rapid changes of geographic and numeric inputs as well as an automated recalculation of maps and quantitative outputs (Walker and Daniels, 2011). It is possible to write Scenario 360 formulas directly with the Formula Editor wizard very easily due to its similarity to Excel formulas. Indeed, formula editor does not only assist in the structuring, editing, and display of the formulas, but also keeps syncing all components of the model (Janes and Kwartler, 2007). When new "Dynamic Attribute" or "Indicator" is needed to be created, the Formula Editor wizard constructs the most common types of analysis formulas (Placeways LLC, 2014). These values are dynamically controlled and updated. A formula is linked to each dynamic attribute, which specifies how the attribute should be calculated. A relative value is calculated for each feature within the data layer. As an example, a snapshot of the Formula Editor showing the formula that calculates the amount of total investment cost for wall insulation retrofitting appears below in Figure 59.

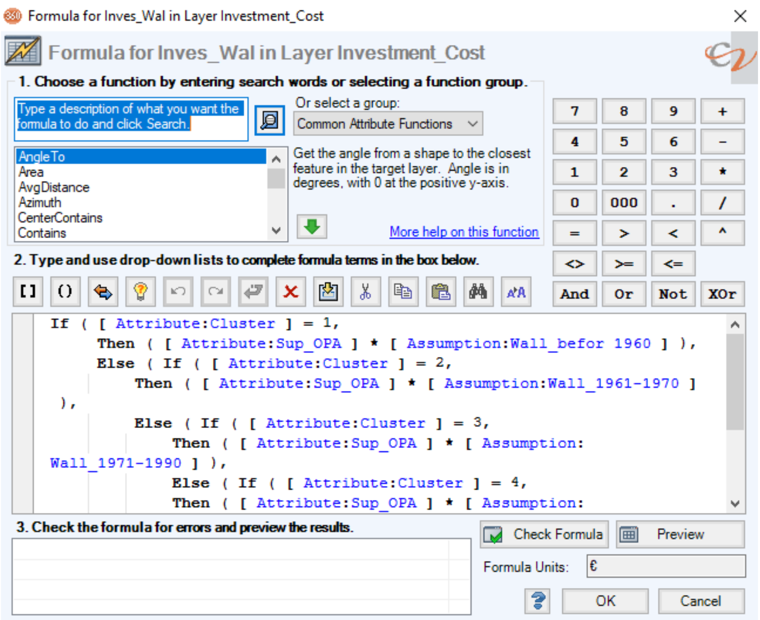


Figure 59: A snapshot of Scenario 360 Formula Editor Interface, an example of investment cost wall insulation formula.

The dynamic attributes change based upon:

- Data: dynamic data layers create new or add existing layers to the Scenario 360 analysis geodatabase. An important feature of Scenario 360 is that it provides a dynamic data about features on a map that can be performed by formulas. Therefore, when one aspect changes, the software recalculates the entire analysis. Dynamic data are used for geo-designing; that means experimenting with alternatives and visualizing the impacts of changes in real-time.

- Assumption: slider bars or tables let change assumptions during analysis. Using the assumptions, the stakeholders can express their preferences and decisions. When an assumption is changed, all associated formulas with that assumption are automatically recalculated within the scenario (Janes and Kwartler, 2007). Figure 60 shows a user-friendly interface for altering assumptions allowing sensitivity testing (Janes and Kwartler, 2007). The stakeholders can visualize the consequences of their changes in real-time.
- Indicators: formula-driven analysis results that are updated automatically while the analysis is performed. Indicators can show the outcome of one or several dynamic attributes.

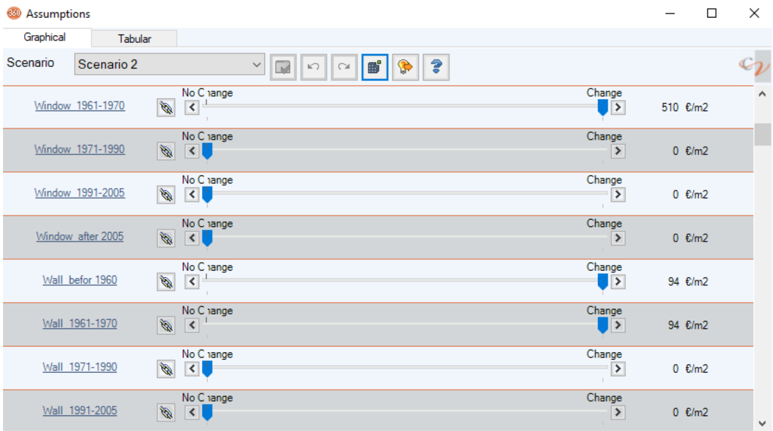


Figure 60: Representative CommunityViz assumption sliders for retrofitting actions, which are applicable for buildings cluster, Settimo Torinese.

Finally, it is possible to visualize all the changes in dynamic charts and alerts. Alerts appear when the outcomes do not meet the specific target value based on related normative or based on stakeholders requested. Once the modelling process is finished (e.g., formulas are coded and linked, dynamic attributes are created etc.), the scenario creation and analysis phase are started to be performed. Indeed, alerts will notify participants if a target, threshold, or constraint condition has been reached (Placeways LLC, 2013). An alert is needed to monitor values during analysis and to report specific conditions. It may be connected with a dynamic attribute, an assumption, or an indicator (Placeways LLC, 2013).

Scenarios

As mentioned before, the project did not aim at creating the specific scenarios. The significant innovative approach is the ability of tool that allows for working on the of future scenarios definition side-by-side with stakeholders using interactive impact assessment and suitability analyses instruments. This section describes some examples of defined scenarios and methods used to model them.

Scenario 0 "baseline"

The first step in establishing future scenarios was to create a baseline scenario (East and Corridor, 2015) as shown in Figure 62. Setting up a baseline analysis is significant to understand what future opportunities exist and where the hot-spots are already concentrated. Obviously, this scenario represents the baseline conditions in which no new retrofitting, modification and investment are planned. This might be a basis for the future scenarios comparison to analyse the differences. As is shown in Figure 62, the results are visible by maps and charts. In the baseline scenario, some indicators such as CO_2 emissions (tonnes) and energy consumption (GWh) indicate a current value of the city. This means that some values do not start from zero value since they already existed in the current state. This description of current conditions can commonly be compared with different future scenarios (e.g., from Scenario 1 to Scenario n).

An additional indicator, so-called "Active Action Control" shown in Figure 61, is created in order to control the active assumptions, especially, when there are several assumptions to be considered. Actions in Figure 61 will be activated when the retrofitting solutions are applied to each cluster of the buildings (see Figure 62). Through this indicator, the analyst and stakeholders can easily control the assumptions considered for each scenario.

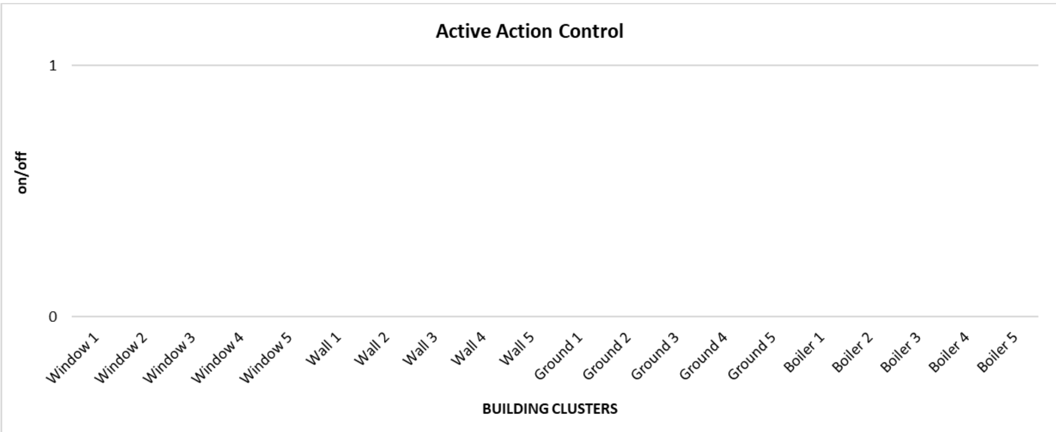


Figure 61: Active Action Control for assumptions of Scenario 0 "baseline", there is no retrofitting actions.

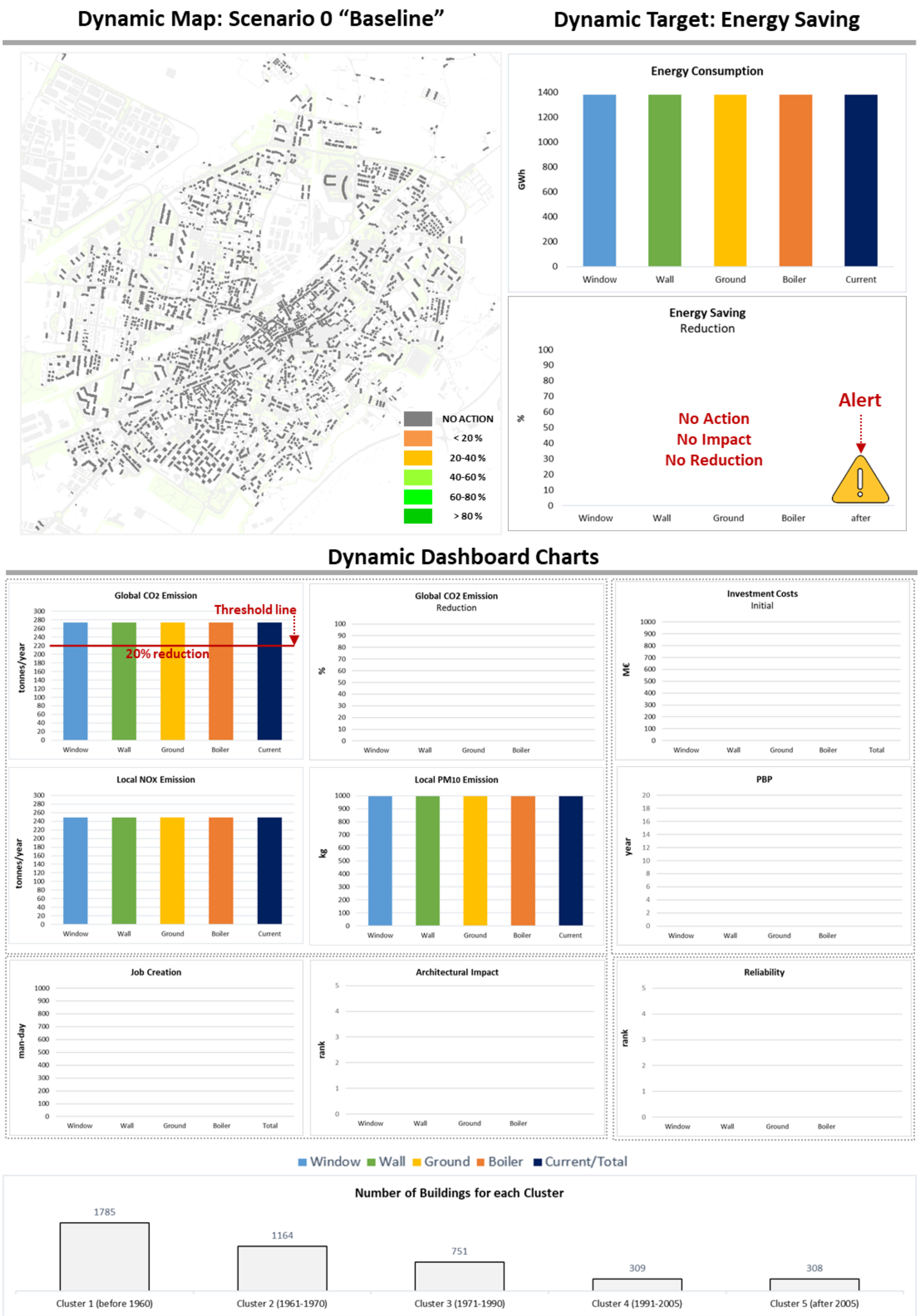


Figure 62: Scenario 0 "baseline" without any retrofitting action.

Future Scenarios

In the next step of this procedure, it is possible to create different scenarios altering the assumptions and data (Figure 63). Each scenario can consist of different alternatives meaning that the stakeholders can experiment their preferences by changing the assumptions and establish their preferred scenario. These scenarios are evaluable by indicators, alerts, and selected thresholds.

In fact, it is possible to establish the thresholds as a target for created scenarios, for example achieving minimum 20% of energy consumption or CO_2 emissions reduction. An alert appears on the chart indicating that a pre-set threshold has not been satisfied, in this case, a 20% of energy consumption reduction. If the scenario meets the requested threshold, it could be acceptable. If not, the alerts appear in order to inform the stakeholders. In fact, some scenarios can be discarded immediately when they do not reach the target of 20% energy saving.

