Doctoral Thesis in Industrial Ecology

Advancing urban analytics for energy transitions

Data-driven strategic planning for citywide
building retrofitting

OLEKSII PASICHNYI

ADVANCING URBAN ANALYTICS FOR ENERGY TRANSITIONS

DATA-DRIVEN STRATEGIC PLANNING
FOR CITYWIDE BUILDING
RETROFITTING

OLEKSII PASICHNYI

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Preface

This thesis aims to summarise and communicate to a broader audience what my PhD studies in 2015–2020 were about. Eventually it started to be seen as urban energy data analytics, the new area which rapid development is powered by the growing ubiquity of data and urgency of climate transitions. Even though it is still very much a human expertise-dominated area, there is growing evidence of our (human) ability to produce machines and algorithms that are capable not only of assisting, but also of running our cities, built infrastructure (and us) in a more intelligent and efficient way. This promises to result in a significantly new level of urban systems integration, leading to great new achievements in humanity's race for a better life and, hopefully, avoidance of a climate catastrophe. At the same time, the future of 'urban energy data and the last human'¹, where machines beat the best energy experts and city planners, does not feel to be so impossible any longer. This places even more responsibility on researchers currently pushing the frontiers to constantly check among ourselves, and with society, about where the currently visible pathways lead, and whether we and coming generations would like to live in such a future. Of course, many things will remain unclear about these changes even when they are already in place. What is certain is that change is happening, it is fast and it can make a difference to the lives of all. That is probably the most challenging, intriguing and astonishing part of the research adventure in which I am engaged.

Oleksii Pasichnyi,

Stockholm, November 2020

¹This expression was coined randomly in one of our traditionally fruitful discussions with my colleague Tim Johansson.

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I wish to thank my old and new colleagues at the former Industrial Ecology, now SEED, and throughout KTH for providing the research environment and making this journey a joyful and pleasant experience. Particular thanks to Karin and Kosta for their care and assistance, and Maria for her encouraging support.

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Oleksii Pasichnyi,

Stockholm, November 2020

Abstract

Decarbonisation of the building stock is essential for energy transitions towards climate-neutral cities in Sweden, Europe and globally. Meeting 1.5°C scenarios is only possible through collaborative efforts by all relevant stakeholders — building owners, housing associations, energy installation companies, city authorities, energy utilities and, ultimately, citizens. These stakeholders are driven by different interests and goals. Many win-win solutions are not implemented due to lack of information, transparency and trust about current building energy performance and available interventions, ranging from city-wide policies to single building energy service contracts. The emergence of big data in the building and energy sectors allows this challenge to be addressed through new types of analytical services based on enriched data, urban energy models, machine learning algorithms and interactive visualisations as important enablers for decision-makers on different levels.

The overall aim of this thesis was to advance urban analytics in the building energy domain. Specific objectives were to: (1) develop and demonstrate an urban building energy modelling framework for strategic planning of large-scale building energy retrofiting; (2) investigate the interconnection between quality and applications of urban building energy data; and (3) explore how urban analytics can be integrated into decision-making for energy transitions in cities. Objectives 1 and 2 were pursued within a single case study based on continuous collaboration with local stakeholders in the city of Stockholm, Sweden. Objective 3 was addressed within a multiple case study on participatory modelling for strategic energy planning in two cities, Niš, Serbia, and Stockholm. A transdisciplinary research strategy was applied throughout.

A new urban building energy modelling framework was developed and demonstrated for the case of Stockholm. This framework utilises high-resolution building energy data to identify buildings and retrofiting measures with the highest potential, assess the change in total energy demand from large-scale retrofiting and explore its impact on the supply side. Growing use of energy performance certificate (EPC) data and increasing requirements on data quality were identified in a systematic mapping of EPC applications combined with assessment of EPC data quality for Stockholm. Continuity of data collaborations and interactivity of new analytical tools were identified as important factors for better integration of urban analytics into decision-making on energy transitions in cities.

Keywords

Urban analytics, building energy data, building retrofitting, urban building energy modelling, data quality, data applications, strategic planning, decision-making, energy transitions, climate-neutral cities.

Sammanfattning

Energiomställningen till ett fossilfritt byggnadsbestånd är avgörande för att uppnå klimatneutrala städer i Sverige, Europa och övriga världen. Alla scenarier som begränsar uppvärmningen till 1,5 °C är beroende av samarbete mellan alla relevanta aktörer - fastighetsägare, bostadsrättsföreningar, byggföretag, energiföretag och i slutändan även medborgarna. Dessa intressenter drivs av olika intressen och mål. Många vinna-vinna-lösningar implementeras inte på grund av brist på information, transparens och tillit gällande byggnaders energiprestanda. Detta leder till att tillgängliga åtgärder, från enskilda byggnader till policyer för hela städer, inte genomförs. Framväxten av big data inom fastighet- och energisektorn öppnar nya möjligheter att hantera denna utmaning. En nyckel i detta är analytiska tjänster baserade på strukturerad data, urbana energimodeller, maskininlärning och interaktiv visualisering som möjliggörare för beslutsfattande på olika nivåer.

Det övergripande syftet med denna avhandling var att vidareutveckla urban energianalys (eng. urban analytics) inom byggnadsbeståndet. Specifika mål var att: (1) utveckla och demonstrera ett ramverk inriktat mot urbana energimodeller för strategisk planering av storskalig energieffektivisering av byggnader; (2) utreda relationen mellan datakvalitet och tillämpningar av urban energidata för byggnader; och (3) utforska hur urban analys kan integreras i beslutsfattande för energiomställning av städer. Mål 1 och 2 uppnåddes genom en enskild fallstudie baserad på kontinuerligt samarbete med lokala intressenter i Stockholms kommun. Mål 3 behandlades inom en multipel fallstudie som var inriktad på deltagande modellering (eng. participatory modelling) för strategisk energiplanering i två städer, Niš i Serbien och Stockholm. En tvärvetenskaplig forskningsstrategi tillämpades inom hela forskningsstudien.

Ett nytt ramverk inom modellering av urban energi utvecklades och demonstrerades för fallstudien i Stockholm. Detta ramverk använde högupplöst byggnadsenergidata för att identifiera de byggnader och renoveringsåtgärder som har störst potential, undersöka förändringen av det totala energibehovet utifrån storskalig renovering och utreda dess inverkan på energisystemet och tillförseln. Ökad användning av data från energideklarationer (eng. EPC, energy performance certificate) och högre krav på datakvalitet identifierades i en systematisk kartläggning av EPC-tillämpningar, där även en kvalitetsgranskning av energideklarationer i Stockholm kommun genomfördes. Långsiktig datasamverkan och ökad interaktivitet i de nya analytiska verktygen identifierades som viktiga faktorer för bättre integration av urbana energimodeller i beslutsfattande gällande energiomställningar i städer.

Nyckelord

Stadsanalys, byggnadsenergidata, renovering av byggnader, urbana energimodeller, datakvalitet, datortillämpningar, strategisk planering, beslutsfattande, energiomställning, hållbara städer, klimatneutrala städer.

Анотація

Декарбонізація будівель є необхідною умовою енергетичного переходу до кліматично нейтральних міст у Швеції, Європі та у всьому світі. Забезпечення 1.5 °C сценаріїв зміни клімату є можливим лише в разі спільних зусиль усіх зацікавлених сторін — власників будівель, енергетичних компаній, міської влади, енергетичних підприємств та, врешті-решт, громадян. Вищеназвані зацікавлені сторони у своїй діяльності керуються різними інтересами та цілями. Велика кількість потенційно безпрограшних рішень не впроваджується через відсутність необхідної інформації, нестачу прозорості та довіри до інформації про поточну енергоефективність будівель та можливі дії щодо її покращення. До таких заходів можуть відноситися як законодавчі ініціативи на рівні міст, так й енергосервісні контракти для окремих будівель. Нещодавна поява великих даних у житловому та енергетичному секторах дає можливість вирішувати ці проблеми за допомогою аналітики нового рівня. Ця аналітика має бути заснована на розширених даних (англ. enriched data), моделях енергетичних систем міст, алгоритмах машинного навчання та інтерактивних візуалізаціях, що дають змогу істотно підвищити ефективність прийняття рішень на різних рівнях.

Метою цього дослідження було вдосконалення міської аналітики для енергетики будівель (англ. urban analytics for building energy). Це передбачало вирішення наступних задач: (1) розробити та продемонструвати методологію для моделювання енергосистеми міських будівель з метою стратегічного планування масштабного покращення енергоефективності будівель; (2) дослідити взаємозв'язок між якістю та ефективністю використання даних про стан енергетики міських будівель; та (3) дослідити можливості інтеграції аналітики міст в процес прийняття рішень задля енергетичного переходу в містах. Задачі 1 та 2 було реалізовано в рамках окремого кейсу, на основі постійної співпраці з зацікавленими сторонами в місті Стокгольм (Швеція). Задачу 3 було розглянуто на базі двох кейсів моделювання з участю зацікавлених сторін (англ. participatory modelling) з метою стратегічного енергетичного планування в двох містах — Ніші (Сербія) та Стокгольмі. В обох кейсах застосовувалася стратегія трансдисциплінарного дослідження.

В результаті дослідження було розроблено нову методологію для моделювання енергосистеми міських будівель, використання якої було продемонстровано на прикладі Стокгольма. Ця методологія

використовує дані енергоспоживання будівель високої роздільної здатності для (а) виявлення будівель та заходів щодо покращення їхньої енергоефективності з найбільшим потенціалом; (б) оцінювання зміни загального енергоспоживання внаслідок масштабної модернізації будівель та (в) аналізу впливу цих змін на енергопостачання. Було здійснено картування випадків використання даних сертифікатів енергетичної ефективності будівель (англ. energy performance certificates, ЕРС) та оцінювання якості цих даних для м. Стокгольм. Це дало змогу виявити збільшення обсягів використання даних ЕРС та зростання вимог до їх якості. Аналіз двох кейсів стратегічного планування в містах продемонстрував, що тривала співпраця щодо збору та використання даних та інтерактивність нових інструментів з аналізу є важливими факторами покращення інтеграції міської аналітики в процеси прийняття рішень задля енергетичних переходів у містах.

Ключові слова

Міська аналітика, дані щодо стану енергоефективності будівель, енергоефективна модернізація будівель, моделювання енергосистеми міських будівель, якість даних, застосування даних, стратегічне планування, прийняття рішень, енергетичні переходи, кліматично-нейтральні міста

Appended papers

Paper I

Zivkovic, M., Pereverza, K., **Pasichnyi, O.**, Madzarevic, A., Ivezic, D. & Kordas, O. 2016. Exploring scenarios for more sustainable heating: The case of Niš, Serbia. *Energy* 115(3), pp. 1758–1770. <https://doi.org/10.1016/j.energy.2016.06.034>

My contributions to this paper were: development of the research idea and research design, data quality analysis, data visualisation, writing sections of the paper and providing comments on the final manuscript.

Paper II

Pasichnyi, O., Levihn, F., Shahrokni, H., Wallin, J. & Kordas, O. 2019. Data-driven strategic planning of building energy retrofiting: The case of Stockholm. *Journal of Cleaner Production* 233, 546–560. <https://doi.org/10.1016/j.jclepro.2019.05.373>

My contributions to this paper were: development of research idea and research design, data collection and analysis, writing the paper, and handling its submission and publication.

Paper III

Pasichnyi, O., Wallin, J., Levihn, F., Shahrokni, H. & Kordas, O. 2019. Energy performance certificates — New opportunities for data-enabled urban energy policy instruments? *Energy Policy* 127, 486–499. <https://doi.org/10.1016/j.enpol.2018.11.051>

My contributions to this paper were: development of the research idea and research design, data collection and analysis, writing the paper, and handling its submission and publication.

Paper IV

Pasichnyi, O., Wallin, J. & Kordas, O. 2019. Data-driven building archetypes for urban building energy modelling. *Energy* 181, 360–377. <https://doi.org/10.1016/j.energy.2019.04.197>

My contributions to this paper were: development of the research idea and research design, data collection and analysis, writing the paper, and handling its submission and publication

Additional results not included in this thesis

Papers in reviewed journals

Pereverza, K., **Pasichnyi, O.** & Kordas, O. 2019. Modular participatory backcasting: A unifying framework for strategic planning in the heating sector. *Energy Policy* 124, pp. 123–134. <https://doi.org/10.1016/j.enpol.2018.09.027>

Pereverza, K., **Pasichnyi, O.**, Lazarevic, & Kordas, O. 2017. Strategic planning for sustainable heating in cities: A morphological method for scenario development and selection. *Applied Energy* 186(2), pp. 115–125. <https://doi.org/10.1016/j.apenergy.2016.07.008>

Zgurovsky, M.Z., Gvishiani, A.D., Yefremov, K.V. & **Pasichny, A.M.**, 2010. Integration of Ukrainian science into the World Data System. *Cybernetics and Systems Analysis* 46(2), pp. 211–219. <https://doi.org/10.1007/s10559-010-9199-9>

Papers in conference proceedings

Kordas, O., Pereverza, K., **Pasichnyi, O.** & Nikiforovich, E. 2015. Developing skills for sustainability change agents with a participatory backcasting teaching toolbox, in Nesbit, S. and Froese, T. M. (eds.), *Proceedings of EESD15: The 7th Conference on Engineering Education for Sustainable Development*, University of British Columbia, Vancouver, pp. 086-1–086-10.

Kordas, O., Mulder, K., Nikiforovich, E., Segalàs, J., **Pasichnyi, A.** & Pereverza, K. 2013. Paper 52. Advancing ESD in Ukraine: From awareness to orientation towards long-term thinking and societal needs, in *Proceedings of the 6th Conference on Engineering Education for Sustainable Development*. Cambridge, UK, pp. 317–325.

Kordas, O., Nikiforovich, E., Pereverza, K., **Pasichny, A.**, Spitsyna, T. & Quist, J. 2013. Towards more sustainable heating and cooling systems in Ukraine: Participatory Backcasting, in the city of Bila Tserkva, in *Proceedings of the 16th ERSCP Conference & 7th EMSU Conference*, Istanbul, pp. 1–13.

Online manuals

Pereverza, K., Eggestrand, H., **Pasichnyi, O.** & Kordas, O. 2019. *Modular Participatory Backcasting (mPB) Manual*, <https://mpb.urban.org>. Urban Analytics and Transitions, KTH Royal Institute of Technology.

Datasets

Pasichnyi, O. 2018. Mapping of energy performance certificates (EPC) data applications. *Swedish National Data Service*. Version 1.0. <https://doi.org/10.5878/xtzj-s624>

Abbreviations

AI	Artificial intelligence
BAU	Business as usual
BE(P)S	Building energy (performance) simulation
BRF	Housing association (Sw. <i>bostadsrättsförening</i>)
CHP	Combined heating and power
CO ₂	Carbon dioxide
DH	District heating
ECM	Energy conservation measure (can also be called <i>energy retrofitting measure</i> or <i>retrofit</i>)
EEW	(Installation of) energy-efficient windows (<i>ECM</i>)
EPBD	European Building Performance Directive
EPC	Energy performance certificate (Sw. <i>energideklaration</i>)
ES	Energy signature
EU	European Union
GIS	Geographic information system
HVAC	Heating, ventilation and air conditioning
HRV	(Installation of) heat recovery ventilation (<i>ECM</i>)
ICT	Information and communications technology
IE	Industrial ecology
IRR	Internal rate of return
IT21	(Adaptation of) indoor temperature to 21 °C (<i>ECM</i>)
KPI	Key performance indicator
LEAP	Long-range energy alternative planning system
LOD	Level of detail
ML	Machine learning

MLP	Multilevel perspective
mPB	Modular participatory backcasting
NPV	Net present value
PVQ	Present value quota
RES	Renewable energy sources
SDG	Sustainable development goals
TdR	Transdisciplinary research
UBEM	Urban building energy model(ling)
UES	Urban energy system
VFR	(Adaptation of) ventilation flow rate to minimum (<i>ECM</i>)

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1 Introduction

“In the beginning there was nothing, which exploded.”

Terry Pratchett, Lords and Ladies

1.1 Research rationale

Cities are major contributors to *climate change*. According to IPCC (Seto et al., 2014), urban areas are accountable for 71-76% of energy-induced CO₂ emissions and 67-76% of global energy use. At the same time, cities are expected to be strongly affected by future climate change (IPCC, 2018; 2014). The ongoing urbanisation and growing concentration of economic power in urban areas equips cities with the best possible capacity for climate change mitigation and adaptation, granting them a central role in humanity’s response to climate change through a deep transition towards carbon neutrality (Wolf-ram, 2016).

Buildings play an important role in urban energy systems. They are responsible for 23% of energy-related CO₂ emissions² and 31% of total final energy use globally (IEA, 2016), and are thus widely recognised as the foremost means for sustainability transition. Buildings and related urban infrastructures are characterised by a very long lifespan. Hence, in order to meet the 1.5°C scenario and avoid further lock-ins, climate actions are urgently needed. Climate response options for buildings include introducing low-energy building codes for newly constructed buildings and retrofitting existing building stock (Rogelj et al., 2018). The vast majority of building stock in the European Union (EU), North America and China is already built and requires energy efficiency improvements (IEA, 2017). Hence, building energy retrofitting³ is an essential part of urban climate response strategies (Zhou et al., 2016). However, its pace is significantly below required targets (Eames et al., 2013; Mangold et al., 2016).

The decarbonisation of the building stock is a *wicked problem* (Thollander et al., 2019), characterised by a multitude of interconnected issues. Volume of investments is undermined by lack of capital, limited short-term benefits,

² Upstream electricity generation is taken into account.

³ Hereafter ‘energy retrofitting’ is synonymous with application of energy conservation measures (ECMs).

split incentives and uncertainty about expected gains (Alam et al., 2019). There is a common shortage of institutional capacity, displayed in weak commitment by public actors and lack of coordination and trust between the multitude of stakeholders involved. Fragmented information and unresolved conflicts of interests can result in misalignment of actors in long-term infrastructural changes, and subsequently poor performance of the urban districts affected (Späth and Rohrer, 2015). The scale-out potential of retrofitting is also limited by lack of knowledge, i.e. general awareness, specific information and professional skills. Finally, social aspects of retrofitting (e.g. unwillingness of occupants to relocate temporarily, possible increases in energy poverty, lack of acceptance for new solutions, protection of cultural heritage) place additional constraints on possible retrofitting projects.

Addressing wicked problems such as large-scale retrofitting requires *transformative change* including innovative forms of governance, increased collaboration and learning, and nexus approaches to infrastructure (McCormick et al., 2013). Particularly, previous research has shown that urban planning is a key arena that should be ‘challenged and reinvented’ (Wolfram et al., 2019). It would also require a new generation of urban-scale models that are based on the actual data, making it possible to reduce the ‘information gap’ about current system performance and evaluate future impacts of alternative climate actions (Cerezo Davila et al., 2016).

Urban building energy modelling (UBEM) has emerged as a new paradigm in modelling the energy performance of building stock at a large scale when manual building energy simulation (BES) for each individual building is no longer feasible. The core idea of UBEM is to reduce the intrinsic complexity of the modelled energy system (of district or city) aiming for a reasonable balance between the detail of the model obtained and its quality. In this way, UBEM can often be performed even in cases with very scarce data available (Sokol et al., 2017).

At the time of publishing this thesis⁴ there are still very few cases of urban building energy models (UBEMs) built using high-resolution actual energy use data at the city scale (Ang et al., 2020). There is also a particular need for "decision-support systems that better integrate the technological, economic and environmental issues and options and societal challenges involved in implementation [of retrofitting]" (Eames et al., 2013, p. 506). Hence, development of a novel UBEM framework that allows analysis of large-scale retrofitting based on actual energy use can be beneficial for further development of this domain and instrumentation of decarbonisation of the building stock.

⁴ November 9, 2020

Rapid digitisation has resulted in remarkable amounts of *data* being generated in cities. Combined with concurrent advances in data science methods and tools, this enables development of new approaches to derive knowledge and develop urban analytics — data-based intelligence for cities. Data are starting to have an essential role in establishing "evidenced-based policy-making and effective investment in and management of infrastructure in a city" (UN-Habitat 2016, p. 43). However, urban building energy data are known to have a number of problems with quality. In particular, Mangold et al. (2015) and Monteiro et al. (2018) reported a lack of validity, consistency, completeness and accuracy in these data. It is well-known that the quality of the input data is strongly correlated with the quality of the model derived. At the same time, there is a lack of knowledge about the applicability of currently existing urban building energy data. Hence, there is a need to explore existing data applications and investigate how these are related with the quality of the input data.

Finally, as with any 'smart city' type of development, urban analytics carries a risk of supporting a purely technocratic and top-down approach to urban governance. However, it does not promote such a form of governance per se. Cities need to "be equipped for complex decision-making about the future in a way that engages the appropriate partners and communities" (GOfS 2016). If well thought through, urban analytics can enable broader public participation and lead to a more democratic and cohesive society. There is more responsibility on public and academic actors (city governments, state agencies, NGOs and researchers) to serve as stewards of the public good and play a more active role in framing the agenda in close collaboration with all stakeholders, for the sake of sustainable and just urban transition (Kitchin, 2019). While such a transdisciplinary setting makes it possible to ensure early assessment and societal relevance of newly developed technologies, it is also very demanding for the partners involved in the research (Reinhart and Cerezo Davila, 2016).

There is a noticeable gap between urban energy analytics and stakeholders. On the one hand, there are many urban energy models developed by experts from an academic or industry perspective that are theoretically correct, but rarely used in real-life due to their complexity and lack of interactivity (Voinov et al., 2018). On the other hand, decision-support tools that are used by decision-makers on a daily basis lack adequate input data, are based on oversimplified models and significantly bias final decisions. Hence, it is crucial to develop and demonstrate approaches for stakeholder involvement in development and prototyping phases for newly created urban energy data models and tools. Such approaches would favour a societal needs

orientation, and subsequent applicability and acceptance of urban analytics as a novel component of urban governance.

1.2 Aim and objectives

The overall aim of this thesis was to advance urban analytics for energy retrofiting of the building stock and to improve understanding of the role of urban energy data in urban sustainability transitions.

Specific objectives of the work were to:

- Objective 1* Develop and demonstrate an urban building energy modelling (UBEM) framework for strategic planning of building energy retrofiting (Papers II and IV).
- Objective 2* Investigate the interconnection between quality and applications of urban building energy data (Papers III and IV).
- Objective 3* Explore how urban analytics can be integrated into decision-making for energy transitions in cities (Papers I, II and IV).

Objective 1 focuses on the overall approach to urban building energy modelling while Objective 2 seeks more insights into quality and applications of urban energy data. Objective 3 concerns how urban analytics (data, methods and tools) can be integrated into decision-making for energy transitions in cities (Figure 1).

Figure 1. Interconnection of the three research objectives addressed and papers included in this thesis.