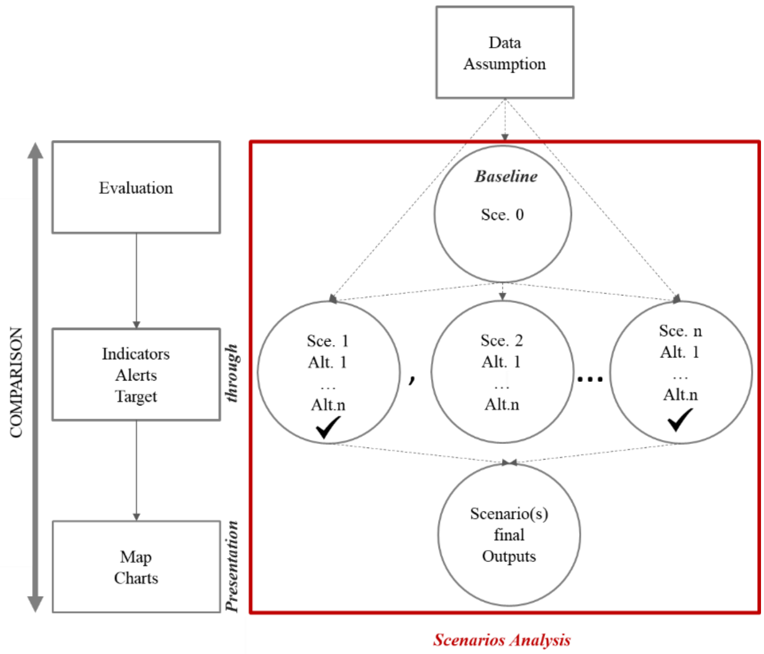


Figure 63: Schematic flowchart of MC-SDSS design; scenario analysis.

The results of different scenarios are displayable by maps and charts in real time. As an example, Figure 65 demonstrates the changes from scenario 0 “baseline” to scenario 1, named “expert-oriented”. The scenario “expert-oriented” is defined by experts (forming an internal focus group) with the aim at creating a scenario characterized by moderate energy performances. This scenario is performed with aim at illustrating it as an example to non-expert stakeholders.

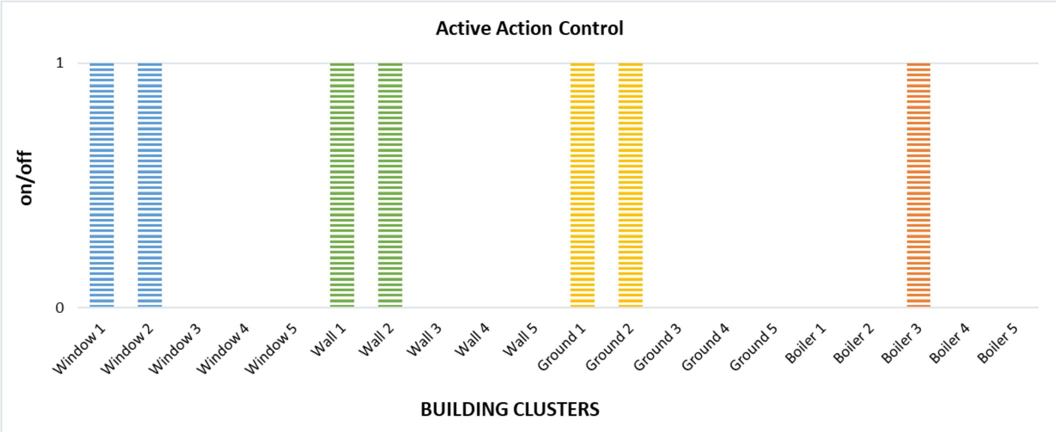


Figure 64: Active Action Control for assumptions for Scenario 1 “expert-oriented”.

In the Scenario 1, the selected technologies were chosen according the experts point of view. They suggested to replace the glazing ratio windows of older buildings (clusters 1 and 2). Likewise, they improved of the floors and roofs thermal insulation of clusters 1 and 2 (building age 1961-1970). The thickness of the insulation is 35 cm, which corresponds to a zero-energy building (see Table 24). Actually, an insulation with a thickness more than 35cm does not help in any additional significant protection to the element. Finally, the experts decided to substitute the boilers for the buildings built during to 1971-1990 (cluster 3). This decision was made because the boilers of the older buildings were have been already replaced due to their lifespan of 20 years.

Figure 65: Scenario 1 "expert-oriented" in CommiuntyViz; maps and charts.

Comparing scenarios

After creating different scenarios, it is possible to compare the scenarios between them and also with the baseline Scenario (0) through maps and charts. As an example, the comparison between scenario 0 “baseline” and scenario 1 “expert-oriented” is shown in Figure 66. The comparison between all the Scenarios is possible (i.e., scenario 1, scenario 2 and scenario n), handling also many scenarios at once. Moreover, modelling approach that is created will automatically be applied to all scenarios, unless scenario-specific changes are needed. When comparing different scenarios, side-by-side maps, charts, and results table are available to facilitate the comparison.

Figure 66: The comparison between scenario 0 (baseline) and scenario 1 (expert-oriented) through analysing maps and charts.

7.3.2 Suitability Analysis

As shown in Figure 67 the outputs of scenarios become as inputs for suitability analysis. After stakeholders have selected their eventual preferred scenarios, at this stage, they need to know the level of their suitability. In the current study, suitability analysis refers to identify the level of suitable retrofitting solutions, that are able to meet the needs of a stakeholder and decision makers (Koulamas et al., 2018). It is required to define energy retrofitting strategies that are acceptable from economic, environmental and social criteria and, mostly, energy. Suitability modelling identifies the continuum of best or worst retrofitting scenarios. The modelling and adapting process is similar to IIA procedure; however, the weights are added playing a key role in the suitability analysis.

According to (Lieske and Hamerlinck, 2013), "*CommunityViz suitability model meets the requirements for planning methods, including increasing insight to a decision situation, the ability to quickly handle changing inputs, transparency, and making values incorporated in a decision process explicit*".

Indeed, CommunityViz is a powerful tool for suitability modelling and spatial MCA, which is built on a Weighted Linear Combination (WLC) model (Lieske and Hamerlinck, 2013). WLC is one of the most best-known analytical methods for GIS-MCA (Malczewski, 2011). It links the weight values to each criterion and automatically updates the model when there are changes in either weight or geographic data inputs. First, evaluation criteria are normalized to a specific numeric range between 1 to 100. Next, the numeric range is combined with a weighted average to create a composite score for each decision scenario by WLC (Lieske and Hamerlinck, 2013). Of course, weights present the importance of each evaluation criterion. For each decision scenario, a score is calculated for each criterion by multiplying the weight by the normalized value of that criterion. Scores are summed for all evaluation criteria to provide an overall suitability score (Lieske and Hamerlinck, 2013). The scores are calculated for all the scenarios and the ones with the highest score may be chosen. The results are visible by maps in which the scores are displayed with a graduated colour ramp as: Unsuitable; Low suitability; Medium suitability; High suitability and Suitable (Figure 68).

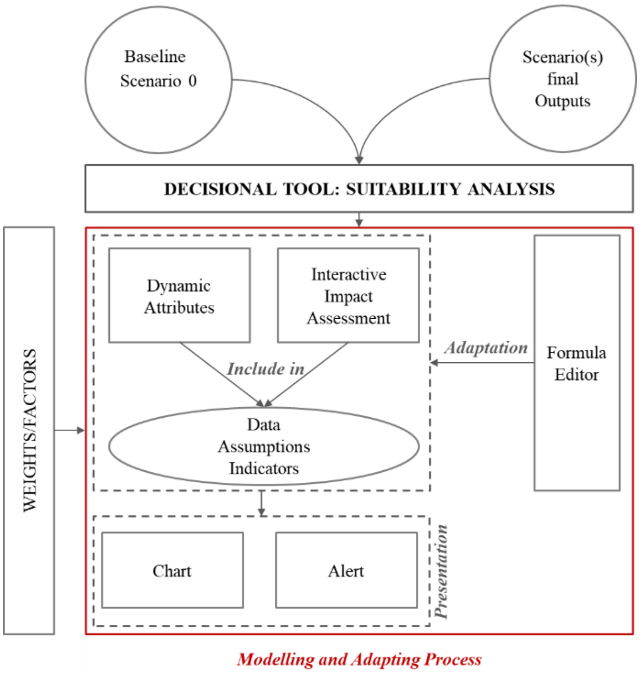


Figure 67: Schematic flowchart of MC-SDSS design; suitability modelling.

Generally, suitability model creates two kinds of evaluation criteria scores: raw and standardized. A raw evaluation criterion score is calculated by using a formula-based dynamic attribute (Lieske and Hamerlinck, 2013). Figure 69 shows how easily it is possible to change the weights by changing the assumption sliders (Walker and Daniels, 2011), which are linked to dynamic attributes.

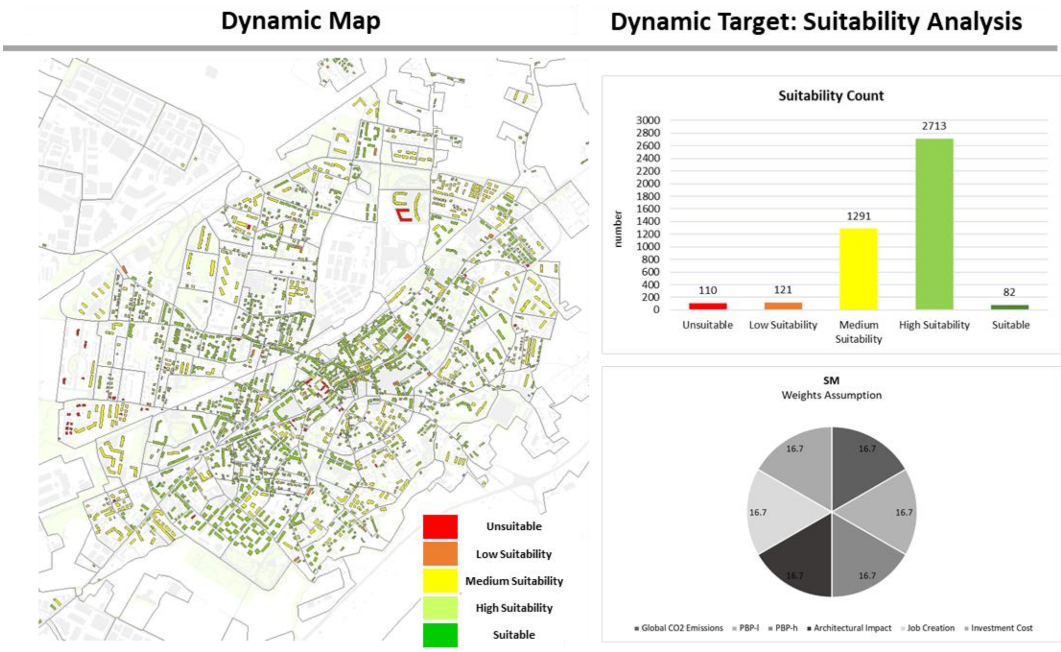


Figure 68: Suitability modelling, Scenario 1 “expert-oriented”, same weights.

Stakeholders can easily change the weights of evaluating criteria by using the graphical display of value (sliders) shown in Figure 69. Consequently, MC-DSS recalculates the suitability analysis considering the new weights. The new results are displayed again by maps and charts (Figure 70). The scale of weights is often set on using numeric point in order to rapidly recalculate a model. Zero is inserted when stakeholders don’t want provisionally or permanently consider some criterion in the analysis. This interactive approach aids to discuss the importance of each criterion. Moreover, it provides a supportive method for working on conflicting preferences and supports sensitivity analysis. It permits SDSS-based suitability analysis to be used as a thinking tool in retrofitting scenarios selection (Lieske and Hamerlinck, 2013).

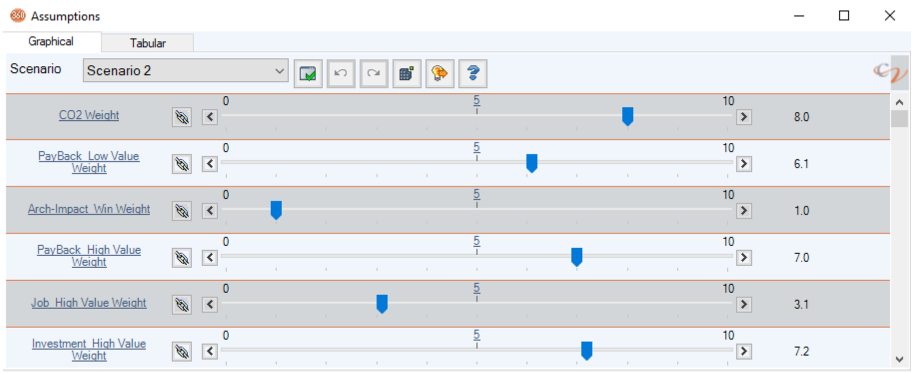


Figure 69: Representative CommunityViz weight sliders on a 10-point scale.