1.3 Scope

The research described in this thesis was largely conducted within the research project “Big data-driven energy retrofitting plan Stockholm”⁵ in 2015–2018. The project was fertilised by a number of previous collaborations between researchers from KTH Division of Industrial Ecology⁶ and City of Stockholm, AB Fortum Värme samägt med Stockholms Stad⁷ and Hammarby Sjöstad Organisation of Housing Associations (Sjöstadsforeningen) (e.g. Iveroth et al., 2013). In particular, the initial versions of datasets with measured heat energy use and energy performance certificates (EPCs) for Stockholm were collected during the “Smart Royal Seaport Dashboard” project⁸ and were first analysed in three papers published in 2014 (Y. Ma, 2014; Shahrokni et al., 2014; van der Heijde, 2014). Therefore, the city of Stockholm served as a case for the development of the UBE framework (Objective 1) presented in Papers II and IV (Figure 1). Paper III also built on the learnings from the Stockholm case, but expanded geography further, presenting the EPC data quality assessment approach applicable for the whole of Sweden with a systematic mapping of EPC data applications for EU member states⁹. Combined with more generic findings on possible urban energy data applications in Paper IV, they constituted the investigation under Objective 2.

My research in the domain of urban energy data and modelling started earlier, with two full-scale participatory scenario projects conducted in Bila Tserkva, Ukraine (2012–2013) and Niš, Serbia (2014–2015). These studies led to the development of a new modular participatory backcasting (mPB) methodology (Pereverza et al., 2019; 2017; Zivkovic et al., 2016). Paper I presents an approach by which urban energy modelling can co-inform the participatory strategic planning process. This approach was applied later in Papers II and IV. Hence Objective 3 was addressed for both Niš and Stockholm in Papers I, II and IV.

⁵Grant no. 40846-1, funded by Swedish Energy Agency.

⁶Now reorganised into a part of the Department for Sustainable Development, Environmental Science and Engineering (SEED).

⁷Now operating as AB Stockholm Exergi.

⁸Funded by the Swedish Energy Agency.

⁹The review in Paper III was not explicitly limited by geography, but as EPC is a policy instrument introduced by the European Commission in its European Building Performance Directive (EPBD), the term is mainly used in research publications related to the EU.

2 Theoretical background

“Great scientific discoveries have been made by men seeking to verify quite erroneous theories about the nature of things.”

Aldous Huxley

2.1 Cities as systems in transitions

Climate agenda

Urbanisation is a current megatrend in human development. More than half of the world’s population now lives in urban areas, and the urban population is expected to reach 68% of the total global population by 2050 (UN 2019). Such rapid transition makes it challenging to achieve urban resilience and quality of life for everyone. However, it also serves as a creative disruption for implementing changes that were not possible before.

Another megatrend today is *climate change* leading to global warming (IPCC, 2014). There is strong scientific consensus on the anthropogenic nature of this climate crisis (Cook et al., 2016; Rockström et al., 2009). Risks to health, livelihoods, food security, water supply, human security and economic growth are projected to increase significantly in the event of global warming exceeding 2°C. In order to limit the global temperature increase to 1.5°C, “deep emissions reductions” and “rapid, far-reaching and unprecedented changes in all aspects of society” are required (IPCC, 2018). The global commitment to pursue such efforts is set out in the COP21 Paris Agreement for Climate Action signed by 189 countries in 2016. This need for change is also highlighted within the United Nations Sustainable Development Goals (SDGs), particularly SDG7 “Affordable and clean energy”, SDG11 “Sustainable cities and communities” and SDG13 “Climate action” (Griggs et al., 2013).

Cities are in the vanguard of the needed global action on climate change. Urban areas account for 71-76% of human-induced greenhouse gas (GHG) emissions (Seto et al., 2014), making them main contributors to the climate (UN-Habitat 2019). Cities are also among the areas greatly affected by climate change, which poses risks to infrastructure, ecosystems, housing, service delivery and the livelihoods and health of urban communities. As

sources of strong economic growth, cities have the greatest potential for adaptation and mitigation, making them central in addressing climate change (IPCC, 2014).

Urban governance of climate change involves intentional actions or interventions by multiple actors to purposefully steer city or urban areas towards low carbon, resilient or sustainable objectives (Castán Broto, 2017). The number of successful climate actions at the urban level has been constantly growing since the very first municipal responses to climate issues in the early 1990s (Bulkeley, 2010). However, cities are much too slow and far off in their transition towards carbon neutrality (Azevedo et al., 2013). Local authorities continue to split policy design and implementation into silos (Sanchez Rodriguez et al., 2018). Hence, very few cities address risks of carbon lock-ins from their climate response, thus missing synergies and inducing unnecessary trade-offs between implemented adaptation and mitigation actions (Ürge-Vorsatz et al., 2018).

Urban sustainability challenges can be categorised as *wicked problems*. This concept was introduced by Rittel and Webber (1973) to characterise challenges in planning and decision-making. According to their definition, 'wicked' problems are "a class of social system problems which are ill-formulated, where the information is confusing, where there are many clients and decision makers with conflicting values, and where the ramifications in the whole system are thoroughly confusing" (Churchman, 1967). The same type of problems that "involve dealing simultaneously with a sizeable number of factors which are interrelated into an organic whole" were pinpointed from an urban studies perspective by Jane Jacobs (1961, p. 432) in her pioneering book '*The Death and Life of Great American Cities*'. The wicked problems in urban energy planning have been identified and analysed by Cajot et al. (2017). Monstadt and Coutard (2019, p. 2202) concluded that "urban studies and planning must reconsider their approaches and must address individual infrastructures as urban systems of systems that together shape urban futures".

Systems perspective

Cities can be seen as *complex adaptive systems*. Bettencourt (2015) highlights five properties that characterise cities as complex systems: 1) *heterogeneity*; 2) *interconnectivity*; 3) *scale*; 4) *circular causality*; and 5) *development*. Rotmans (2006) categorises cities as complex systems due to: 1) *nonlinearity* of cause-effect relations between components; 2) *regulation* — positive and negative feedback loops; 3) *openness* of the system (existence of *system boundaries* per se); 4) *heterogeneity* — diversity of the system structure and variety of its

components; 5) *multitude of goals* (system attractors); 6) *nestedness* of the structure (presence of complex subsystems); 7) *emergence* — appearance of new patterns from interactions between components; and 8) *adaptability* — capacity to adapt to changes in environment.

The conceptualisation of cities as systems (or systems of systems) using urban big data is a core approach in *urban science* (US), "an interdisciplinary approach that practices and promotes a scientific and computational explanation of city systems and the processes of urbanization" (Kitchin, 2017, p. 2). Beside natural linkages with urban studies, urban science is closely connected with *urban modelling*. The complexity of cities has been utilised in urban modelling at least since Jay Forrester had published his book '*Urban Dynamics*' in (1969). The more recent advances in urban complexity studies are exemplified in '*The New Science of Cities*' by Michael Batty (2013a), which develops approaches to analysis of cities via the networks and flows that constitute them. Urban science has advanced markedly in recent decades and can be praised for providing additional valuable insights on cities. However, as it is based mainly on positivism paradigm, it is often criticised for providing rather naïve and overmechanistic representations of real cities, and should therefore be used as a complement to other approaches (Kitchin, 2017).

Complex systems are also the main object of study within *industrial ecology* (IE), "a systems-based, multidisciplinary discourse that seeks to understand emergent behaviour of complex integrated human/natural systems" (Allenby, 2006, p. 33). In particular, *urban metabolism* focuses on the study of material and energy flows in cities as "the sum total of the technical and socio-economic processes that occur in cities, resulting in growth, production of energy, and elimination of waste" (Kennedy et al., 2007, p. 44). Industrial ecology can be praised for its toolbox of quantitative methods for comprehensive analysis of measurable physical phenomena and framing future system visions (Pauliuk et al., 2017). However, similarly to urban science, it lacks inclusion of societal aspects (governance, power, actors and institutions) and, in particular, tools for implementation of transformative change (Rotmans and Loorbach, 2009).

Finally, cities can be analysed as socio-technical systems (STS). In the domain of sustainability transitions (ST), these systems are characterised by such properties as multi-dimensionality and co-evolution; multi-actor processes; stability and change; long-term processes; open-endedness and uncertainty; values, contestation and disagreement, and normative directionality (Köhler et al., 2019). Cities were not clearly articulated in the sustainability transitions research agenda until the last decade (Hodson and Marvin,

2010). Since then, there has been steady growth in the number of studies on urban sustainability transitions. These include studies on experimentation (Bulkeley and Broto, 2013) and urban living labs (Voytenko et al., 2016), transformative capacity (Wolfram, 2016) and reconfiguration (Hodson et al., 2017), urban junctions (Späth and Rohrer, 2015) and nexus (Monstadt and Coutard, 2019). Sustainability transitions research can be complimented for its particular focus on systemic change, providing a number of useful analytical frameworks for understanding and governance of transitions. It also challenges more managerial and technocratic paradigms of thinking about cities. However, it can sometimes be confusing, due to its multitude of theoretical concepts and underlying ontologies and epistemologies that are not always compatible with each other. Furthermore, the sustainability aspects of transitions are often overlooked, due to the permanent spotlight on the phenomenon of change. Aiming for better representation of the complex nature of urban systems, McPhearson et al. (2016) propose broadening the scope beyond socio-ecological and socio-technical approaches to study "social-ecological-technical systems".

Strategic planning for sustainability

Integrated approaches and tools are needed in strategic planning and decision-making for urban sustainability. *Integrated assessment (IA)* is defined by Rotmans (1998, p. 155) as "a structured process of dealing with complex issues, using knowledge from various scientific disciplines and / or stakeholders, such that integrated insights are made available to decision-makers". The challenge of the integrated approach lies in finding a balance between holistic and reductionistic thinking about the system (Shaked and Schechter, 2017). The integrated approach to strategic planning improves planning cycles, making them more transparent and systematic, integrates sectorial policies and increases efficiency through organisational, policy, monitoring and evaluative functions (Rotmans et al., 2000). Hence, integrated strategic planning and decision-support tools should provide calculative, monitoring and evaluative capabilities. Chifari et al. (2018) provide the example of one such holistic framework for integrated assessment of urban waste management.

There is need for a shift towards *participatory governance* and *reflexive planning*. Arguments for public participation can be divided into three groups: 1) *normative*, reflecting rights to participate and the process of democracy; *substantive*, affirming that participation improves the quality of decisions; and *instrumental*, asserting that participation improves trust and acceptance of subsequent decisions (Stirling, 2006). Participation can be distinguished by the level of intensity. As demonstrated by the 'ladder of participation'

(Arnstein, 1969), if not addressed consciously, citizen participation can be used for manipulative reasons. Krutli (2010) distinguishes four levels of public participation: information, consultation, collaboration and empowerment. Following a review of 200 local climate plans, Heidrich et al. (2016) concluded that there is no standardised way for a city to plan for climate change. Multiple interests and motivations are inevitable. *Transdisciplinarity* is a research approach that "includes multiple scientific disciplines (interdisciplinarity) focusing on shared problems and the active input of practitioners from outside academia" (Brandt et al., 2013, p. 1). The gap between analytical and decision-making processes can be reduced through active involvement of stakeholders in modelling within a transdisciplinary setting, such as *participatory integrated assessment (PIA)* (Salter et al., 2010) or *participatory modelling (PM)* (Voinov et al., 2016). Similarly to the integrated approach, the main quest of participatory modelling lies in finding a balance between comprehensive representation of the real-world system and maximisation of engagement and understanding for the stakeholders involved. This can be achieved through interfacing between qualitative and quantitative methods, interactivity of modelling and user interfaces. The current rapid digitalisation of cities allows for development of novel tools for large-scale participation and citizen engagement, such as crowdsourcing and crowdsensing, urban probes, interactive public displays, interactive and participatory urban interventions, urban spectacles and the public Internet of Things (IoT) (Salim and Haque, 2015). Kingston (2013) provides an example of a map-based e-participation platform developed to increase the level of access by citizens to the decision-making process in Manchester.