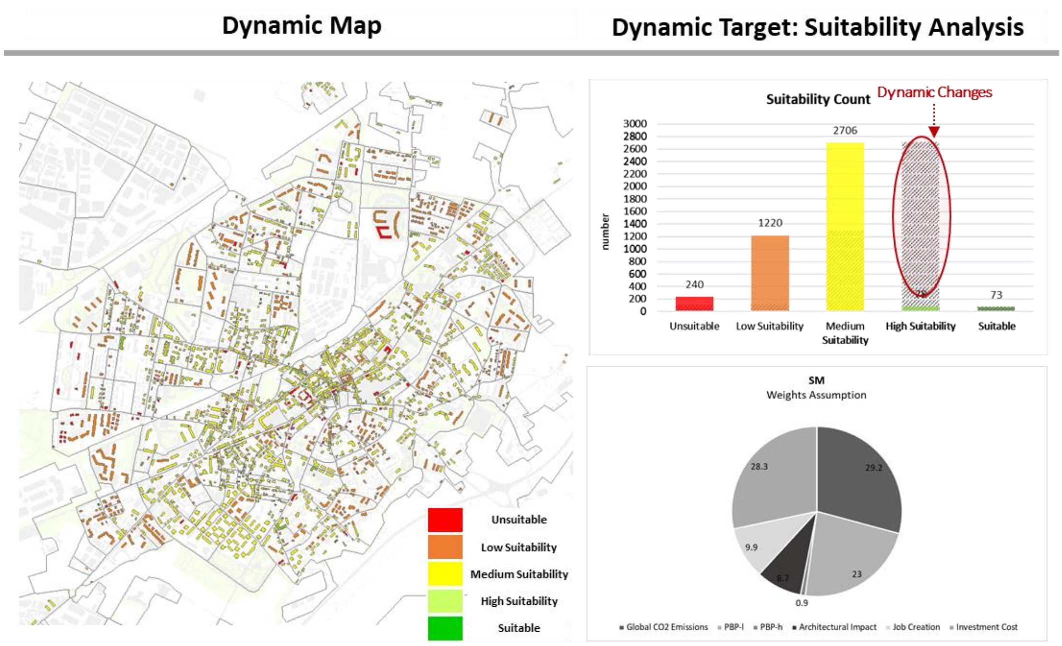


Figure 70: Suitability modelling, i.e., Scenario 1 “expert-oriented”, different weights.

After selecting scenarios, they can be analysed and also compared as it is explained in the previous section Figure 70.

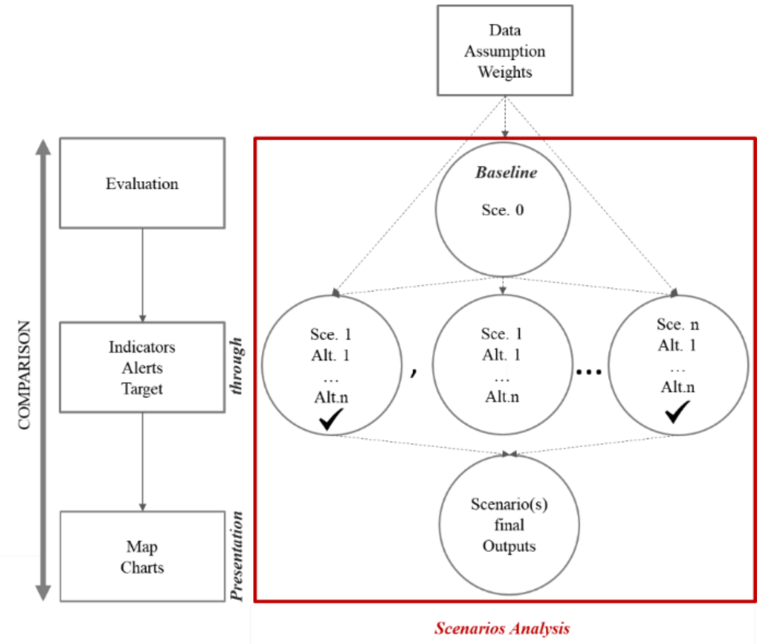


Figure 71: Schematic flowchart of MC-SDSS design; Scenario analysis.

Again, the comparison between different suitability scenarios is possible as shown in Figure 72.

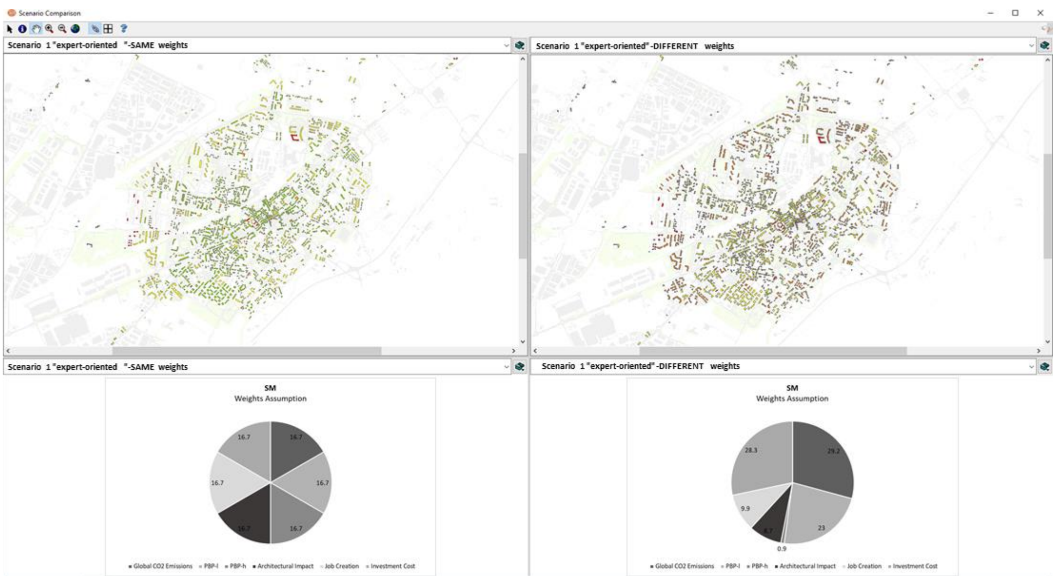


Figure 72: The comparison between suitability scenarios (1 same weights-1 different weights) through analysing maps and charts.

7.4 Test and validation of MC-SDSS

In section 7.3, the basis of MC-SDSS is modelled and adapted for the case study of Settimo Torinese. Afterward, the second workshop is organized in order to test and assess the usability of the developed tool for urban energy planning. In this second workshop, scenario 1 as an example was shown to the participants to provide them information and guideline how to define scenarios. During the workshop, two focus groups were formed to test the tool. Indeed, focus group provide a more natural environment rather than an individual interview since participants are influencing and influenced by each others (Krueger and Casey, 2000). As MC-SDSS tool is still in its pilot phase, receiving opinions from the stakeholder and DMs, was the best option in order to improve it (Brömmelstroet et al., 2014). For more detail, the material of workshop is attached in Appendix B.

7.5 Results of the validation process of MC-SDSS: through the 2nd workshop design

Setting the workshop

The second half-day workshop was set up on 12th July 2017 at Politecnico di Torino (Italy) (Figure 73 and Figure 74). The purpose of the workshop was to assess the usability of the developed MC-SDSS tool, especially collecting feedback from stakeholders in order to improve it. The stakeholders involved in this workshop were mostly the same as those in the first one (9 participants). However, the new stakeholders, DH provider and the environmental representative of the municipality of Turin were added.

Figure 73: Second workshop at Politecnico di Torino with the aim of testing the usability of the developed MC-SDSS.

Figure 74: The participants in the second focus group.

First, a brief introduction about the progress of the research project and the structure of the workshop organization is reduced to the participants. Moreover, the MC-SDSS tool, its functionality and practical applications are presented (Figure 75). The progress of the workshop depends strongly also on the stakeholders' knowledge. Therefore, there is a need to precisely describe the tool and maps in order to give them a comprehensive vision about the data used and the type of analyses (Brömmelstroet et al., 2014). Notably, strong moderation skills are required to moderate an exchange of opinions when the discussion gets stuck in the focus groups (Brömmelstroet et al., 2014).

Figure 75: Presentation of the instrument.

Describing the workshop

The workshop was structured into three main steps to facilitate the understanding and working with the interactive energetic plug-in (Figure 76). Moreover, these three steps ease the comprehension of the workshop process for the participants. At the end of each step, evaluations took place (i.e., questionnaires). The stakeholders were asked to fill out the questionnaires regarding the usability of the tool for each step. All participants were asked 17 questions about the usability of the instrument. The number of participants who answered the questions was limited to 8 participants because one of the stakeholders left before the appointed time. The limited number of invited stakeholders was targeted due to the complexity and specificity of the theme of the workshop. Therefore, high levels of concentration and expertise were needed in order to fulfil the objective of the workshop, which was improving the tool and its usability. Step 1 included a two-hour interactive focus group to define different energy saving scenarios utilizing IIA instrument of MC-SDSS. In this step, the facilitator (author) worked side-by-side with the stakeholders. As said before, initially, facilitator showed the already created scenario, so-called scenario 1 “expert-oriented” to the stakeholders in order to give them a better understanding how to use the tool. Scenario 1 “expert-oriented” represents that moderate investments in building renovations lead to the moderate emissions reduction. The choice of the strategy depends on the willingness to invest relative to achieving the emissions target (Delmastro et al., 2017). Thereafter, different scenarios were defined altering and experimenting the sliders (assumptions) directly by stakeholders. Stakeholders changed the assumptions several times and they were greatly interested to see the results changing in the consequence of their decisions very quickly.

When this step was finished, the participants were asked to fill out the questionnaire by giving them about 30 minutes to evaluate the first step usability. Summing up the step, the major activities were performed in this step:

- Demonstrating how to use the tool for defining different scenarios;
- Experimenting the energy refurbishment assumption to achieve different energy saving scenarios in real-time;
- Questionnaire compiling.

In step 2, the stakeholders could visualize the suitability maps of the scenarios which were created in step 1. Likewise, in this step, the side-side collaboration of facilitator and the stakeholders was requested. After step 2, another brief questionnaire regarding the usability of the tool is provided to the participants. Again, summing up the step 2, the major activities were performed in this step:

- Demonstrating how to use the suitability maps;
- Experimenting the changes in the weights and seeing their real-time impacts;
- Questionnaire compiling.

Finally, the workshop survey was designed as step 3 in order to analyse the general evaluation of the workshop organization. For the whole workshop process, the voices and notes are recorded just like the first workshop.

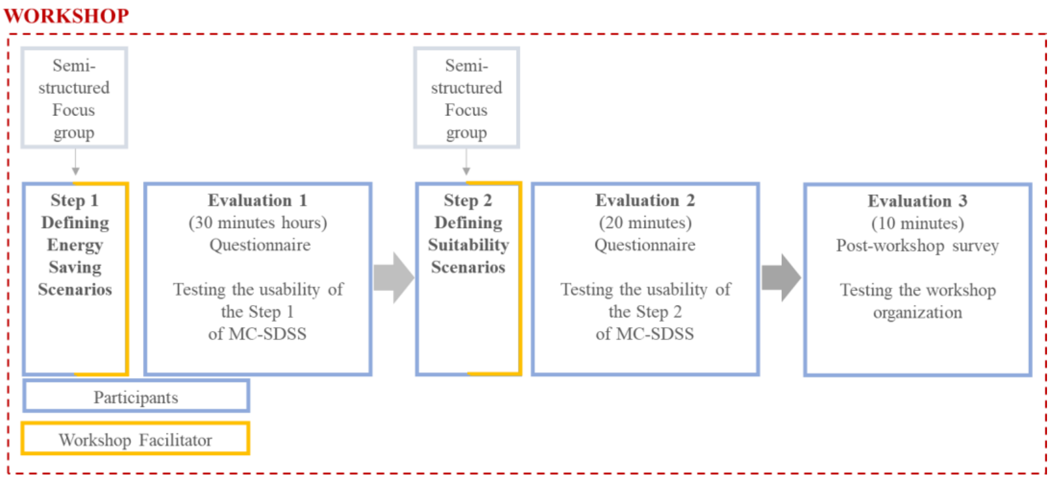


Figure 76: Workshop Structure.

The questionnaire included eleven end-closed questions and the six open-ended ones. The close-ended questions were designed in order to answer the following three criteria: Usefulness (U), Ease of use (E) and Visualization effectiveness (V). While the open-ended questions sought further suggestions regarding each step. For each question, respondents were asked to answer by selecting: very much, somewhat, a little and not at all. The results emerged from this workshop are graphically shown and some important stakeholders' considerations are reported in this dissertation. The questions are presented in Table 35, Table 36 and Table 38, and consequently, the responses are presented in Figure 80, Figure 81, Figure 82, Figure 83 and Figure 84.

Step 1

The first step aimed at defining different energy saving scenarios considering stakeholders' preferences. In this step, the participants worked with the MC-SDSS tool and they defined different scenarios in real-time. They experimented changing the assumptions (i.e. retrofitting measures). For instance, they moved the sliders based on their desires such as glazing window replacement for certain cluster of buildings. At this point, the scenario 1(Figure 65) which was previously created by the expert is illustrated to the participants in order to make them understand how to define the new scenarios by altering the assumptions.

With the help of the double-display visualization and printed maps (of the current states of the city), the stakeholders could discuss several alternatives. The double-display facilitated the negotiation task, giving the participants a better understanding and vision of the scenarios on their proposed changes (Pelzer et al., 2015). Additionally, a better understanding increases the participants' interactions. Indeed, the workshop was scheduled to give an opportunity for more discussions on each participant's own practices relative to their daily work.