Future visions play an important role in strategic planning. Visions and pathways are tools of transition governance to facilitate and empower actors and networks, so that they can work more strategically on transitions, explore more radical innovation trajectories and formulate alternative goals and agendas (Loorbach et al., 2017). *Scenarios* are known to be a useful method for strategic planning, allowing planners to elaborate a desirable future vision, explore the space for possible alternative solutions and pathways, ensure the robustness of the strategy developed and anticipate its effects. In a broader sense, scenarios can be defined as internally consistent pictures of possible futures. Detailed typologies of scenarios can be found in the literature (Amer et al., 2013; van Notten et al., 2003). *Modular participatory backcasting (mPB)* is a new scenario development framework that was initially developed for strategic urban energy planning (Pereverza et al., 2019). It allows analytical and participatory approaches to be combined. Its earlier version was used in the Niš case in this thesis (Section 3.2), to demonstrate integration of urban analytics into a participatory process of urban energy planning in Paper 1, as described in Section 4.3. Elements of scenario planning were

integrated into the urban building energy modelling framework developed in Paper II, as described in Section 4.1 of this thesis.

2.2 Urban analytics

Smart cities

The development of *information and communications technology (ICT)* has noticeably affected life in cities in recent decades. Regular introduction of new radical innovations, such as IoT, 5G or cloud services, is sustaining exponential growth in sensing, computational, networking and storage capacity (Deloitte, 2017). Together with subsequent data deluge and advances in data science (DS), artificial intelligence (AI) and machine learning (ML) techniques, it creates brand new opportunities for how cities can be perceived, rationalised and governed. The paradigm of urban development based on intensive utilisation of ICT is usually denoted by the term '*smart cities*' (Batty et al., 2012; Hollands, 2008). Although *sustainability*¹⁰ is often recognised as the aim of such development, it should not be automatically assumed. To avoid ambiguities, the term '*smart sustainable cities*' has been introduced. In this, the sustainable development of cities is highlighted as the ultimate goal, while ICT tools are designated as means for reaching this goal (Kordas et al., 2015).

The ICT-driven development of cities has yielded a plethora of new methods and tools for analysis of urban processes. A new area, *urban informatics*, has been framed as a superset (Batty, 2013b), a subset (Townsend, 2015) or complementary field (Kitchin, 2017) to urban science. Foth (Foth, 2009) defines the scope of urban informatics as "collection, classification, storage, retrieval, and dissemination of recorded knowledge of, relating to, characteristic of, or constituting a city"¹¹. While urban informatics can include urban modelling or statistical analysis, its primary focus is on the development of information tools and management systems for control and communication of urban processes, understanding human interactions with urban systems, and analysis of relationships between people, places and digital technologies. The ICT-enabled evolution of urban metabolism studies can be illustrated by the *smart urban metabolism (SUM)* framework proposed by Shahrokni et al.

¹⁰Hereafter, sustainability is usually intended in a broader sense, i.e. not only environmental resilience, but also quality of life for current and future generations.

¹¹As Foth showed this definition can also be rephrased as "the collection, classification, storage, retrieval, and dissemination of recorded knowledge in a city" to highlight physical city's persistent role as a container for information-based human activity.

(2015). It advances conventional urban metabolism studies by provisioning a real-time dynamic understanding of urban energy and material flows through utilisation of urban big data and smart-city technologies. *Planning support systems (PSS)* are an example of such new 'smart city'-influenced digital tools in the urban planning domain (Christopher Pettit et al., 2018). Planning support systems also use urban big data, but are oriented instead towards support of land-use and transport planning.

Despite distinctions imposed by different application domains and research fields of origin, all above-mentioned areas share the practice of using new forms of data, in combination with computational approaches, to gain insights into urban processes, a practice defined by Singleton et al. (2017) as *urban analytics (UA)*. Yamagata et al. (2020, p. 29) define urban data analytics as "methods of data capturing, screening, processing, and modelling, for urban problems defined within geographic territories in near real-time". Urban analytics is instrumentalised by the 'urban stack', the concept used by Mattern (2014) to conceptualise the relationship between data and materiality in the smart city. Shapiro (2018) outlines three layers of urban stack: distributed infrastructure (sensors and networks), control and interface. These layers correspond to the core components of urban analytics, which are *data*, *methods* (models and algorithms) and *tools* (services).

Data

Data are raw elements that can be abstracted from an object through measurement or record. Data can be classified by their *form* (quantitative, qualitative), *structure* (structured, semi-structured, unstructured), *origin* (captured, derived, exhaust, transient), *generation* (directed, automated, volunteered), *source* (primary, secondary, tertiary), *type* (indexical, attribute, metadata), *access* (closed, shared, open) or *ownership* (private, public) (Kitchin, 2014). The creator of the World Wide Web, Tim Berners-Lee (2006), proposed the concept of *Linked Open Data* and its five-star deployment scheme to characterise the interchange-readability of any dataset. A sample overview of urban data can be found in the literature (Barbosa et al., 2014; Barlacchi et al., 2015). Data are often regarded as neutral, but are not. Ribes and Jackson (2013) show that data are always affected by the way in which they are produced, stored and shared. Furthermore, data reshape the surrounding actors and institutions. Hence, transparency in data management and in input and output data is crucial for derivative decision-support tools (González et al., 2013).

The term *big data* is usually applied to describe data characterised by high volume, velocity, variety and veracity (the 4Vs)¹², handling of which requires specific technologies and analytical methods (Chen and Zhang, 2014). In a wider framing, big data comprise the whole stack, i.e. not only data as-sets themselves, but also tools and services required to process those data (Pan et al., 2016). Batty (2013c) sets a rule of thumb that defines big data as ‘any data that cannot fit into an Excel spreadsheet’¹³. The phenomenon of big data has fuelled much optimism and expectations in the past two decades, not only for smart cities (Bettencourt, 2014), but also for science in general (Science Staff, 2011). In particular, the prominent Microsoft computer scientist Microsoft Jim Gray presented the fourth paradigm of exploratory data-driven science, which is based on the growing availability of big data and new analytics (Hey et al., 2009). However, in more recent publications the role and potential of big data have been evaluated more critically. For instance, Kitchin in (2016a, p. 12) concludes that “there is little doubt that much of the rhetoric concerning big data is hyped and is boosterist”. Instead, small and mid data (Xia, 2017) are seen to be a crucial part of the research landscape. It is expected that small data will continue to be popular and valuable, and increasingly become more big data-like (Kitchin and Lauriault, 2015).

Methods

Data by themselves have no value. To derive value from data, data analytics *methods* are applied. *Data science (DS)* is a fusion of statistics and computer science. This field is closely related to a number of other disciplines, i.e. cybernetics, artificial intelligence, operational research, knowledge discovery in databases and data mining (Cao, 2017). Its origins can be traced in particular to the concept of ‘data analysis’ discussed by John Tukey over half a century ago (1962). Donoho (2017) divides contemporary data science issues into the following six classes: 1) data gathering, preparation and exploration; 2) data representation and transformation; 3) computing with data; 4) data visualisation and presentation; 5) data modelling; and 6) science about data science. This list corresponds to the typical workflow structure shared by the vast majority of data analytics processes, namely 1) import; 2) pre-processing; 3) transformation; 4) visualisation; 5) modelling; and 6) communication¹⁴ (Wickham and Grolemund, 2017) (see Figure 3 in Section 3.5). The

¹²These are well-known characteristics, but many more are proposed in the literature (e.g. Kitchin, 2016a).

¹³In live conference presentations the definition ‘any data that cannot be treated with methods and tools conventional for this application domain’ has also been frequently used.

¹⁴Steps 3-5 are usually conducted multiple times in an iterative manner.

purpose of *data analyses* can be quite diverse. Leek and Peng (2015) distinguish six types of data analysis questions: descriptive, exploratory, inferential, predictive, causal and mechanistic. Depending on the type of question, different constellation of methods should be used. For instance, Shmueli (2010) demonstrates the distinction between models developed with an explanatory and predictive purpose.

Data import, pre-processing and transformation are often described in the literature on data warehousing as the *ETL* (extract-transform-load) process (Johansson et al., 2017). Despite being often disregarded in research publications on energy modelling, this step is extremely effort-intensive, corresponding to around 80% of the whole time spent on data analysis (Wickham, 2014). However, it is crucial for enabling further analysis. Pre-analytics stages can provide significant added-value to the original data through *data enrichment* — the process of integration and cross-examination of data originating from different sources (Marinakos et al., 2018). It is particularly relevant for urban analytics, due to the usual multiplicity of input datasets and diversity of their quality and coverage, as shown further in Section 4.2 in this thesis and in Paper III.

Statistical models and computational algorithms are blended in *data modelling* to solve discipline-specific data-intensive problems (Blei and Smyth, 2017). Hence, data science combines two cultures of thinking about the role of data in modelling (Breiman, 2001). On the one hand is ‘*generative modelling*’ coming from traditional *statistics*. It aims at development of stochastic models which fit the data and can potentially re-generate the data. On the other hand is ‘*algorithmic modelling*’, which originates from *machine learning* (ML). It aims at development of an algorithm which can solve a problem through optimising for a certain performance metric (e.g. accuracy of prediction). In this way, the model obtained reflects the phenomenon only from the lens of the given dataset, while the mechanism underlying the whole data universe is completely disregarded. There are many applications in which algorithmic models have proven to be more efficient than generative modelling. The underlying machine learning algorithms can be distinguished into three main categories: *supervised* (classification and regression), *unsupervised* (clustering, outlier detection, dimensionality reduction) and *reinforcement learning* (sequential decision-making in environment). However, machine learning has certain drawbacks, such as limited interpretability of models to users and low robustness of the models obtained to data not available for model training (Jordan and Mitchell, 2015).

Data visualisation is usually the only evident part of the data science workflow, but is often avoided in academic circles (Kelleher and Wagener, 2011).

It is not only an efficient method for data analysis, but also a means of displaying the data and communicating modelling results, playing an important role of interface between stakeholders and underlying data and models. Hence, visualisation is often associated with an interface layer of urban stack and related to tools and services of urban analytics.

Tools

There is a strikingly wide range of *tools* for data analysis (Turck, 2019), and most of them can be relevant for certain urban analytics tasks. However, there are several types of tools that are directly connected to urban analytics.

The concept of *urban data platforms (UDPs)* has been in use at least since being introduced by European Commission (2015), but there are still quite diverse framings of urban data platforms in the academic literature (Schieferdecker et al., 2016). For instance, Hernandez et al. (2019, p. 1) position the urban data platform as a data integration medium, defining it as an "implemented realization of a logical architecture / design that brings together vertical data flows within and across city systems on a horizontal layer". However, Eicker et al. (2020) view this pure data management orientation of urban data platforms as insufficient and call for inclusion of modeling and optimization in the concept. Finally, Barns (2018) presents a typology of urban data platforms, classifying them into: 1) data repositories, 2) data showcases (dashboards), 3) cityscores (scorecards) and 4) data marketplaces.

Urban data portals (a.k.a. data repositories, data hubs) can be defined as specialised web resources where datasets can be documented (provided with high-quality metadata), published, viewed and downloaded (Delaney and Chris Pettit, 2014; for overview see Pinto et al., 2018). *Data marketplaces* are the next step of evolution for data portals, aiming for decentralised solutions to exchange data between data owners and data users (Ramachandran et al., 2018).