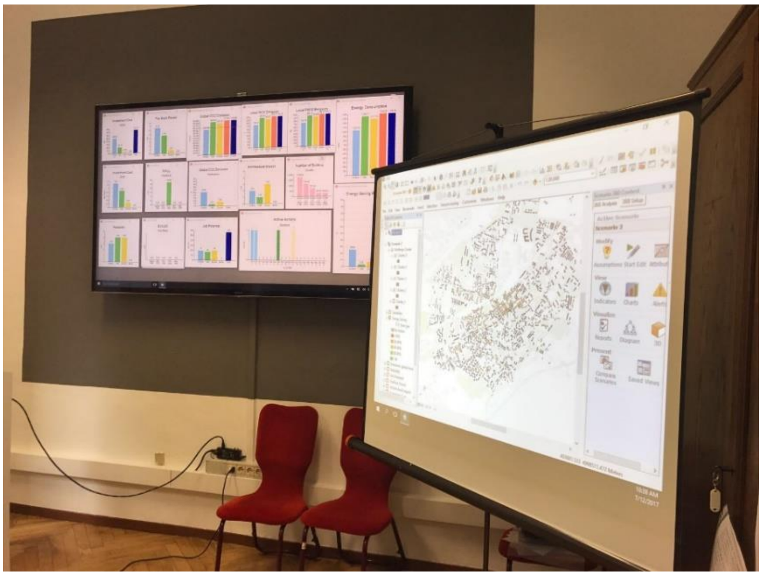


Figure 77: Double-display in order to facilitate the analysis of charts and maps simultaneity.

Figure 79 shows an example of one of the scenarios defined by stakeholders, so-called scenario 2 "stakeholder-oriented". Finally, they could compare different scenarios. In this specific scenario, they replaced the glazing ratio windows of most older buildings (clusters 2,3 and 4) and they isolated the walls and floors of clusters 2 (building age 1961-1970) and 3 (building age 1971-1990); while, they preferred to do not renovate any intervention in terms of energy system (see Figure 78). This decision was made because they wanted to see the impact of the envelope system refurbishment that leads to significantly reduce the energy consumption. In this workshop, the aim of defining different scenarios was not to find the "best" performance scenarios, but it was to test the usability of the tool experimenting it. Therefore, here the author recalls just one of the defined scenarios among others (from scenario 1 "expert-oriented" to scenario 2 "stakeholders-oriented") in order to illustrate the potentiality of the tool as well as its functionality.

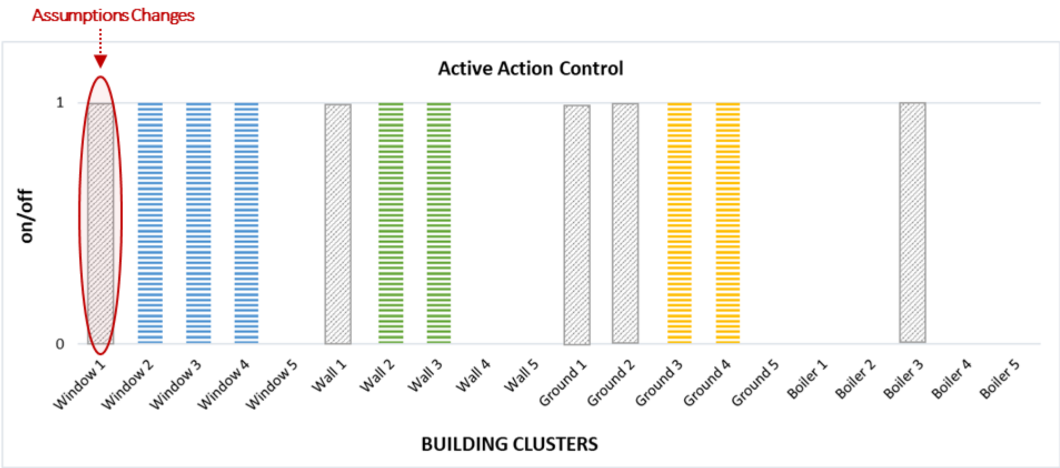


Figure 78: Active Action Control for assumptions of Scenario 2 "stakeholder-oriented".

Figure 79: Scenario 2 "stakeholder-oriented" in MC-SDSS; maps and charts.

At the end of step 1, each individual participant completed a questionnaire, which had two primary objectives:

- To understand how the stakeholders experienced the process of energy saving scenarios creation.
- To collect their suggestions in order to improve the tool.

Further goals were to collect opinions on the utility of the assumptions, indicators, and attributes. They also sought to evaluate the clarity of the charts and maps and the potential barriers to planning practice (Brömmelstroet et al., 2014). The aim was to address any weaknesses in order to improve the tool for future experiences. The ultimate goal was to apply the stakeholders' requests into the future development of a new MC-SDSS tool for planning practices. The questionnaire of the step 1 was divided into three main macro-sections: (i) Questions regarding the considered "Retrofitting Measure"; (ii) Questions regarding created "Indicators"; (iii) Questions regarding the emerged "Map of Results". The questions types of each macro-section are shown below (see Table 34, Table 35 and Table 36):

Table 34: Questions regarding considered (i) macro-section "Retrofitting Measure".

(i) Retrofitting Measures		
A-Retrofitting the heating energy system for building groups (i.e., boiler replacement)		
Q1. Are the heating system retrofitting simulations for buildings clusters useful?	U	□ *Very much* □ *Somewhat* □ *A Little* □ *Not at all*
Q2. Are they understandable and easy to use?	E	
Q3. Are the results of these simulations visualized effectively?	V	
Q4. Do you have any suggestions to improve these simulations and/or their visualization?		
B- Retrofitting the envelope system of buildings (i.e., window replacement, wall insulation)		
Q5. Are the envelope system retrofitting simulations for buildings clusters useful?	U	□ *Very much* □ *Somewhat* □ *A Little* □ *Not at all*
Q6. Are they understandable and easy to use?	E	
Q7. Are the results of these simulations visualized effectively?	V	
Q8. Do you have any suggestions to improve these simulations and/or their visualization? Q9. Do you have any suggestions to modify or add retrofitting measures?		

Explain your motivation.

Table 35: Questions regarding created (ii) macro-section "Indicators".

(ii) INDICATORS		
Q10. How useful are the indicators in the instrument? • Investment Cost (M€) • Investment Cost (M€/GWh) • Global CO_2 Emissions (tonnes) • Global CO_2 Emissions-Reduction (%)	*U*	□ *Very much* □ *Somewhat* □ *A Little* □ *Not at all*

• Local NO_X emission (tonnes) • Local PM_{10} emission (kg) • Architectural Impact (rank) • Job Potential (man-day) • Reliability (rank) • Energy Consumption (GWh) • Energy Saving (%) • Socio-Economic feasibility (%)		
Q11. Are they understandable and easy to use?	*E*	□ *Very much* □ *Somewhat* □ *A Little* □ *Not at all*
Q12. Do the proposed indicators adequately provide the information you need to support the understanding of energy scenarios on a local scale?	*V*	
Q13. Do you have any suggestions to improve their visualization / other indicators that might be essential? Which?		

Explain your motivation.

Table 36: Questions regarding emerged (iii) macro-section "Map of Results".

(iii) MAP OF RESULTS		
Q14. Are the final results of the energy saving map in percent useful?	*U*	□ *Very* □ *Enough* □ *Little* □ *Not at al*
Q15. Are they understandable and easy to use?	E	
Q16. Are the results of these maps visualized effectively?	V	
Q 17. Do you have any suggestions to improve these simulations and/or their visualization?		

Explain your motivation.

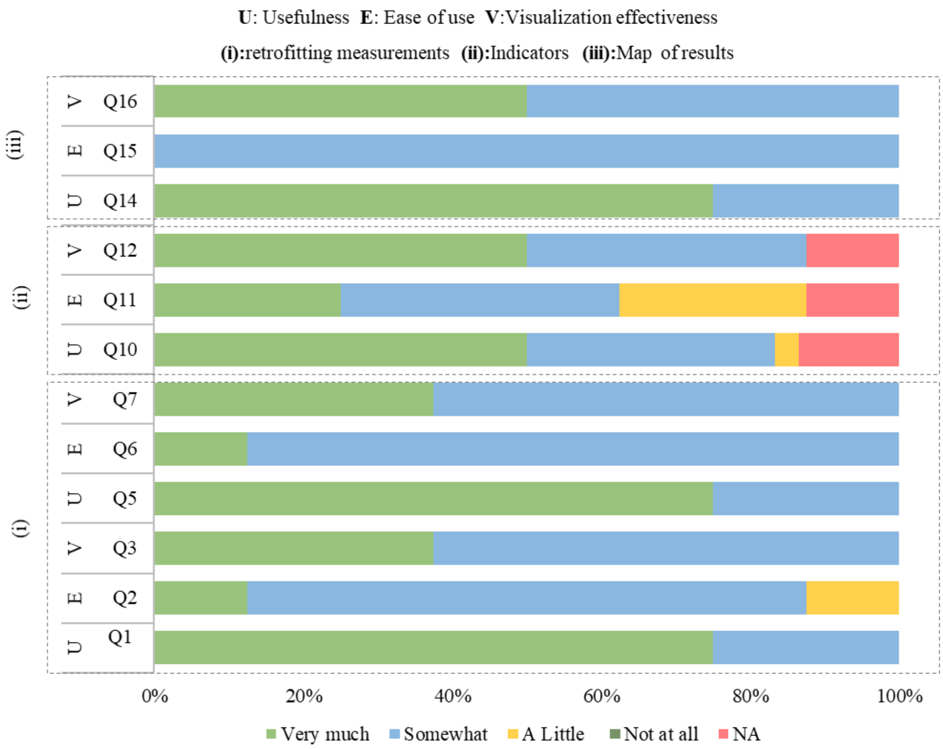


Figure 80: Answers received in step 1.

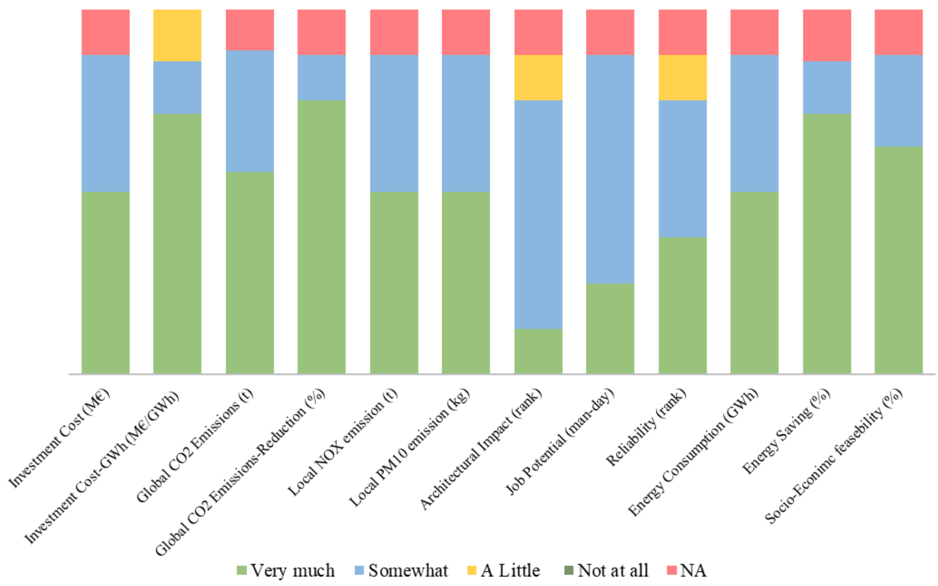


Figure 81: Answers received for Q10 regarding individual indicator.

The questions regarding the retrofitting measures simulations and their usability were designed in the first nine questions (Figure 80). Generally, the participants expressed very positive views regarding the usefulness of the instrument (U: q1, q5: 75%). Moreover, they stated that the MC-SDSS tool is easy enough to use emerged from questions 2 and 6 (E). However, about 13% of respondents reported that the simulations were not very easy to understand. They had some difficulties to understand how the simulations were previously calculated. Finally, they stated that the results are visualized around 38% in a very effective way and about 63% in a way that was effective enough (V: q3, q7). Regarding the (ii) Indicators, fifty-eight percent of the participants responded that the indicators were very useful for them (U: q10), just 4% found the indicators of little use.

Q10 is also separately analysed as shown in Figure 81. An interesting outcome from this figure is that they were satisfied enough with the created indicators. This fact emerges due to their effective participation from an early phase of the development of MC-SDSS tool. Indeed, in the first workshop, the same stakeholders were asked to define their preferred criteria and indicators. However, it can be seen that the stakeholders stated that especially two qualitative indicators, architectural impact and reliability, were little useful them, while most of the quantitative indicators seemed very useful. One participant did not answer the indicator question stating that the time was not enough to evaluate all the indicators.

Q14 to Q16 were about the maps of results and their presentation. The instruments were useful and easy to understand to stakeholders. Regarding the presentation of maps, the stakeholder who was an expert in the visualization stressed the attention of the grade of the colour of the maps.

Listening to the voice records, during the discussion some important points emerged. A number of respondents found that they needed to have more options for retrofitting measurements (i.e., photovoltaic panel, district heating, etc.). In particular, they found it is significantly necessary to implement more energy system retrofitting, which increase the energy efficiency of buildings at the district level. One suggested that:

"I think the presence of the energy system refurbishment is significantly necessary. In this tool, I see more envelope system refurbishment for a demand-side of energy but not retrofitting solutions for the energy supply-side. Please add photovoltaics and DH connection solutions. They help decrease the harmful environmental impacts and they enhance the energy efficiency system in the buildings".

They also insistency asked to enlarge the number of clusters in order to have more flexibility for applying the retrofitting actions. They desired to regroup the building into more than thirty clusters instead of five considering buildings age and typology. Currently, five clusters of the building were identified.

"In order to make better decisions, I need to have more flexibility to apply the refurbishment actions. I think it is better to be able to choose the number of buildings by ourselves and not by default".

They also suggested to consider the renovation ratio for the buildings, however, the data regarding the renovation status is not available yet in order to add it within the tool. Moreover, the stakeholders asked strongly to add some back-costing objectives. This means fixing an objective for energy saving (e.g., 20% for all scenarios) and to define the different scenarios which can always achieve that target. While, currently they could define what-if scenarios where the energy saving targets were different in each scenario, however, the different alerts and threshold were set to give them the indications. The regards made by one of the participants are reported as follows:

"In my opinion, instead of achieving different targets for each energy saving scenario, it is better to fix a specific target for all scenarios, for example, the target of the reducing energy consumption by 20% as an European 20-20-20 targets. Then, we can try to create different scenarios which lead to achieving that specific target".

Another interesting discussion was related to installing the sensors in order to obtain the real-time data instead of the historical ones. However, installing the sensors for obtaining the real-data data needs a huge effort in terms of costs ad time.

Step 2

The second step aimed at generating the suitability maps from the scenarios that were defined in the first step. In this step, participants were asked to change weights through sliders (Figure 69). Consequently, the participants made a comparison between different suitability maps based on different distributed weights. Again, at the end of step 2, each stakeholder was asked to fill out the relative questionnaire, which had two primary objectives:

- To understand how the stakeholders experienced the process of suitability analysis.
- To collect their suggestions in order to improve the suitability modelling in MC-SDSS.

Further goals were to collect opinions on the clarity of the charts and maps of suitability (Brömmelstroet et al., 2014). As mentioned before, the aim was to improve the tool. The questionnaire of the step 2 has only one macro-sections: (iii) Information regarding the emerged Map of Results.

Table 37: Questions regarding emerged (iii) macro-section "Map of Results".

(iii) MAP OF RESULTS		
Q18. Are the final results of the suitability map in percent useful?	*U*	□ *Very* □ *Enough*
Q19. Are they understandable and easy to use?	E	□ *Little*
Q20. Are the results of these maps visualized effectively?	V	□ *Not at al*
Q21. Any suggestions to improve this simulation and/or its display mode.		

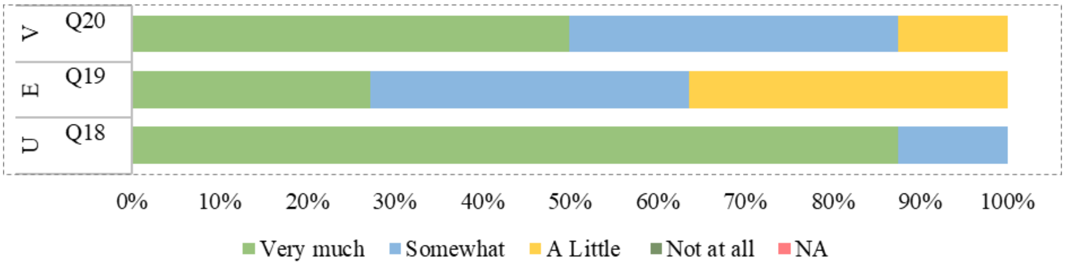


Figure 82: Perceived usability of the instruments in step 2.

Regarding the suitability maps, the participants were asked four questions (Figure 82 and Table 37). Most of the respondents stated that the suitability maps were very useful. This is because they needed to visualize an aggregated evaluation about their decisions. Moreover, they wanted to see the impact of changes made to weighing on their decisions. For about 50 % of the stakeholders, the complexity level of the generated suitability maps was simple; while for 50 percent found them very complex. Around 85% of the respondents stated that the emerged results of suitability were presented and visualized in an effective manner.

Specifically, during the discussion, the participants stated that the suitability map was significantly useful. This instrument aided the DMs in order to analyse their decisions by visualizing a unique map. One of the very important statements in this step made by all participants was:

"*The suitability maps instrument is very useful because it assembles all our decisions outcomes together and we can see the decision suitability by colours. Sometimes, we made the decisions without knowing if they were suitable or not. For making our decisions, we absolutely need instruments such as suitability in order to be able to visualize the best scenario*".

Step 3

The final evaluation was conducted to see how the workshop was organized. the following questions were used (Brömmelstroet et al., 2014).

Table 38: General questions on the workshop Session.

General Questions on the Workshop Session	
Q1. The session produced useful results Q2. I am confident that the group solution is correct Q3. I am satisfied with this session Q4. Now I have more information about energy-related decision-making on the urban level	□*Very* □*Enough* □ *Little* □ *Not at al*

Q5. Now I have a better vision regarding the views of the other participants
Q6. I would use the presented tool and the results of this session in working practice
Q7. We have reached a shared view of the problem
Q8. We have achieved a shared vision of the goals
Q9. We have achieved a shared vision of possible solutions
Q10. I felt as part of a working group
Q11. The presented instrument has highlighted a new approach to energy at the urban level
Q12. The basic hypothesis presented for model development is clear
Q13. The terms used during the session are understandable

All participants were asked 13 questions about the session evaluation survey. Their answers are evaluated in Figure 83. The participants shared a very positive general opinion about the process. Specifically, most of the participants (88%) stated that the session resulted in useful results (q1). Fifty percent of the stakeholders felt that the results of the session were based on correct assumptions, and consequently, they were confident that the group solution they had reached was correct (22). Furthermore, 88% of participants were satisfied with the session itself by answering q3. Question 4 explored how the workshop was useful to increase the information regarding urban energy planning. As many as 63% of the respondents stated that the session provided better information. According to the answers to Question 5, 63% of stakeholders stated that the session was very useful in order to understand the other stakeholders' opinion. While 25% thought it was useful enough, and 1 participant didn't answer in this case. Seventy-five percent of the respondents also stated that they would probably use the tool from the session in their daily planning practice (q6). Questions 7 to 9 explore how the patricians achieved a shared vision problem (q7; 50%) and the goals (q8: 50%) and solutions (q9; 25%). 75% had a strong sense of being part of a group during the session (q10).

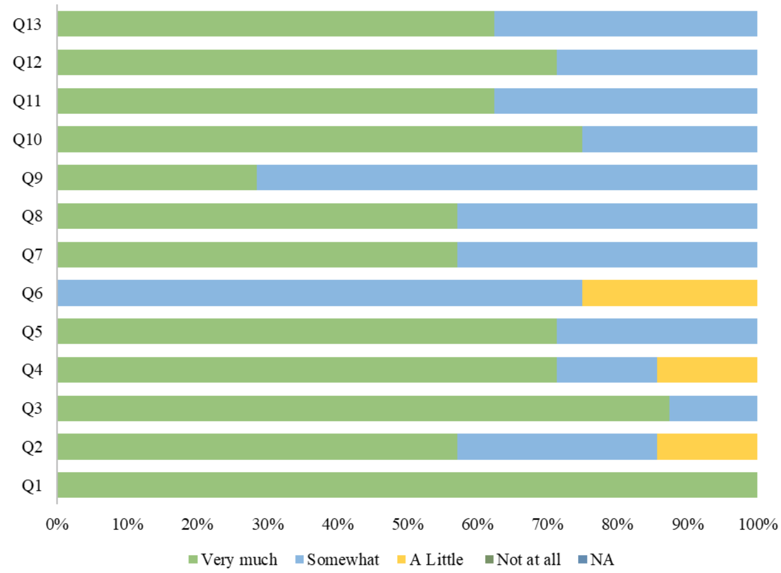


Figure 83: Perceived usability of the instruments step 3.

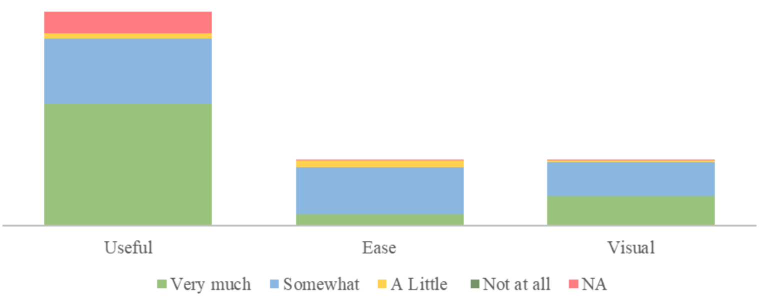


Figure 84: The total received answers based on usefulness, ease of understanding and visual effectiveness of the tool.

Finally, Figure 84 Shows the total answers received regarding the usability of the developed MC-SDSS tool based on three criteria of usefulness, ease of use, and the visual effectiveness. Most participants found that the tool was very useful to use for making better decisions in the sustainable development of their city. Regarding the ease of use, most stakeholders found that tool was easy enough to use and it was effective in its visualization way. However, the improvements are to be performed based on the stakeholders' opinions are needed.

7.6 Concluding remarks

This chapter started by identifying the potential of developing MC-SDSS tool to support planning practices. Two integrated instruments of CommunityViz software, Interactive Impact Assessment and Suitability Analysis, are modelled and adapted in order to provide an appropriate MC-SDSS for urban energy planning purposes. It should be noted that the CommunityViz suitability model closely follows the methods of MCA modelling, WLC. The main advantages of the developed MC-SDSS in the field of urban energy planning can be summarized as follows:

- To allow the participative processes;
- To give a visualization opportunity for the decision process in specific areas;
- To consider multiple criteria (e.g., economic, environmental, technical and, particularly, social aspects);
- To manage and store a very large amount of georeferenced data; to illustrate results requested by users according to different spatial forms (e.g., maps, graphs);
- To show the distribution of buildings' geometrical characterization and buildings' energy consumption.

Moreover, an experiential research design is set up to investigate the usability of the tool and to gain insights into the types of interventions that can improve usability. In this regard, the second workshop, which is fully reported in section 7.5, has been organized to test the tool by stakeholders in order to improve the future development design of the tool. Within this workshop, three main considerations emerged that will be linked to the tool for future developments: (i) improve data entry accuracy; (ii) access to real-time data, and (iii) enlarge retrofitting solution.

Chapter 8

Conclusion and future work

8.1 Conclusive summary

This chapter summarizes the overall research and conclusions. Additionally, suggestions are made for further development in research. As illustrated in chapter 1, the foremost goal of this Ph.D. dissertation was to develop a new MC-SDSS to support the participative process for defining effective scenarios to improve the energy performance of the urban areas. In particular, this work creates a link between energetical, economical, societal, technical and environmental performances of retrofitting interventions. The research boundaries were delineated by focusing on existing residential building stock since they characterize the context of most European cities. The relative available data of these buildings were first collected and georeferenced from various sources. Based on the created geospatial database, the buildings energy consumption patterns were statistically modelled to map the current energy patterns over the entire city. Afterwards, the archetype model of the city was created in order to speed up and ease the future energy saving simulations by applying the retrofitting solutions. The geospatial database was used as the object of multi-criteria analysis assessments. Finally, an interactive MC-SDSS was created to support the DMs in defining energy saving scenarios in real-time. This Ph.D. work provides a significant innovative progress in the research field as it has developed an interactive plug-in for UIEP in the GIS environment (MC-SDSS).

Given the goal and the boundaries of the research, three research questions were formulated, and they were addressed within the Ph.D. research path. As shown in Table 1, corresponding Ph.D. chapter/s contributed to response to each research question. In this concluding section, instead, the synthetic answer is proposed by the author summing up the key findings presented throughout the thesis.

8.2 Key findings and main limitations

Research question 1

Are current research studies able to support the challenges provided by Urban Integrated Energy Planning (UIEP), taking into account the variety of all the sustainable planning aspects? What are current challenges and barriers in this research field?

As described in chapter 2, this study has drawn on an understanding of UIEP towards a more sustainable development of the built environment. A systematic review of the available spatial approaches has been proposed towards UIEP. This systematic review showed that many spatial energy modelling approaches have been recently developed. Nevertheless, a unique UIEP framework is not available or agreed on among the several experts and scientific disciplines dealing with sustainable energy planning. The meta-analysis shown in Figure 8 highlighted that how the great majority of current approaches do not integrate all the phases of UIEP. Consequently, not all planning aspects are taken into account in conventional practices to guide policies along sustainable development paths. Hence, this study suggests reinforcing the collaboration between different research disciplines dealing with socio-economic, environmental, and technical aspects with emphasis on spatial issues. In order to understand how to structure the UIEP, it is important to analyse how it is possible to implement the interaction among the different stakeholders, how to select different approaches and how to choose them considering the decision context peculiarities and the type of planning project. From this perspective, the proposed SWOT analysis of the conducted literature review in section 2 (see Figure 9) is useful for all urban actors including the new research and DMs in order to understand the most important characteristics of the available approaches for different planning phases. Although the approaches have not yet been integrated in order to cover and accomplish the whole UIEP, it is important to push future research and practice to take into account the integration process. This will allow the possibility to explore urban energy transition strategies in the spatial planning field according to sustainable development. The ultimate aim of this research is to highlight the potential of existing approaches to be combined in order to cover all UIEP phases and to reduce the current uncertainty faced by DMs at the urban energy planning level. As a preliminary theoretical framework proposed by this study, the outcome helps urban actors to develop energy planning projects, guiding them in the choice among a significant number of existing planning approaches. Finally, the theoretical framework represents a substantial step towards the sustainable urban development in the contexts of built environment.