Urban dashboards (UD) are used to aggregate and consolidate urban information in a single interactive view (for overview see Kitchin et al., 2015; Christopher Pettit et al., 2017). This concept of a dashboard as "a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance" (Few, 2006, p. 26), originates from business intelligence. *Scorecards* with urban indicators for monitoring or benchmarking are often included as part of urban dashboards and can be thus recognised as their particular case. Lock et al. (2020) provide the most recent view on

participatory urban dashboards, reframing them as interfaces for participatory planning and monitoring of urban environments and systems. In this way, urban dashboards serve not just as consolidators of information, but also of detailed task-specific tools, such as planning and spatial decision support systems (PSS & DSS).

Socio-technical perspective

Smart urbanism can be a powerful vision to guide urban transitions and reshape urban governance (Luque-Ayala and Marvin, 2015). However, its transformative change may not only bring benefits of cities becoming more efficient, but also result in a number of pernicious effects. Urban analytics is more than a technological phenomenon, it is a nucleus of urban *data assemblage* or a "complex socio-technical system, composed of many apparatuses and elements that are thoroughly entwined, whose central concern is the production of a data" (Kitchin and Lauriault, 2014, p. 6). Hence, particular attention should be paid to non-technological aspects of urban data, i.e. instrumental rationality and realist epistemology; privacy, datafication, dataveillance and geosurveillance; and data uses, such as social sorting and anticipatory governance (Kitchin, 2016b).

The *barriers* to uptake of urban data systems were first formulated by Downs (1967) and most of these still apply. Perceptions of individual and collective actors about redistribution of power resulting from automation of decision support can nourish reluctance to collaborate, or even a desire to block or sabotage such developments. The efficient utilisation of urban data is to a great extent limited by the institutional complexity underlying the required data integration. For instance, digitalisation of urban planning requires knowledge not only about the technical artefacts (digital resources), but also about contextual, organisational and human influences (Granath, 2016). Frontrunner cities are more proactive in development of their data infrastructure and cross-departmental collaborations (e.g. Greater London Authority, 2016). However, as a rule, local governments have low capacity for set-up and further support of urban analytics functions. Hence, the majority of urban analytics cases are demonstrators for local pilot sites traditionally outsourced to corporate actors (Giest, 2017).

Nevertheless, the capabilities of cities are becoming increasingly dependent on data, making data *basic urban infrastructure* (Suzuki and Finkelstein, 2018). Such diffusion of urban data will undoubtedly affect the current mode of governance. On the one hand, it creates a lot of new opportunities for citizen participation and co-creation. It can also support more long-term, whole-system-oriented evidence-based decisions. On the other hand, it can lead to

reinforcement of top-down management and technocratic data-driven decisions of questionable ethics. Furthermore, it increases risks of lock-ins where cities are bound to certain technological platforms and corporate vendors in the long-term, thereby supporting corporatisation of governance and creation of new monopolies. Therefore, it is of great importance to ensure early involvement of a wide range of stakeholders in assessment and co-creation of these new data-driven technologies.

2.3 Urban energy

Urban energy systems & energy transition

There are many approaches to define urban energy systems (UES). Functional, socio-technical and complexity perspectives were found to be relevant for this thesis.

The *functional* perspective is traditional in the energy modelling community. For instance, Grubler et al. (2012, p. 1314) define urban energy systems as "all components related to the use and provision of energy services associated with a functional urban system". In this context, energy service demands include heating and cooling for buildings, indoor and outdoor lighting, and electric power for appliances, mobility and communication services. Furthermore, the full urban energy system in such cases entails direct energy flows, but also embodied energy. Similarly, Rutter and Keirstad (2012, p. 72) define urban energy systems as "processes for acquiring and using energy to meet the energy service demands of an urban population".

The *socio-technical* perspective on energy systems has been recognised to be useful for analysis of large technological systems since prominent work by Hughes on networks of power (1983). It has gained a noticeable boost to development recently, due to the 'energy transition', i.e. a "radical reconfiguration of the way we generate and use energy in cities and beyond" (Rohracher and Späth, 2014, p. 1416). According to Rutherford and Coutard (Rutherford and Coutard, 2014, p. 1355), urban energy transitions involve "a diverse and discrete set of processes, practices and policies which come together differently and are differently interpreted, translated, experienced and grounded, at particular moments in specific places". Energy systems can then be defined as "socio-technical configurations where technologies, institutional arrangements (for example, regulation, norms), social practices and actor constellations (such as user–producer relations and interactions, intermediary organisations, public authorities, etc.) mutually depend on and co-evolve with each other" (Rohracher and Späth, 2014, p. 1417). In this framing,

transformation of urban energy system is "shaped by (and is shaping) socio-political and socio-technical contexts at different spatial scales" (Rohracher and Späth, 2014, p. 1416). Eames et al. (2013) show how an integrated socio-technical perspective on long-term systems innovation can be used to develop urban building retrofitting scenarios.

Finally, urban energy systems can be studied from a *complexity* perspective. For instance, Bale et al. (2015) analyse energy systems through: 1) agents, interacting through networks; 2) objects, such as technologies and infrastructures; and 3) environment, which provides resources and also establishes social, political, and cultural scenarios in which the energy system operates. Basu et al. (2019) propose a conceptualisation of urban energy systems based on integration of urban complexity studies (Batty, 2012; Bettencourt, 2015) and urban energy studies (Grubler et al., 2012; Keirstead et al., 2012). The water-energy-food nexus approach can be applied to elaborate an integrative view on the interconnected nature of urban infrastructures (Artioli et al., 2017). Ultimately, complexity framing can be useful for urban energy planning, as demonstrated by Cajot et al. (2017) in an analysis of different challenges and obstacles to energy planning at the urban scale as wicked problems.

Decarbonisation, digitalisation and decentralisation are highlighted as the main drivers for the ongoing *urban energy transition* (Di Silvestre et al., 2018; Webb et al., 2020). These drivers can also be recognised under the label *smart energy city* frequently used in the corporate discourse (Mosannenzadeh et al., 2017). *Decarbonisation* refers to a continual decrease in carbon intensity through substitution of fossil fuels with renewable energy sources (RES), combined with substantial electrification of energy services (IEA 2018). *Digitalisation* refers to substantial penetration of intelligent devices (smart meters, sensors and control systems), nowadays generalised as Internet of Things (IoT), and subsequent development of artificial intelligence (AI) and machine learning (ML) techniques to utilise this hardware. This paved the way for the whole set of new technologies for asset coordination, automation and control in 'smart grids' (Howell et al., 2017), in energy management for intelligent buildings (Molina-Solana et al., 2017). *Decentralisation* refers to distribution of energy assets and management supported by new renewable energy sources and storage technologies. It is characterised by emergence of micro-grids, 'prosumers' and demand-side management (Nilsson, 2018). In combination, these three trends allow for new business models, policy instruments and modes of governance, e.g. green certificates, energy cooperatives, peer-to-peer (P2P) energy trading and digital marketplaces (Andoni et al., 2019). Given the policy support to these trends, the power sector is

expected to be mostly decarbonised by 2050, and the main challenge is to reduce CO₂ emissions in end-use sectors (Rogelj et al., 2018).

Buildings & retrofitting

Building stock is an important component of urban energy. Globally, buildings account for 31% of total final energy use, 54% of electricity, 51% of district heat and 23% of GHG emissions (Rogelj et al., 2018; Werner, 2017). Furthermore, 1.6 billion people globally live in inadequate housing (UN Habitat 2019). Hence, construction of new buildings according to low-energy standards is a natural strategy for growing economies. However, the majority of buildings in the EU, North America and China already exist and will be part of the building stock in 2050 (EU Commission, 2016). Therefore, building energy retrofitting is a regular element of urban climate response strategies (Lamb et al., 2019).

Building retrofitting involves alteration of existing buildings with one or several retrofitting measures (or just ‘retrofits’). These measures typically aim for improvements in the energy and environmental performance of the building. Therefore, in the literature they are frequently referred to as energy-saving or *energy conservation measures (ECMs)*. Retrofits can be classified by the component of change, i.e. *fabric* (structural elements of the building), *services* (the building’s heating, ventilation and air conditioning (HVAC) and related engineering systems, e.g. water, lightning) and *behaviour* (the way in which people (tenants or visitors) interact with the building). Applicability of retrofits is defined depending on the specific building, i.e. geographical location, building type (residential, office, service), fabric, size, age, installed systems, occupancy schedule, ownership etc. The effectiveness of retrofitting can be characterised by its economic viability (capital expenditure or return on investment), effect on sustainability (energy and emission savings), complexity and ease of implementation (Z. Ma et al., 2012).

Retrofitting is usually regarded as a cost-effective option for decarbonisation of cities (Lucon et al., 2014; Mata et al., 2014). Besides, implementation of energy conservation measures can bring a wide range of co-benefits, especially when conducted at district/urban scale (Becchio et al., 2018). However, there are multiple *barriers* to retrofitting uptake (Bertone et al., 2018), which can be classified into the following categories: 1) *financing* — lack of funds, priorities in investments, split incentives and uncertainties over gain; 2) *administrative* — passiveness of government, lack of interdisciplinary expertise and collaboration, multi-stakeholder issues; 3) *knowledge* — lack of information and awareness, lack of motivation, lack of skills and knowledge of building professionals; and 4) *social* — interruption to building operations,

consequent increase of inequality (Alam et al., 2019). Urban retrofit transitions are complex, co-evolutionary, non-linear processes involving a range of actors and focusing on different levels and dimensions over time (Dixon et al., 2018).

There are different *strategies* to cope with these barriers. Van Doren et al. (2016) distinguish *informative* (face-to-face communication, dissemination of experiences, online and offline information points), *cooperative* (process assistance, training and activation of supply-side actors), *financial* (collective purchasing, valorising the co-benefits, public-private partnerships) and *regulative* (regulatory support) approaches. Alam et al. (Alam et al., 2019, p. 68) advocate a top-down approach, where "governments need to show determination and be willing to take on debt beyond the forward estimate period in order to fund feasible retrofit projects". Caputo and Pasetti (2015) recognise that local public administrations can play a fundamental role in establishing energy planning and, particularly, in setting up a common model and obligations for collecting knowledge about the features of the building stock. However, there is an evident gap between relatively short-term planning horizons and longer-term environmental ambitions and targets. The lack of a whole system perspective, the prevalence of sectoral approaches in urban governance and the growing complexity of cities create higher risks of trade-offs and lock-ins, as well as unutilised synergies. Hence, there is a need for an integrated approach and "appropriate modelling and decision-support tools to aid long-term planning for sustainable urban retrofiting" (Eames et al., 2014, p. 6).

Urban building energy modelling

Urban energy modelling (UEM) is known to be useful for the understanding of urban energy systems by stakeholders and for supporting strategic energy planning. It can be used to analyse expansion potential of existing infrastructure, new energy demand requirements and effects of energy conservation measures on urban level. Urban energy modelling can be defined as "a formal system that represents the combined processes of acquiring and using energy to satisfy the energy service demands of a given urban area" (Keirstead et al., 2012, p. 3849). Keirstead et al. (2012) classify models by *key areas* (technology design, building design, urban climate, systems design, policy assessment, and transport/land use), *spatial* and *temporal* scale, *method* (e.g. simulation, optimisation, empirical), role of *supply* and *demand* (none, exogenous, endogenous) and *purpose* (e.g. system planning, technology design, operational control). In their review of simulation tools, Sola et al. (2018) distinguish urban energy modelling domains such as 1) urban

meteorology, 2) building energy demand, 3) building energy supply, 4) transportation and 5) energy optimisation. The generally recognised challenges in urban energy modelling are complexity, data availability and uncertainty, model integration and policy relevance (Keirstead et al., 2012).