Limitations

This study suggests an integrated procedure of urban energy planning. This faces several barriers including:

- the necessity of changing traditional thinking that may lead users to be discouraged since it requires integrating a wide range and diversity of disciplines.
- a high level of expertise is required to combine the different methods and to simultaneously handle the different sustainability aspects.
- the evaluation process difficulties may be time-consuming and costly. This fact emerges from the need for high-level data (quantity and quality) and expertise for the assessment processes.
- the availability and reliability of large standardized databases and public data sources are limited at the local level. This issue is very challenging since the data is not always open-source, available and updated. Furthermore, the data collection process requires new instruments (e.g. smart meters) and new physical resources to analyse them.

Research question 2

How to model the energy consumption at urban scale in a spatial way for the current and future scenarios? Which kind of data are needed? And how to connect different data type from different and scattered sources?

As illustrated the full development of this part in chapters 4 and 5, for modelling the energy consumption over the entire city, a large number of historical data are needed. The most challenging issue was related to collecting and integrating the built environment data and information since the data are significantly scattered among several entities at the local level, and there is a lack of interoperability among the data sources (see section 4.3.1). Actually, this section reports that one of the main barriers to developing a robust and detailed analysis is correlated with the data collection procedure. Especially in Italy, information about building stock and their energy performances are derived from different regional and local authorities and they are not often homogeneous. Therefore, in order to set up an effective energy planning at the local scale, it is crucial to improve the quality of data availability and management. Data availability of buildings energy consumption will hopefully improve in the future thanks to smart metering and real-time data monitoring following recent open data policy. To this end, a supportive GIS database where all the scattered information and data were geo-referenced is first created (Figure 18).

Referring to the energy consumption modelling at the urban scale developed in section 4, this research proposed a geospatial statistical modelling. Generally, statistical methods estimate the energy consumption based on a historical data. The proposed model was based on MLR approach considering various predictors, which are cross-validated. The results show a good agreement on error around 20% at the city as reported in Table 13. The model succeeded to estimate the energy consumption of most existing buildings, where the monitored data was not available. However, due to the strong dependency of statistical models on existing available data, these methods are not able to predict the impact of the future refurbishment solutions. Therefore, there was a need to simulate the future city energy performances. However, the simulation of the whole city may be extremely time-consuming.

Therefore, the research in section 5 proposed a novel engineering methodology to accelerate the urban area energy consumption simulations, including urban planning renovation scenarios. The energy demand of cities, as well as the microclimatic conditions, was calculated by using a simplified archetype 3D model designed as a function of the city urban characteristics. This method shows that the number of buildings to be simulated can be drastically reduced with no particular influence on the accuracy of the results. On one hand, the main advantage of an engineering-based method is the capability of predicting energy savings for buildings after the application of renovation measures. On the other hand, these methods are very detailed models based on thermodynamic relationships and heat transfer calculations. As a general remark, the historical data can be used for the comparison against measured consumption data.

Limitations

This study suggests first a spatial data collection and then an integrated procedure of urban energy modelling approaches based on the data collected (i.e., statistical and engineering). This faces several barriers including:

Regarding the data collection:

- the energy consumption data is not usually open source; thus, a huge effort was needed to collect the data from different entities and to ask the collaboration from local stakeholders.
- the geo-referencing procedure of data could be also a challenging issue. In many cases, the necessary information related to the buildings are associated with the buildings number (as points) rather than the buildings polygon. The tricky issue is that these points are sometimes situated between two or three buildings having the same distance. Thus, it is not easy to understand that the data belongs precisely to which building. Especially, when we talk about a vast number of building like 3600 buildings in this research, the geocoding process cannot be manual, and some errors will emerge.

Regarding the statistical modelling approach:

- a vast amount of historical available data is needed. For many regions, it is almost impossible to have a monitored data in terms of energy performances.
- the intrinsic limitation of statistical methods concerns the microclimate effects, which were not taken into account in the present work. In fact, a microclimate model that would give a single value for the whole city for air temperature would not significantly improve the results of the current model presented in this work.

Regarding engineering modelling approach:

- the need for high-level detailed thermo-physical data of the buildings in the city.
- setting up the simulations can be a tedious task requiring a lot of time and expertise.
- the simulations themselves are very time-consuming and they require high-performing processors in order to perform the entire city.

Research question 3

How useful are interactive MC-SDSS in supporting the stakeholders in urban energy planning decisions? how their usability can be improved?

As illustrated in chapters 6 and 7, a MC-SDSS has been developed to support the stakeholders with different background and preferences. The tool is an interactive plug-in in ArcGIS environment. MC-SDSS is able to help participants in a user-friendly way to define energy refurbishment scenarios. Moreover, the tool gives an opportunity to generate the suitability maps, with which the stakeholders can analyse the grade of the suitability of their decisions. The development of MC-SDSS is based on an existing tool, named CommunityViz. Originally, CommunityViz is a software used to support urban planning purposes. Within this research, CommunityViz was adapted and modelled to support UIEP. Two main integrated instruments, Interactive Impact Assessment and Suitability Analysis, were modelled. The main difficulties were to adapt the tool to energy urban planning, considering many complex aspects of this issue. Modelling of all retrofit dynamic attributes and the type of connection between all the attributes was another difficulty of this part. The modelling design process is quite complex. The model should chain all the data, attributes and indicators. This means that once the stakeholders change one parameter, others will change automatically in their proposed scenario. In fact, by this research, an attempt is made to create a basic model considering five retrofitting measures for five clusters (Table 22 and Table 24) of buildings and evaluate eight criteria simultaneously (Table 28). The participants are able to rapidly experiment different energy renovation scenarios and change the assumption. This creates an effective interaction between the stakeholders. They can visualize very complex problem of energy saving scenarios simply by different dynamic colourful maps, charts and indicators. Two workshops were organized to fulfil the objective of the research.

- The first workshop involved real stakeholders in order to identify the related evaluation criteria and their importance (section 6.3).
- The second workshop involved almost the same stakeholders in order to test the usability of the MC-SDSS tool based on their considerations of the first workshop, and especially, to improve the tool (section 7.5).

Furthermore, the answers collected from the distributed questionnaires during the second workshop were analyzed considering three criteria: usefulness, ease of use, and the visual effectiveness (Figure 84). Most participants found that the tool was very useful for making better decisions, easy enough to use and it was effective in visualizing processes. Besides comments on the tool usability, three main suggestions to improve the instrument were as following: the improvement of the data entry quality in order to increase the accuracy of scenarios analyses; the installation of smart metres in order to access to real-time data; and the enlargement of retrofitting solutions (e.g., adding photovoltaics and DH network options).

Limitations

This study suggests the development of a new MC-SDSS, which can define dynamic retrofitting scenarios side-by-side with stakeholders. This faces several barriers including:

- The need for the tool that to be Open Source.
- The limitation of the number of retrofitting solutions, buildings cluster and stakeholders in this Ph.D. research.
- The difficulty of the workshops to be time-consuming involving real stakeholders.
- The difficulty of the inclusion of conflicting point of views and then aggregation of stakeholders' preferences in a participative decision-making context.

8.3 Future developments

The current MC-SDSS provides a basic framework for developing scenarios in IUEP area. The MC-SDSS tool has a high potential to be developed. First, one case study was selected for applying the methodology in this Ph.D. research since an immense detailed data is required. However, more case studies will be necessary for exploring the applicability and the usability of new developed MC-SDSS.

The refurbishment solution, as well as the building clusters, will need to be extended. Furthermore, more historical data will be added to the geospatial database including other new databases regarding natural gas measured consumption (for a larger part of the city) and regarding building stock characterization (for each building). Additionally, Smart Meters can be installed in future to transfer directly real-time data to the MC-SDSS tool. Possessing more data helps significantly in the validation process of modelling phase (statistical and engineering) presented in chapters 4 and 5. Interestingly, the MC-SDSS developed during this Ph.D. work could be a basis for many further spatial analysis areas such as transportation, territorial, environmental, real estate and landscaping. It is possible to adapt the tool to its functions; however, technical expertise and relative data are needed for modelling and adaption. Another fruitful area of research would be to further investigate the details of understanding the topic of social evaluation criteria related to energy retrofitting projects. To fulfil this goal, more qualitative methods such as interviews as well as online questionnaire are needed. The willingness of the citizen to requalify their buildings need to be investigated by a real data.

As mentioned in section 7.2, this research uses the Weighted Linear Combination (WLC) model to analyse the suitability of the defined scenarios. Further research can be dedicated to investigate about MCA methods, which give ratings outcome to DMs. Some methods which might be particularly interesting for this purpose are ELECTRE, PROMETHEE, and MACBETH. These methods could be integrated with the developed tool in order to give a more comprehensive vision regarding the “best” decision-making process. This will be a challenging development because it requires a complicated programming language and more efforts on speed reduction of the process will be required.

An additional development is to integrate BIM (Building Information System) into GIS platform. This will help to analyse different target scales from building to district and urban level. Some mid-term results are described in [Papers 6 and Paper 9], which were not included in this dissertation.

Finally, an interesting possibility that can be developed further is to create an Open Access MC-SDSS for UIEP in order to spin it off. During this Ph.D. research, a new web-based MC-SDSS has been developed and it is still on progress. This is named V-smart (Visualisation-sustainable multicriteria analysis retrofitting for territory); it allows dynamically interactive sessions among stakeholders permitting the exchange of information in order to support UIEP processes (Figure 85). V-smart is developed in collaboration of the technical support of the Information System Consortium of the Piedmont region (CSI-Italy). It is mainly based on the Quantum GIS (QGIS) software (GNU General Public License, free available at www.qgis.org) and the virtual globe CESIUM (cesiumjs.org) systems. The guidelines of V-smart are under preparation in order to aid urban actors and DMs in planning low-carbon cities.

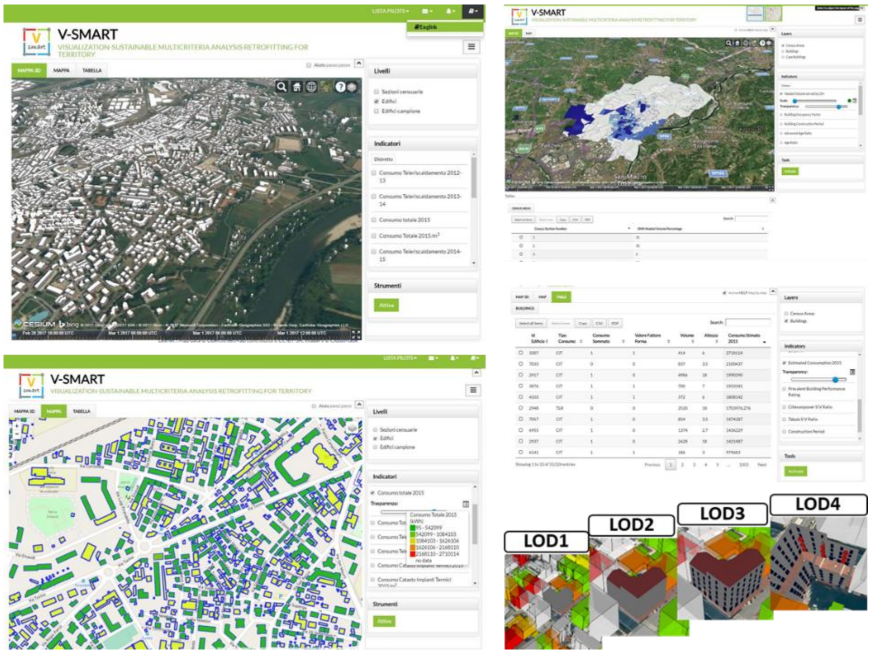


Figure 85: V-smart interface, an Open Access tool under progress by Ph.D. candidate.

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Appendix A. Simulation Material

A1. Thermo-physical properties of building envelope

1. Cluster-Period of construction-Before 1919-Before 1919-TH

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- **Minergie-P**

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- **Tabula**

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<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="849" Conductivity="0.21" Thickness="0.01"/>
</Composite>
-<Composite name="P01 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="799" Conductivity="1.00" Thickness="0.005"/>
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.04" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="1.23" Cp="640" Conductivity="0.068" Thickness="0.01"/>
<Layer ubp="0" gwp="0" nre="0" Density="700" Cp="1598" Conductivity="0.18" Thickness="0.04"/>
</Composite>
-<Composite name="P01 Floor" category="Floor" id="10">
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="700" Conductivity="0.7" Thickness="0.22"/>
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.04" Thickness="0.11"/>

<Layer ubp="0" gwp="0" nre="0" Density="1800" Cp="900" Conductivity="1.8" Thickness="0.01"/>
</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.0200"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

2. Cluster-Period of construction-1919-1945-SFH

-<Composite name="P02 Wall" category="Wall" id="4">
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="1400" Conductivity="0.7" Thickness="0.01"/>
<Layer ubp="0" gwp="0" nre="0" Density="1080" Cp="2000" Conductivity="0.55" Thickness="0.26"/>
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="1200" Conductivity="0.58" Thickness="0.01"/>
</Composite>
-<Composite name="P02 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="799" Conductivity="1.00" Thickness="0.005"/>
<Layer ubp="0" gwp="0" nre="0" Density="1.23" Cp="640" Conductivity="0.068" Thickness="0.01"/>
<Layer ubp="0" gwp="0" nre="0" Density="700" Cp="1598" Conductivity="0.18" Thickness="0.04"/>
</Composite>
-<Composite name="P02 Floor" category="Floor" id="10">
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="700" Conductivity="0.7" Thickness="0.22"/>
<Layer ubp="0" gwp="0" nre="0" Density="1800" Cp="900" Conductivity="1.8" Thickness="0.01"/>
</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.0200"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

- **Minergie-P**

-<Composite name="P02 Wall" category="Wall" id="4">
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="1400" Conductivity="0.7" Thickness="0.01"/>

<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.03" Thickness="0.35"/>
<Layer ubp="0" gwp="0" nre="0" Density="1080" Cp="2000" Conductivity="0.55" Thickness="0.26"/>
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="1200" Conductivity="0.58" Thickness="0.01"/>
</Composite>
-<Composite name="P02 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="799" Conductivity="1.00" Thickness="0.005"/>
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.03" Thickness="0.35"/>
<Layer ubp="0" gwp="0" nre="0" Density="1.23" Cp="640" Conductivity="0.068" Thickness="0.01"/>
<Layer ubp="0" gwp="0" nre="0" Density="700" Cp="1598" Conductivity="0.18" Thickness="0.04"/>
</Composite>
-<Composite name="P02 Floor" category="Floor" id="10">
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="700" Conductivity="0.7" Thickness="0.22"/>
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.03" Thickness="0.35"/>
<Layer ubp="0" gwp="0" nre="0" Density="1800" Cp="900" Conductivity="1.8" Thickness="0.01"/>
</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.0200"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

- **TABULA**

-<Composite name="P02 Wall" category="Wall" id="4">
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<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.04" Thickness="0.11"/>
<Layer ubp="0" gwp="0" nre="0" Density="1080" Cp="2000" Conductivity="0.55" Thickness="0.26"/>
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="1200" Conductivity="0.58" Thickness="0.01"/>
</Composite>
-<Composite name="P02 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="799" Conductivity="1.00" Thickness="0.005"/>
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.04" Thickness="0.10"/>

<Layer ubp="0" gwp="0" nre="0" Density="1.23" Cp="640" Conductivity="0.068" Thickness="0.01"/>
<Layer ubp="0" gwp="0" nre="0" Density="700" Cp="1598" Conductivity="0.18" Thickness="0.04"/>
</Composite>
-<Composite name="P02 Floor" category="Floor" id="10">
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="700" Conductivity="0.7" Thickness="0.22"/>
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.04" Thickness="0.11"/>
<Layer ubp="0" gwp="0" nre="0" Density="1800" Cp="900" Conductivity="1.8" Thickness="0.01"/>
</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.0200"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

3. Cluster-Period of construction-1946-1960-SFH

-<Composite name="P03 Wall" category="Wall" id="4">
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="1400" Conductivity="0.7" Thickness="0.01"/>
<Layer ubp="0" gwp="0" nre="0" Density="1080" Cp="2000" Conductivity="0.5" Thickness="0.3"/>
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="1200" Conductivity="0.5" Thickness="0.01"/>
</Composite>
-<Composite name="P03 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="799" Conductivity="1.00" Thickness="0.05"/>
<Layer ubp="0" gwp="0" nre="0" Density="2400" Cp="1100" Conductivity="0.9" Thickness="0.35"/>
</Composite>
-<Composite name="P03 Floor" category="Floor" id="10">
<Layer ubp="0" gwp="0" nre="0" Density="700" Cp="1500" Conductivity="0.7" Thickness="0.22"/>
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="1800" Conductivity="1.8" Thickness="0.01"/>
</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.0200"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>

<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

4. Cluster-Period of construction-1961-1970-MF

-<Composite name="P04 Wall" category="Wall" id="4">
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="850" Conductivity="0.21" Thickness="0.02"/>
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="1000" Conductivity="0.7" Thickness="0.15"/>
<Layer ubp="0" gwp="0" nre="0" Density="1.23" Cp="1000" Conductivity="0.656" Thickness="0.12"/>
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="1000" Conductivity="0.7" Thickness="0.08"/>
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="850" Conductivity="0.21" Thickness="0.01"/>
</Composite>
-<Composite name="P04 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="1000" Cp="1100" Conductivity="0.3" Thickness="0.20"/>
</Composite>
-<Composite name="P04 Floor" category="Floor" id="10">
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="900" Conductivity="0.7" Thickness="0.20"/>
<Layer ubp="0" gwp="0" nre="0" Density="500" Cp="1000" Conductivity="0.16" Thickness="0.10"/>
</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.0200"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

- **Minergie-P**

-<Composite name="P04 Wall" category="Wall" id="4">
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="850" Conductivity="0.21" Thickness="0.02"/>
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.03" Thickness="0.35"/>
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="1000" Conductivity="0.7" Thickness="0.15"/>
<Layer ubp="0" gwp="0" nre="0" Density="1.23" Cp="1000" Conductivity="0.656" Thickness="0.12"/>
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="1000" Conductivity="0.7" Thickness="0.08"/>
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="850" Conductivity="0.21" Thickness="0.01"/>

</Composite>
-<Composite name="P04 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.03" Thickness="0.35"/>
<Layer ubp="0" gwp="0" nre="0" Density="1000" Cp="1100" Conductivity="0.3" Thickness="0.20"/>
</Composite>
-<Composite name="P04 Floor" category="Floor" id="10">
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="900" Conductivity="0.7" Thickness="0.20"/>
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.03" Thickness="0.35"/>
<Layer ubp="0" gwp="0" nre="0" Density="500" Cp="1000" Conductivity="0.16" Thickness="0.10"/>
</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.0200"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

- **<u>TABLUA</u>**

-<Composite name="P04 Wall" category="Wall" id="4">
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<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="1000" Conductivity="0.7" Thickness="0.15"/>
<Layer ubp="0" gwp="0" nre="0" Density="1.23" Cp="1000" Conductivity="0.656" Thickness="0.12"/>
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="1000" Conductivity="0.7" Thickness="0.08"/>
<Layer ubp="0" gwp="0" nre="0" Density="900" Cp="850" Conductivity="0.21" Thickness="0.01"/>
</Composite>
-<Composite name="P04 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.04" Thickness="0.11"/>
<Layer ubp="0" gwp="0" nre="0" Density="1000" Cp="1100" Conductivity="0.3" Thickness="0.20"/>
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<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="900" Conductivity="0.7" Thickness="0.20"/>
<Layer ubp="0" gwp="0" nre="0" Density="17" Cp="1080" Conductivity="0.04" Thickness="0.11"/>

<Layer ubp="0" gwp="0" nre="0" Density="500" Cp="1000" Conductivity="0.16" Thickness="0.10"/>
</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.0200"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

5. Cluster-Period of construction-1971-1990-MFH

-<Composite name="P05 Wall" category="Wall" id="4">
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="900" Conductivity="0.58" Thickness="0.02"/>
<Layer ubp="0" gwp="0" nre="0" Density="40" Cp="1029" Conductivity="0.058" Thickness="0.05"/>
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="1029" Conductivity="0.7" Thickness="0.12"/>
<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="900" Conductivity="0.58" Thickness="0.01"/>
</Composite>
-<Composite name="P05 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="2400" Cp="850" Conductivity="2.1" Thickness="0.02"/>
<Layer ubp="0" gwp="0" nre="0" Density="65" Cp="1450" Conductivity="0.043" Thickness="0.05"/>
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
</Composite>
-<Composite name="P05 Floor" category="Floor" id="10">
<Layer ubp="0" gwp="0" nre="0" Density="2400" Cp="1000" Conductivity="2.1" Thickness="0.02"/>
<Layer ubp="0" gwp="0" nre="0" Density="65" Cp="1450" Conductivity="0.043" Thickness="0.03"/>
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="850" Conductivity="1.5" Thickness="0.09"/>
</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.0200"/>
<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

- **Minergie-P**


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-<Composite id="4" name="P05 Wall" category="Wall">
	<Layer Thickness="0.02" Conductivity="0.58" Cp="900" Density="1200" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="0.35" Conductivity="0.03" Cp="1080" Density="17" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="0.05" Conductivity="0.058" Cp="1029" Density="40" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="0.12" Conductivity="0.7" Cp="1029" Density="1200" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="0.01" Conductivity="0.58" Cp="900" Density="1200" nre="0" gwp="0" ubp="0"/>
	</Composite>
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	<Layer Thickness="0.02" Conductivity="2.1" Cp="850" Density="2400" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="0.35" Conductivity="0.03" Cp="1080" Density="17" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="0.05" Conductivity="0.043" Cp="1450" Density="65" nre="0" gwp="0" ubp="0"/>
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	</Composite>
-<Composite id="10" name="P05 Floor" category="Floor">
	<Layer Thickness="0.02" Conductivity="2.1" Cp="1000" Density="2400" nre="0" gwp="0" ubp="0"/>
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	<Layer Thickness="0.03" Conductivity="0.043" Cp="1450" Density="65" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="0.09" Conductivity="1.5" Cp="850" Density="2100" nre="0" gwp="0" ubp="0"/>
	</Composite>
-<Composite id="21" name="Concrete" category="Ground">
	<Layer Thickness="0.10" Conductivity="1.5" Cp="1000" Density="2100" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="0.0200" Conductivity="2.0000" Cp="1051.19995" Density="2000" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="0.1000" Conductivity="2.0000" Cp="1051.19995" Density="2000" nre="0" gwp="0" ubp="0"/>
	<Layer Thickness="3.8550" Conductivity="1.5000" Cp="2098.80005" Density="1500" nre="0" gwp="0" ubp="0"/>
	</Composite>
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- **TABULA**


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-<Composite name="P05 Wall" category="Wall" id="4">
	<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="900" Conductivity="0.58" Thickness="0.02"/>
	<Layer ubp="0" gwp="0" nre="0" Density="40" Cp="1029" Conductivity="0.058" Thickness="0.12"/>
	<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="1029" Conductivity="0.7" Thickness="0.12"/>
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<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="900" Conductivity="0.58" Thickness="0.01"/>
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-<Composite name="P05 Roof" category="Roof" id="12">
<Layer ubp="0" gwp="0" nre="0" Density="2400" Cp="850" Conductivity="2.1" Thickness="0.02"/>
<Layer ubp="0" gwp="0" nre="0" Density="65" Cp="1450" Conductivity="0.043" Thickness="0.15"/>
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
</Composite>
-<Composite name="P05 Floor" category="Floor" id="10">
<Layer ubp="0" gwp="0" nre="0" Density="2400" Cp="1000" Conductivity="2.1" Thickness="0.02"/>
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</Composite>
-<Composite name="Concrete" category="Ground" id="21">
<Layer ubp="0" gwp="0" nre="0" Density="2100" Cp="1000" Conductivity="1.5" Thickness="0.10"/>
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<Layer ubp="0" gwp="0" nre="0" Density="2000" Cp="1051.19995" Conductivity="2.0000" Thickness="0.1000"/>
<Layer ubp="0" gwp="0" nre="0" Density="1500" Cp="2098.80005" Conductivity="1.5000" Thickness="3.8550"/>
</Composite>

6. Cluster-Period of construction-1991-2005-MFH

-<Composite name="P07 Wall" category="Wall" id="4">
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<Layer ubp="0" gwp="0" nre="0" Density="1200" Cp="1000" Conductivity="0.7" Thickness="0.15"/>
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- **Minergie-P**

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7. Cluster-Period of construction-since 2006-TH

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- **Minergie-P**

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- **TABULA**

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Appendix B. Workshop Material

B1. 2nd workshop

12th July 2017 at Politecnico di Torino

EEB – Edifici a Zero Consumo Energetico in Distretti Urbani Intelligenti
Durata del progetto: 01.01.2014-31.12.2017
codice identificativo: CTN01_00034_594053
Progetto di ricerca e formazione ammesso ai finanziamenti previsti dal Programma Operativo Nazionale Ricerca e Competitività 2007-2013 (PON R&C)

UNIONE EUROPEA
Fondo europeo di sviluppo regionale

PON Ricerca e Competitività 2007-2013

Ministero dell'Istruzione, dell'Università e della Ricerca

Ministero dello Sviluppo Economico

Smart Communities Tech
Italian Technology Cluster for Smart Communities

EEB (Energy Efficiency Building)
Edifici a Zero Consumo Energetico in Distretti Urbani Intelligenti

CTN01_00034_594053

WORKSHOP
LA VALUTAZIONE DI SCENARI ENERGETICI
Caso Studio: Settimo Torinese (TO)

12 Luglio 2017
Politecnico di Torino
sala S3+LAB
Castello del Valentino
Viale Mattioli 39-10129 Torino

Dipartimento Interateneo di Scienze, Progetto e Politiche del Territorio
Politecnico di Torino   Viale Mattioli, 39 – 10125 Torino – Italia   tel: +39 011.090.7456   fax: +39 011.090.7499
Università degli Studi di Torino   Via Sant'Ottavio, 20 – 10122 Torino – Italia   tel: +39 011.670.9754   fax: +39 011.670.9751
P. IVA 00518460019
dist@polito.it – www.dist.polito.it – www.dist.unito.it

MISURE DI RETROFITTING

A – Variazione sistema riscaldamento per gruppi di edifici (sostituzione del Boiler)

Domanda 1. La simulazione relativa alla variazione del sistema riscaldamento per gruppi di edifici è utile?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Motiva la risposta____

Domanda 2. È comprensibile e di facile utilizzo?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Motiva la risposta____

Domanda 3. I risultati derivanti da tale simulazione sono visualizzati in modo efficace?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Motiva la risposta____

Domanda 4. Eventuali suggerimenti per migliorare tale simulazione e/o la sua modalità di visualizzazione:

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B– Riqualificazione energetica dell'involucro edilizio (sostituzione delle finestre, isolamento dei muri,...)