City-scale building energy modelling has emerged in recent years, driven by the need for urban integrated energy planning, enabled by the uptake of smart metering and growing availability of data and computation capacity. The early efforts in modelling buildings on district/urban scale are reviewed in papers by Swan and Ugursal (2009) and Kavgić et al. (2010) that categorise the main modelling approaches, and particularly distinguish between *top-down* and *bottom-up* models. The latter are positioned as a new research field, *urban building energy modelling (UBEM)*, in a review by Reinhart and Cerezo Davila (2016). A state-of-the-art overview can be found in recent publications (Hong et al., 2020; Johari et al., 2020; Li et al., 2020). The two main modelling approaches utilised in urban building energy modelling are *physical/engineering (white box)*, based on dynamic building physics energy simulations (BES), and *statistical/data-driven (black box)*, based on the measured data about building energy performance (Nageler et al., 2018a). Another approach that is frequently recognised in the literature is a *reduced-order/hybrid (grey box)* modelling approach (Hong et al., 2020). It falls between the physical and statistical approaches and is based on simplified models of urban building stock using limited amounts of data. An example of a reduced-order model is the energy signature (ES) model applied in development of the urban building energy model in Paper II (see Section 4.1 of this thesis). Despite its simplicity, the energy signature model is praised for its robustness (Vesterberg et al., 2014) and is used as a European standard (EN 156036:2008).

The vast majority of urban building energy models, including that developed in Paper II, use *building archetypes* to reduce the complexity of the constructed models and compensate for the lack and quality of the input data. More information on archetypes, including the functions of archetypes identified in the literature and proposed criteria for developing archetypes, is provided in Paper IV.

Urban building energy modelling is a rapidly growing area of research that has many open questions on its agenda. Further developments for flowless automation of building simulation process are vital for scale-out of urban applications (Dogan and Reinhart, 2017). It is equally important to address the issues of availability and quality of input data (Mangold et al., 2015; Monteiro et al., 2018; Nouvel et al., 2017), and methods to compensate for its deficiencies, e.g. probabilistic building parameter estimation (Burke et al.,

2017; Nagpal et al., 2018) or data enrichment (Neun, 2007; Remmen et al., 2016; Schiefelbein et al., 2019). This goes hand in hand with development of approaches for managing the uncertainty embedded in the models and calibration of the models obtained in order to ensure good quality of the modelling outcomes (Sokol et al., 2017). The ongoing diffusion of data science techniques gives good promise of further advances in capabilities in both the data pre-processing and computation stages in urban building energy modelling. For example, Kontokosta and Tull (2017) employed linear regression, random forest and support vector machine algorithms to predict energy use of properties in New York City. Another point of interest is integration of urban building energy models with other urban energy models, including possible mode of co-simulation. For instance, Nageler et al. (2018b) demonstrated dynamic interaction of urban building stock with a heat supply unit through a thermal network. In same way, integration of urban building energy models with urban microclimate models can allow whole-system effects such as the urban heat island to be captured (Johari et al., 2020). Finally, there is a well-recognised necessity for stronger engagement between planners, policymakers, utility representatives and the building modelling community, in order for urban building energy models to have a larger societal impact (Reinhart and Cerezo Davila, 2016).

3 Research design and methods

“When I examine myself and my methods of thought, I come to the conclusion that the gift of fantasy has meant more to me than any talent for abstract, positive thinking.”

Albert Einstein

3.1 Transdisciplinary research and participatory modelling

Transdisciplinary research (TdR) is a research strategy to address ‘wicked’ problems through involving actors from outside academia in the research process. This makes it possible to integrate best available knowledge, incorporate values and preferences, and create ownership for problems and solutions. Lang et al. (2012, p. 26) define transdisciplinarity as “a reflexive, integrative, method-driven scientific principle aiming at the solution or transition of societal problems and concurrently of related scientific problems by differentiating and integrating knowledge from various scientific and societal bodies of knowledge”. According to Pohl (2010), transdisciplinary research is usually characterised by four functional features: (a) it relates to socially relevant issues; (b) it transcends and integrates disciplinary paradigms; (c) it does participatory research; and (d) it searches for a unity of knowledge. Transdisciplinary research is recognised as an appropriate form of research for addressing real-life problems with a high degree of complexity, factual uncertainties, value loads and societal stakes (Wiesmann et al., 2008).

This thesis work was conducted following the three phases of a typical transdisciplinary research process, namely: 1) collaborative problem framing; 2) co-creation of solution-oriented and transferable knowledge; and 3) integration and application of the knowledge produced (Lang et al., 2012). *Participatory modelling* is a family of approaches to link modelling with participation (Dreyer and Renn, 2011). In this thesis, it was used to integrate analytical and participatory parts, and to address Objective 3. Voinov and Gaddis (2008) define participatory modelling as the process of incorporating stakeholders into an otherwise purely analytical modelling process. An overview of research methods applied in Papers I-IV in this thesis is provided in Table 1.

Table 1. Research methods used to address the thesis objectives in relation to papers.

Objectives	Methods	Paper
<i>Objective 1</i> Develop and demonstrate an urban building energy modelling framework for decision-support of building energy retrofiting	Urban building energy modelling Data science Case study	Paper II Paper IV
<i>Objective 2</i> Investigate the interconnection between quality and applications of urban building energy data	Systematic mapping Data quality assessment Urban building energy modelling Case study	Paper III Paper IV
<i>Objective 3</i> Explore how urban analytics can be integrated into decision-making for energy transitions in cities	Participatory modelling Data visualisation Rapid prototyping Case study	Paper I Paper II Paper IV

3.2 Case studies

The *case study* method allows for detailed, in-depth investigation of a phenomenon within its context (Yin, 2009). It is particularly recommended for studies where the research object and its context do not have clear boundaries between each other. While the case study approach is regularly criticised for the impossibility of statistical generalisation (Yin, 2013), analytical generalisation is usually possible and gives good opportunities for knowledge development for the whole field of study (Steinberg, 2015).

The case studies described in this thesis were based on two cities, Niš ([nîːʃ], Serbia) and Stockholm (Sweden). Both cases represent strategic planning processes for urban energy domain. The cases were based on active collaboration between researchers and societal stakeholders, and intensive interaction between modelling and participation stages. Choice of these cases was justified by in-depth local knowledge among the researchers, accumulated from direct involvement in these projects in the role of modeller and facilitator. The case study method was utilised throughout to address Objectives 1-3. Figure 2 shows the structure of both cases in relation to the objectives and the papers included in this thesis.

Figure 2. Connection of objectives (teal) and papers I-IV (white) in this thesis to two cases (grey) and their embedded units of analysis (orange).

Niš, Serbia

The Niš case was used as an example of a transition management process for urban energy with a strong focus on participation and the role of stakeholders. It provided opportunities to investigate mechanisms of interaction between analytical and participatory processes addressed in Objective 3.

The city of Niš is one of the most active municipalities in the Western Balkans in terms of sustainable development. In 2014, the city did not have any earlier experience with participatory planning, but had formulated a Sustainable Energy Action Plan (SEAP) and had the ambition to advance further in its municipal strategic planning. The city council was particularly interested in development of a dedicated strategy for heating its building stock, which makes it comparable with the Stockholm building retrofitting case. The Niš case was an excellent opportunity to refine a prototype strategic planning framework that emerged from an earlier strategic planning project in Bila Tserkva (Ukraine) (Kordas et al., 2013). Active collaboration with local researchers with expertise in energy system modelling was an important factor in the Niš case, allowing examination of integration of the urban

analytics process with the participatory process for strategic planning within Objective 3.

At the time of the study, the city of Niš did not have any well-established energy data collection routines. Hence, one-time data collection was performed by local Serbian researchers with assistance from a municipal energy strategist. This task was partly simplified as some of the needed data had already been collected earlier, during preparation of the SEAP. However, due to the highly heterogeneous nature of the input data, there was still a need for significant efforts in data cleaning and refinement.

The project in Niš was conducted during the period January 2014–May 2015. It involved participation of a wide set of stakeholders, namely:

- The City Department for Energy Efficiency
- Three city authorities
- The City Department for Planning and Construction
- The Division for Sustainable Development, City Department of Commerce, Sustainable Development and Environmental Protection
- The Energy Division of the City Department of Energy
- A private company — producer of energy equipment
- A private company — natural gas supplier
- A public district heating (DH) company
- A non-government organisation (NGO) of DH customers
- Representatives of users of individual heating solutions
- Researchers from two Serbian universities, University of Belgrade and University Kragujevac
- Researchers from KTH, Sweden.

Stockholm, Sweden

The Stockholm case was used in this thesis as a data-rich arena to develop, test and further refine urban analytics for strategic energy planning in cities. It served as a test case for the novel urban building energy modelling framework developed within Objective 1. It also served as a representative case for the Swedish energy performance certificates (EPC) data to address Objective 2.

The Stockholm case was initially chosen due to the high level of interest and support from key local actors (municipal environmental department — Stockholms stads Miljöförvaltningen; and local district heating (DH) company — AB Stockholm Exergi) for open exploration of opportunities for strategic urban energy and climate planning introduced by high-quality meter

data. The Stockholm case provided the important advantage of securing access to meter data on heat consumption in the city's district heating network, which were made available for research within this PhD study.

The City of Stockholm has an ambitious goal to become climate-positive by 2040 (Stockholms stad, 2019a). The vast majority of Stockholm City climate initiatives are 'self-governing', i.e. oriented towards improvement of their own (municipal) buildings and infrastructure (Bulkeley and Kern, 2016). For instance, another key target set in its environmental programme is to become a fossil-free organisation by 2030. Heating and cooling of the building stock produces approximately 40% of total GHG emissions in Stockholm and thus this is a fundamental target for the City of Stockholm to decrease its energy use.

Setting advanced building standards in newly developed areas is a part of the strategy for Stockholm. However, most of the city's building stock already exists. Total heated area for building stock in Stockholm is around 65 Mm², of which around 10 Mm² are managed by public or municipal companies directly or closely affiliated to Stockholm City Council (Stockholms stad, 2019b). In order to achieve its environmental goals, the city intends to introduce energy efficiency measures (varying for different categories of buildings) that will achieve an average decrease of 10% in energy use for heating and cooling in next four years.

The Greater Stockholm area is covered by an extensive district heating system supplying half of the overall heating demand in the region, namely around 12 TWh with a dimensioning load of 4.8 GW annually. AB Stockholm Exergi (co-owned by Fortum Group) is its largest actor, generating around 8 TWh of heat annually (Levihn, 2017). The system is one of the most advanced multi-energy systems in the world, corresponding to "fourth-generation district heating" (Lund et al., 2014).

The project in Stockholm was conducted during the period September 2015–December 2018 and is being continued with two offspring projects ongoing at the moment. The initial project for this PhD study involved participation of stakeholders, namely:

- The City Environmental Department
- A semi-private (50/50) company — DH utility
- A private company — property services
- An organisation of housing associations in city districts
- The Swedish Association of Property Owners
- Researchers from KTH, Sweden.

3.3 Systematic mapping

Systematic mapping (SM) is a type of literature review that is used to structure and provide an overview of a research area (Grant and Booth, 2009). Mapping is performed through classification and obtaining descriptive statistics for research contributions (Petersen et al., 2015). It does not aim to answer a specific question, which is the role of a *systematic review*. Instead, systematic mapping aims to collate, describe and catalogue available evidence (e.g. primary, secondary, quantitative or qualitative) (Clapton et al., 2009). The resulting sample of studies can be used to develop a better understanding of the domain, identify evidence for policy-relevant questions, fill knowledge gaps (to direct further research) and produce knowledge clusters (subsets of studies that are relevant for secondary research, e.g. systematic review or meta-analysis) (James et al., 2016).

The advantage of systematic mapping is that its procedure is accurate, objective and transparent, thus avoiding typical pitfalls of traditional literature reviews. However, due to the breadth of systematic mapping it has to be time-constrained and thus often lacks more in-depth analysis. Systematic mapping can also mask the diversity of studies considered, due to inevitable simplification in the classification stage.

Systematic mapping was applied in Paper III to investigate energy performance certificate (EPC) data applications by time, geographical spread, data features & auxiliary data used, problem domains addressed and complexity of data analysis (Objective 2).

3.4 Urban energy modelling

Urban energy modelling was performed in both the Niš and Stockholm cases, as presented in Papers I and II, respectively. In both cases, the models developed can be viewed as bottom-up accounting models. However, there were significant differences between the models. Modelling in Papers III-IV was conducted using the urban building energy modelling (UBEM) framework developed in Paper II as a base, and can therefore be also attributed to the Stockholm case model.

First, there was a difference in the *purpose* of these models. The Niš model aimed at quantified exploration of normative stakeholder scenarios, providing accounting for urban energy balance in the temporal range 2010-2030. Hence, it modelled urban energy bound to the factual baseline values of 2010 and normative values envisioned for 2030. In contrast, the Stockholm model aimed for quantification of retrofitting scenarios, providing

calculations of projected energy demand in the modified urban building stock for a typical meteorological year. While this analytical process also served the purpose of stakeholder exploration, it did not have any normativity imposed on the model. Furthermore, despite containing a certain degree of temporality in its investment analysis component, it did not account for the possible distribution of the individual retrofitting projects in time and performed as if all of these would have occurred in a single moment.

Second, there was a difference in the *system boundaries* devised for the models. While both of the cases had city building stock as the focus, the Niš model considered the whole city building stock and also included the heat supply as a component under change as part of the modelled urban energy balance. The Stockholm model instead focused explicitly on the buildings, limiting those to certain categories (archetypes), to compute the projected changes in energy demand as a result of retrofitting. The cumulative changes in heat demand were then used to obtain the subsequent changes in the heat supply of district heating (DH). Hence, in this case external models for DH production were used, with the assumption that the production structure for DH supply would remain constant¹⁵.

Third, there was a difference in the *modelling techniques* and the *input data* used. Selection of the Niš case was driven in the first instance by the willingness of local stakeholders to test the novel strategic planning method of modular participatory backcasting (mPB) (Pereverza et al., 2019). While some initial data available from the city's Sustainable Energy Action Plan was clearly a bonus, it still could not compensate for the overall data scarcity characteristic of the generally non-modernised energy infrastructures and institutions of the Western Balkans. Hence the statistical approach typical for such cases was applied for modelling in the Niš case (Paper I). The model was built in a well-recognised tool, LEAP¹⁶ (Heaps, 2018). The input data stemmed from the data collected from stakeholders, with gaps filled using reference data found in the literature.

In contrast, the Stockholm case was initially designed to benefit from the availability of high-quality and high-resolution data. Two datasets were particularly exploited in this case — *energy performance certificates (EPC)* and *measured* heat consumption:

¹⁵The future vision for district heat production after phase-out of coal-based combined heat and power was applied. Since actual phase-out has already occurred, on April 19, 2020 (SVT Nyheter, 2020), the modelling results corresponded to the current district heat production structure.

¹⁶At the time of the case implementation and publication of Paper I, LEAP stood for the 'Long-range Energy Alternatives Planning System'. In 2020, it was renamed the 'Low Emissions Analysis Platform'.

1. The EPC dataset was obtained from the Swedish Board of Housing, Building and Planning (Boverket). The EPC dataset covered 30 472 buildings in Stockholm and contained information on building type, construction year, floor area, envelope form, energy use per source, energy system installations etc. EPCs are mandatory for all buildings that are: a) subject to sale or rent; b) frequently visited by the public; or c) newly constructed¹⁷.
2. The measured data were obtained from the local energy utility AB Stockholm Exergi. This dataset covered the year 2012 with hourly precision, representing all customers of the local district heating network. The data also contained information on type of building usage, building age category and total heated area (A_{temp}).

A hybrid approach combining statistical and physical modelling was implemented for the urban building energy model developed in Paper II. Statistical modelling employed energy signatures (ES), a reduced order model, to estimate building energy demand from ambient temperature. As this stage exploited measured heat consumption data, it was limited to the buildings using district heating. As was later shown in Paper IV, the dimensionless statistical characterisation of archetype buildings obtained made it possible to produce fast estimates of heat demand for the remaining part of the building stock, provided that those are buildings of the same type. However, statistical modelling alone would not allow energy demand for retrofitting measures to be projected, unless a statistically sufficient sample of measurements with retrofitting labels was available. Hence, physical modelling of archetype buildings was used to project the impact of various retrofitting packages. The EPC data were used to characterise archetype buildings that were further simulated in DesignBuilder (DesignBuilder Software Ltd, 2019), a popular building energy performance simulation tool based on the EnergyPlus tool (U.S. Department of Energy, 2018). Statistical models were then used to calibrate baseline models and project retrofitting-induced changes in heat energy demand.

The concept of *archetypes* as classes of typical buildings representing virtual average buildings was applied in both models. Although not articulated as such, it was used in the Niš case where building stock was distinguished into existing/new and single family/multifamily/public buildings, with different baseline/target parameters used to characterise these categories. It was a central concept for the Stockholm case. The diversity of archetype

¹⁷EPC data are subject to regular updates. See Paper III for details regarding the dataset versions used in the Stockholm case.

functions and demonstration of two different archotyping schemes constructed for the same Stockholm context are discussed in Paper IV.

Finally, while urban energy modelling was the underlying basis for analytics in both cases, it was clearly not performed solely for the purpose of modelling. In the Niš case, it was used to evaluate the scenarios developed, using criteria that included energy efficiency, environmental performance and energy security. It was also used to inform stakeholders of the participatory process in that city, as described in Paper I. In the Stockholm case, the urban building energy model obtained provided the possibility to investigate expected environmental impacts and required investments for analysed retrofitting projects. These formed part of the stakeholder input and results presented to stakeholders, as described in Paper II. While use of urban energy modelling permeated the whole thesis work, this method was particularly used to address Objectives 1 and 2.

3.5 Data science

The methodology of *agile* software development (Agile) has been found to fit well with the idea of transdisciplinary research (Highsmith and Cockburn, 2001). Hence, development of any computer-based activities in this thesis aimed to follow the values and principles of Agile (Beck et al., 2001). The data analysis workflow implemented in the Stockholm case was based on the suggestion by Wickham and Grolemund (2017) (Figure 3). RStudio IDE (RStudio Team, 2015), based on the R programming language (R Core Team, 2013), served as the main data analysis tool.

Figure 3. Data analysis workflow (reproduced from Paper II).

All datasets used were *imported* to the local working machine and stored either in the form of flat files or in database management systems (DBMS). The subsequent data curation and pre-processing process (TIDY in Figure 3) was performed following the conversion of *tidy data* implemented with functionality from the R package *tidyverse* (Wickham, 2014). The *data pre-*

processing and *transformation* steps were regularly revisited and improved throughout all five years of this thesis work, with the following two methodological issues kept constantly in focus:

- 1) *Data curation* was recognised as an important stage for the validity and practical relevance of the modelling results. After the first proof-of-concept UBEM was established, a critical mass of data quality findings had already been accumulated. Hence, in the next round of workflow improvement, a data quality assessment framework was developed using the recommendations from Eurostat (Simon, 2013). This systematisation of the quality assessment and application of evidence from the scientific literature (described in Paper III) raised awareness of the second issue.
- 2) *Data enrichment* was found to be a key enabler for the application potential of data. In the Stockholm case, data-linking (Christen, 2019) between EPC and measured data was conducted to improve the quality of the results for the existing model and to develop new applications for the same data, as described in Paper IV. Positive effects were also obtained from two other less grand data enrichments. Data about Swedish postal codes were helpful in curation of identification fields in EPC data (municipality, locality, postal code) and in increasing its further usability. Geocoding EPC data (obtaining geographical coordinates for each address in use) with the help of Google Maps API enabled spatial analysis of EPC data. This improved the quality of the data used and was particularly helpful for increasing the communication potential of the data analysed, with the help of digital maps.

Data modelling conducted within the urban building energy framework is described in detail in the Results section in this thesis (Section 4.1) and in Papers II and IV. Data visualisation was conducted with the help of R, Tableau (Tableau Software, 2019) and MS Excel (Microsoft 2019). The R package *ggplot2* (Wickham, 2016) was used for all quick visualisations for the purpose of exploration or diagnostics. It was also used for the majority of diagrams in research publications, due to the high replicability of diagram production run from scripts. MS Excel was used mainly to prepare R-produced diagrams for presentations, allowing for manual addition of supportive graphical elements. It was also used to produce graphical illustrations for scenario modelling in the Niš case. Finally, Tableau was used as a visualisation tool for exploration of curated and produced data, allowing for interactive visualisations. The significant advantage of Tableau is its high-level constructor of visualisations, allowing for fast development of interactive analytical products ready for sharing and external use. It was also important that data visualisations developed for datasets with a particular structure could be automatically regenerated after data updates. Hence, Tableau was

used to set up flexible aggregation and visualisation of data for large sets of buildings in interactive prototyping sessions with research collaborators and representatives of stakeholders. Later, this capability of Tableau was used to conduct rapid prototyping¹⁸ of Oden — an interactive urban energy dashboard for Stockholm discussed in Section 4.3.

Data science methods were used throughout the research process. Data science workflow and its embedded practices were utilised in urban building energy model development to fulfil Objective 1. Understanding current EPC data usage practices and potential for data enrichment and data curation and introducing a more systematic way to address data quality issues was the driving force to investigate Objective 2. Finally, data collaboration, and data visualisation as one of its main enablers, were vital for exploration of Objective 3.

¹⁸The term ‘rapid prototyping’ originates from the domain of additive manufacturing; in the case of software it is normally associated with the Rapid Application Development (RAD) methodology. Similarly to Agile, RAD uses iterative improvements, but it differs in prioritisation of speed and flexibility at the cost of structure.

4 Results and discussion

“Science may be described as the art of systematic oversimplification.”

Karl Popper

4.1 Urban building energy modelling framework for strategic planning of building energy retrofitting (Papers II and IV)

Research to fulfil Objective 1 resulted in the development of a new city-wide urban building energy modelling (UBEM) framework for strategic planning of building energy retrofitting. This UBEM is based on abstraction of building stock using ‘*building archetypes*’ — sample or virtual buildings that characterise homogenous subsets of buildings. The model was built by a hybrid scheme, combining *statistical* energy signature (ES) models to estimate building energy performance and *physical* building energy simulations to estimate the effects of energy conservation measures (ECMs) analysed. This was possible due to utilisation of high-resolution datasets, namely data from *energy performance certificates (EPC)* and *measured* heat energy use. Using the method developed, it is possible to assess the change in total energy demand from large-scale retrofitting and explore its system impact on the supply side, along with climate and economic consequences on the individual building level.

The main stages in the novel UBEM framework presented in Paper II are shown in Table 2. The modelling approach was demonstrated for the case of retrofitting ‘Million Programme’¹⁹ buildings in Stockholm. Modelling was conducted to estimate the potential of large-scale retrofitting of 5400 multi-residential buildings constructed in 1946–1975 with two energy conservation measures that are most common for this type of building — heat recovery ventilation (HRV) and energy-efficient windows (EEW).

¹⁹Swedish national programme for affordable housing 1961–1975, which resulted in large amounts of typical multi-residential buildings with low energy performance throughout the whole country (Lind et al., 2016).

Table 2. The nine stages of the modelling framework developed (reproduced from Paper II).