Domanda 5. La simulazione relativa alla riqualificazione energetica dell'involucro edilizio per gruppi di edifici è utile?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Motiva la risposta____

Domanda 6. È comprensibile e di facile utilizzo?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Motiva la risposta____

Domanda 7. I risultati derivanti da tale simulazione sono visualizzati in modo efficace?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Motiva la risposta____

Domanda 8. Eventuali suggerimenti per migliorare tale simulazione e/o la sua modalità di visualizzazione:

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Domanda 9. Eventuali suggerimenti per modificare oppure aggiungere la **misure di retrofitting**:

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STRUMENTO INTERATTIVO ENERGETICO

Visualizzare dati ed indicatori energetici

Domanda 10. Quanto sono utili gli indicatori presenti nello strumento?

Totale dei costi di investimento per ogni misura di retrofitting ***Investment Cost (M€)*** (Totale del costo di acquisizione, installazione e manutenzione dell'intervento calcolato in 30 anni considerando VAN, espresso in MilioneEuro)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Totale dei costi di investimento per GWh per ogni misura di retrofitting ***Investment Cost-GWh (M€/GWh)*** (Totale del costo di investimento per unità di GWh, espresso in MilioneEuro/GWh)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Totale emissioni globali ***Global CO_2 Emissions (t)*** (Totale delle emissioni di CO2 (anidride carbonica) a livello globale calcolati per ogni misura di retrofitting, espresso in tonnellate)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Percentuale della riduzione delle emissioni globali ***Global CO_2 Emissions-Reduction (%)*** (Riduzione totale delle emissioni di CO_2 per ogni misura di retrofitting, espresso in Percentuale)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Totale emission locali ***Local NO_X emission (t)*** (Totale delle emissioni di NO_X (ossidi di azoto) a livello locale cacolati per ogni misura di retrofitting espresso in Tonnellate)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Totale emission locali ***Local PM_{10} emission (kg)*** (Totale delle emissioni di PM_{10} (Materia Particolata di diametro equivalente inferiore a 10 μm) calcolati a base per ogni misura di retrofitting espresso in Chilogrammo)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Impatto architettonico per ogni misura di retrofitting ***Architectural Impact (rank)*** (Impatto visivo di qualità sull'ambiente costruito espresso in un rank da 1 =positive a 5=negative)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Creazione di occupazione locale ***Job Potential (man-day)*** (Totale del lavoro creato per l'installazione e la manutenzione in un anno	❑ Molto ❑ Abbastanza ❑ Poco

per ogni misura di retrofitting e per numero delle azioni, espresso in uomo-giorno)	❑ Per niente
Affidabilità ***Reliability (rank)*** (Affidabilità della misura retrofitting per quanto riguarda l'interazione con gli utenti, il rischio di rompere, la dipendenza dagli effetti della temperatura e alle efficienze attese e ai possibili fermi macchina espresso in rank da 1=low a 5=high)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Consumo energetico ***Energy Consumption (GWh)*** (Consumo annuo per il riscaldamento GWh)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Percentuale della riduzione del consumo energetico ***Energy Saving (%)*** (Risparmio del consumo energetico, esresso in percentuale)	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Fattibiltà socio-econimico ***Socio-Econimc feasebility (%)*** a) Fattore d'epoca di costruzione degli edifici: rapporto percentuale tra gli edifici prima di 1960 e tutti gli edifici b) Fattore di età: rapporto percentuale tra la popolazione con 25-69 anni e la popolazione Totale c) Fattore di Genere: rapport prcentuale tra la popolazione machi e la popolazione totale d) Fattore di educazione : rapporto percentuale tra la popolazione residente con diploma o laurea e la popolazione residente con la popolazione residente e) Tasso di occupazione: rapporto percentuale tra gli occupati di 15-74 anni e più e la popolazione residente di 15-74 anni f) Fattore di famiglia: rapporto tra la popolazione residente in famiglia 1 o 2 componenti e il numero delle famiglie g) Fattore di proprietà: rapporto percentuale tra le famiglie proprietà e il totale numero delle famiglie h) Fattore di occupazione degli edifici: Il rapporto percentuale tra edifici occupati e aloggi vuoti	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente

Motiva le principali ragioni della tua risposta____

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Domanda 11. È comprensibile e di facile utilizzo?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Domanda 12. Gli indicatori proposti durante la sessione del workshop rappresentano adeguatamente le informazioni di cui si necessita per supportare la comprensione degli scenari energetici a scala locale?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Motiva la risposta____

Domanda 13. Eventuali suggerimenti per migliorare la visualizzazione/ Ci sono altri indicatori che potrebbero essere essenziali? Quali?

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Mappe dei Risultati

C – Il risultato finale della mappa "Il risparmio energetico in percentuale"

Domanda 14. Il risultato finale della mappa del risparmio energetico in percentuale è utile?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Motiva la risposta____

Domanda 15. Come reputi il livello di complessità di tale risultato?

- ❑ Molto complesso
- ❑ Complesso
- ❑ Semplice
- ❑ Molto semplice

Motiva la risposta____

Domanda 16. I dati derivanti da tale risultato sono visualizzati in modo efficace?

- ❑ Molto
- ❑ Abbastanza
- ❑ Poco
- ❑ Per niente

Motiva la risposta____

Domanda 17. Eventuali suggerimenti per migliorare tale simulazione e/o la sua modalità di visualizzazione:

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EEB – Edifici a Zero Consumo Energetico in Distretti Urbani Intelligenti
Durata del progetto: 01.01.2014-31.12.2017
codice identificativo: CTN01_00034_594053
Progetto di ricerca e formazione ammesso ai finanziamenti previsti dal Programma Operativo Nazionale Ricerca e Competitività 2007-2013 (PON R&C)

UNIONE EUROPEA
Fondo europeo di sviluppo regionale

PON Ricerca e Competitività 2007-2013

Ministero dell'Istruzione, dell'Università e della Ricerca

Ministero dello Sviluppo Economico

Smart Communities Tech
Italian Technology Cluster for Smart Communities

EEB (Energy Efficiency Building)

Edifici a Zero Consumo Energetico in Distretti Urbani Intelligenti

CTN01_00034_594053

WORKSHOP
LA VALUTAZIONE DI SCENARI ENERGETICI
Caso Studio: Settimo Torinese (TO)

12 Luglio 2017
Politecnico di Torino
sala S3+LAB
Castello del Valentino
Viale Mattioli 39-10129 Torino

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Mappe dei Risultati

E – Il risultato finale della mappa finale "Suitability"

Domanda 1. Il risultato finale della mappa finale "Suitability" è utile?

- ❏ Molto
- ❏ Abbastanza
- ❏ Poco
- ❏ Per niente

Motiva la risposta____

Domanda 2. È comprensibile e di facile utilizzo?

- ❏ Molto
- ❏ Abbastanza
- ❏ Poco
- ❏ Per niente

Motiva la risposta____

Domanda 3. I dati derivanti da tale risultato sono visualizzati in modo efficace?

- ❏ Molto
- ❏ Abbastanza
- ❏ Poco
- ❏ Per niente

Motiva la risposta____

Domanda 4. Eventuali suggerimenti per migliorare tale simulazione e/o la sua modalità di visualizzazione:

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Domande Generali sulla sessione del Workshop

La sessione ha prodotto risultati utili	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Sono fiducioso che la soluzione del gruppo sia corretta	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Sono soddisfatto di questa sessione	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Ora ho più informazioni riguardo ai problem decisionali energetici a livello urbano	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Ora ho una vision migliore relativa ai punti di vista degli altri partecipanti	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Utilizzerei lo strumento presentato e I risultati di questa sessione nella pratica lavorativa	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Abbiamo raggiunto una visione condivisa del problema	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Abbiamo raggiunto una visione condivisa degli obiettivi	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Abbiamo raggiunto una visione condivisa sulle possibili soluzioni	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente

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Mi sono sentito parte di un gruppo di lavoro	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Lo strumento presentato ha evidenziato un nuovo approccio relativa alla pinificazione enerrgetica al livello urbano	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
Le ipotisi di base presentate per lo sviluppo del modello sono chiare	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente
I termini utilizzati durante la sesione sono comprensibili	❑ Molto ❑ Abbastanza ❑ Poco ❑ Per niente

Motiva le principali ragioni della tua risposta____

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Appendix C. List of Papers

C1. Journals

Paper 1. S. Torabi Moghadam, C. Delmastro, S.P. Corgnati, P. Lombardi. (2017). Urban energy planning procedure for sustainable development in the built environment: a review of available spatial approaches. Journal of Cleaner Production, vol. 165, pp. 811-827. doi: 10.1016/j.jclepro.2017.07.142.

Paper 2. S. Torabi Moghadam, G. Mutani, P. Lombardi. (2017). A mixed methodology for defining a new spatial decision analysis towards low carbon cities. Procedia Engineering, vol. 198, pp. 375–385. doi: 10.1016/j.proeng.2017.07.093.

Paper 3. S. Torabi Moghadam, J. Toniolo, G. Mutani, P. Lombardi. (2018). A GIS-Statistical Approach for Assessing Built Environment Energy Use at Urban Scale. Journal of Sustainable Cities and Society, vol. 37, pp. 70-84. doi: 10.1016/j.scs.2017.10.002.

Paper 4. P. Lombardi, F. Abastante, S. Torabi Moghadam, J. Toniolo. (2017). Multicriteria Spatial Decision Support Systems for Future Urban Energy Retrofitting Scenarios. Sustainability, vol. 9, n. 7. pp. 1-13. ISSN 2071. doi: 1050, 10.3390/su9071252.

Paper 5. S. Torabi Moghadam, C. Delmastro; P. Lombardi; S.P. Corgnati. (2016). Towards a New Integrated Spatial Decision Support System in Urban Context. Procedia Social & Behavioural Sciences, vol. 223, pp. 974-981. ISSN 1877-0428. doi: 10.1016/j.sbspro.2016.05.334.

***Paper 6**. S. Torabi Moghadam, P. Lombardi, F.M. Ugliotti, A. Osello, G. Mutani. (2016). BIM-GIS Modelling for Sustainable Urban Development. NEWDIST, vol. Special Issue n. July 2, pp. 339-350. ISSN 2283-8791.

Paper 7. S. Torabi Moghadam, C. Delmastro; P. Lombardi; S.P. Corgnati., J. Toniolo. (2017). Verso nuovi modelli di supporto alle decisioni contesto urbano, LaborEst, n. 13, pp. 60-65. ISSN 2421-3187.

***Paper 8**. D. Dirutigliano, C. Delmastro, S. Torabi Moghadam. (2017). Energy efficient urban districts: A multi-criteria application for selecting retrofit actions. International Journal of Heat and Technology, Vol. 35, Special Issue 1, September 2017, pp. S49-S57. ISSN: 0392-8764.doi: 10.18280/ijht.35Sp0107.B 2.

* The paper associated with the asterisk are not included in his dissertation, however, they are aligned to the Ph.D. path.

C2. Book chapters

***Paper 9**. S. Torabi Moghadam, P. Lombardi, J. Toniolo. (2017). Towards the establishment of a District Information Modelling. Advances in Construction ICT and e-Business, Routledge, London and New York, pp. 245-262. ISBN 978-1138914582.

Paper 10. S. Torabi Moghadam, G. Mutani, P. Lombardi. (2016). GIS-Based Energy Consumption Model at the Urban Scale for the Building Stock. JRC Conference and Workshop Report, Paolo Bertoldi. European Union, Luxembourg, pp. 56-63. ISBN 978-92-79-59779-4.

C3. Proceedings of international conferences and seminars

***Paper 11**. S. Torabi Moghadam, G. Mutani, P. Lombardi. (2016). A spatial energy consumption assessment for building stock supporting low carbon scenarios development, Energy Systems Conference 2016: 21st Century Challenges, QEII Centre, Westminster, London, UK, June 14th -15th.

***Paper 12**. S. Torabi Moghadam, P. Lombardi, J. Toniolo, F. Abastante, I. Lami (2017). Map-based Multicriteria Analysis to Support Stakeholder-oriented Urban Energy Scenarios, 21st Conference of the International Federation of Operational Research Societies IFORS, Quebec City, Canada, July 17th-21th.

C4. In progress

Paper 13. S. Torabi Moghadam, S. Coccolo, G. Mutani, P. Lombardi, J.L. Scartezzini, D. Mauree. A new clustering and visualization method to evaluate urban energy planning scenarios. Submitted and under revision to Applied Energy Journal.

Paper 14. S. Torabi Moghadam, A. Matta, P. Lombardi, M. Campagna. Interactive Multi-Criteria Spatial Planning Support System for Energy Retrofitting Using CommunityViz. In preparation.

Paper 15. Domenico Dirutigliano, Chiara Delmastro, Sara Torabi Moghadam, A multi-criteria application to select energy retrofit measures at the building and district scale, Thermal Science and Engineering Progress, ISSN 2451-9049, In Press, Accepted Manuscript. Available online 11 April 2018 https://doi.org/10.1016/j.tsep.2018.04.007.