Stage	Summary
<p>1. Data import</p>	<p>Data are imported from external data sources (data dumps from partner data warehouses, open data sources etc.) to a single database engine, which serves as a unified data source for the computation environment. General compliance of formats, scales and measurement units is established at this stage.</p>
<p>2. Data pre-processing</p>	<p>The collected data are curated, treating missing data and outliers. Auxiliary parameters (e.g. specific energy consumption, aggregates per various grouping factors) are calculated. The dataset is restructured in accordance with the 'tidy data' paradigm (Wickham, 2014).</p>
<p>3. Segmentation</p>	<p>The entire building stock is divided into different building clusters corresponding to several archetypes. Stages 4-5 are performed for each building cluster separately.</p>
<p>4. Characterisation</p>	<p>Parametric models of building energy performance based on the energy signatures method are identified for each building through regression from the measured data.</p>
<p>5. Building energy simulations</p>	<p>An archetype building energy model is created based on the statistics for the whole building cluster. The model is then calibrated through matching energy signatures.</p>
<p>6. Scenarios</p>	<p>Retrofitting packages, target key performance indicators (KPIs) and available investment mechanisms are identified and translated into the scenarios to be analysed in the model. Scenarios can differ for different building clusters.</p>
<p>7. Aggregation</p>	<p>Building energy performance for each building in the entire building stock is projected from the results of the archetype building simulations for baseline and with possible retrofitting packages. Energy savings, emissions reductions and economic performance indicators for the proposed retrofitting measures are calculated and then aggregated for the city level.</p>
<p>8. Testing and optimisation</p>	<p>Sensitivity analysis is performed for the solutions identified. The optimisation problem is solved to meet the targets identified in Stage 6 with regard to the various optimisation objectives (e.g. capital investment required).</p>
<p>9. Communication</p>	<p>The potential of proposed retrofitting packages identified for the whole city building stock is communicated to the research community and project stakeholders through various visualisation tools. Feedback is also used to improve the workflow.</p>

The effects from three retrofitting packages (HRV only, EEW only and combined HRV+EEW) were then analysed on individual building and whole city level. The modelling framework made it possible to estimate overall energy savings for each package analysed. Projected changes in heat power demand on the individual building level were then used to evaluate the effect of large-scale retrofitting on the production structure for district heat supply (Figure 4).

Figure 4. Annual load duration for Stockholm district heating (DH) production before and after implementation of the combined retrofitting package (HRV+EEW). The change in demand before and after retrofitting is the area between the two dotted lines (reproduced from Paper II).

Changes in emissions associated with energy use in the target buildings after retrofitting were calculated in two ways: using the district heat production model Minerva and using statistical factors for electricity and heating production mixes involved. Feeding in base assumptions for installation and operation costs associated with the ECMs analysed allowed the expected cashflows to be calculated for each individual building and the social investment costs for the measures to be evaluated via commonly used indicators (CAPEX, NPV, IRR and PVQ).

While this first version of the UBEM clearly had a number of issues to be resolved, it was an important milestone, serving as proof-of-concept for large-scale building energy modelling. It made it possible to highlight and discuss a number of issues emerging beyond the modelling, e.g. data quality and

availability, stakeholder perspectives etc. Papers III and IV elaborate further on the particular aspects of the UBEM framework created, in terms of data quality and integration (Section 4.2), and archotyping, respectively.

Paper IV advanced the archotyping approach for analysis of urban building energy, focusing on two subcases for Stockholm — building retrofitting and electricity-based heating. The UBEM framework from Paper II was refined to improve its quality and applicability. The newly established linkage between meter and EPC data (Section 4.2) improved the overall quality of the modelling, enabling removal of buildings with a high level of data uncertainty and more accurate segmentation of the building stock. The quality of the modelling was assessed by commonly used error metrics (MASE, NRMSE, R^2).

The retrofitting analysis was expanded for three archetypes, adding to archetype A1 (multi-residential, 1946–1975) two more archetypes: A2 (offices) and A3 (multi-residential, 1996–...). The set of energy conservation measures analysed was also extended with two more measures: adaptation of indoor temperature to 21 °C (IT21) and adaptation of ventilation flow rate (VFR). A summary of estimated potential energy savings from retrofitting the analysed buildings is provided in Figure 5.

Figure 5. Specific (a) and absolute (b) heat savings of the different retrofitting packages per selected archetype (reproduced from Paper IV).

The estimates of potential for large-scale building energy retrofitting presented in Papers II and IV have since been used as input to a comparative study of climate mitigation measures for the City of Stockholm (Bondemark et al., 2018) and in the Environmental Programme for the City of Stockholm 2020-2023 (Stockholms stad, 2019a).

The main advantage of the proposed UBEM is the intensive utilisation of high-resolution metered data on actual energy use. This avoids use of more complex approaches to building energy simulations, including automatic generation of individual building geometry-based ‘shoebox’ models (Dogan and Reinhart, 2017) and their further calibration (Nagpal et al., 2018). Hence, the UBEM employs a much smaller number of simulations, as they are created for virtual archetype buildings only, making it computationally lighter than its geometry-based analogues. At the same time, the strong dependence of this UBEM on high-resolution data is also its main drawback. However, the further roll-out of smart meter technologies suggests that this modelling approach will become relevant in future for more and more cities around the globe.

Development of the UBEM was largely driven by the need for involvement of stakeholders (see Section 4.3). This led to inclusion of a number of relevant perspectives for analysis, i.e. system effects of large-scale retrofitting on district heat supply, subsequent changes in emissions or associated social investment costs. However, it did not include other aspects, i.e. variance imposed by residents’ behaviour, a lifecycle perspective on retrofitting, urban climate etc. A data-driven automatic segmentation of the building stock would have allowed for more precise representation of the buildings modelled. However, as this would require creation of a different interface between UBEM and building energy performance simulation (BEPS) in order to automate building simulations, it was beyond the scope of this thesis work.

The UBEM framework created can be used to analyse the effects of various retrofitting options when applied to a large part of the urban building stock. Exploration of possible scenarios from multiple perspectives (energy, environment, economic), as was done for the case of Stockholm, makes it possible to assess the benefits and drawbacks of each retrofitting measure in a holistic way and make strategic decisions that avoid suboptimal pathways imposed by the siloed structure of conventional decision-making.

4.2 Interconnection between quality and applications of urban building energy data (Papers III and IV)

Investigations to fulfil Objective 2 started with the initial findings collected from both the modelling (Objective 1) and stakeholder interaction (Objective 3) processes, as described in Papers I and II. These learnings were further systematised and expanded upon in Papers III and IV. Paper III addressed issues with data quality and how those relate to the applicability of

the data for EPC data. Paper IV refined the archotyping approach for urban building energy modelling and demonstrated how it can be used for a wider span of applications enabled by availability of rich urban energy data.

Paper III focused on EPC data to investigate the ways in which they are used and to propose a new systematic approach to data quality assurance. First, existing applications of EPC data were analysed through a systematic mapping of the literature. The mapping of 79 selected papers showed that some of the EPC data applications had a clear connection to the initial goal of the EPC policy instrument (e.g. mapping the current building stock performance and evaluating the design of newly constructed buildings), while other applications went beyond these objectives. For instance, Gelezenis et al. (2014) used EPC data to analyse the diffusion of energy-saving technologies in the Greek residential building sector. Another study (Parkinson et al., 2013) explored how energy labels can be used to estimate occupant satisfaction with workplaces. One of the conclusions from the mapping was that, as a rule, merging EPC data with auxiliary data (data enrichment) makes it possible to address more complex issues and obtain results that have more potential with regard to further policy making.

Next, the quality of Swedish EPC data was assessed via a validation framework based on six validation levels (Table 3), for the case of application of EPC data in a large-scale retrofitting study (Objective 1, Section 4.1).

Table 3. Data validation levels (reproduced from Paper III).

No.	Validation level	Description
0	Data structure	Check of format and structure (no data)
1	Within the file/table	Checks between cells, records, aggregate statistics
2	Within the dataset/source	Checks between file revisions, time series
3	Within the domain	Mirror checks between different sources
4	Within the data collector	Consistency checks between domains
5	Between data collectors	Consistency checks between data collectors

Level 5, which refers to consistency checks on data obtained from other data collectors, became possible after the EPC and measured data on heat energy use were linked for Stockholm building stock connected to district heating. While this was a good opportunity for this particular research project to develop, it is an example of a data integration (and subsequent data quality assessment) barrier traditionally experienced by practitioners in the field.

On the one hand, the proposed quality assurance is application-driven, hence less holistic and cannot provide full coverage of the data quality issues. At the same time, it sets stronger requirements on the input data and consequently can provide more insights regarding further quality

requirements on the dataset used. Based on the study of EPC data applications, Swedish EPC data can be commended for relatively good quality and availability. However, the extension of EPC data applications observed in recent years exposes more problems than in countries where EPC data have lower levels of value and trust.

To conclude, the study of EPC data quality and applications showed that data quality is a context-affected issue that cannot be defined in absolute terms, but should rather be considered in relation to its current and potential future applications. Furthermore, the quantity and complexity of these applications closely relate to the quality of the datasets employed, and can be used as indicators that characterise the current state of development of the whole data ecosystem.

Paper IV advanced the UBEM framework presented in Paper II, building on the data quality findings and dataset linkage established in Paper III. The paper demonstrated how various urban energy challenges can be addressed using the same datasets via different building archotyping schemes. In particular, beside further advancement of the building retrofitting analysis (Section 4.1), it allowed for characterisation of electric heating (EH) of Stockholm building stock. Figure 6 provides a condensed overview of typical patterns of heat consumption represented by shares of particular solutions used for heating in Stockholm building stock (for in-depth description of this figure see Paper IV).

While in methodological terms it would be preferable to estimate the maximum electric power demand for electric heating based on the numbers of installations combined with high-resolution measurements of actual dedicated electricity use, this was not feasible in practice due to non-availability of such data. This does not mean that such data do not exist at all or are of insufficient accuracy. However, these data were recognised as being very problematic to obtain and work with, due to high inconsistency from market fragmentation, strong privacy protections and lack of interest by data collectors in collaborating. Hence, instead of searching for scattered data of questionable efficiency, estimates were obtained using the UBEM workflow established earlier for the retrofitting case.

The case of electric heating is thus an example of when scarcity of urban data in one subdomain can be compensated for by data and models available in another subdomain. It also serves as an illustration of how new, unplanned applications for datasets can emerge. Data enrichment was applied in this thesis to datasets with sufficient resolution and consistency, to allow their joint integration and to enable emergence of new applications that were not possible for previous separate input datasets.

Figure 6. Shares of particular solutions for heating in the total heat supply of each building, segmented by building types (scheme B3: S = single-family, M = multi-residential, O = other) and two target groups (scheme G2: G_I = EH mainly and G_{II} = EH partly). Heating solutions are structured by the scheme H6 (DH = district heating, FBH = fossil- and biofuel-based, EH = electric, split into ER = electric radiators, GSHP = ground-source heat pumps, EAHP = exhaust air-source heat pumps, and ASHP = air-source heat pumps) (reproduced from Paper IV)

Despite certain problems with EPC data, they have been proven to be a useful and relevant data source for the wide range of building energy studies, e.g. on building energy use analysis and prediction, design of new buildings and energy- and cost-efficient retrofitting of existing buildings, occupant behaviour and building operation. The systematic mapping conducted in Paper III demonstrated that the quality of EPC data is largely application-driven. Finally, as shown in Paper IV, data integration readiness of urban energy data plays a decisive role for the range of possible applications.

4.3 Integration of urban analytics into decision-making for energy transitions in cities (Papers I, II and IV)

The investigations to fulfil Objective III explored how urban analytics (data, methods and tools) can be integrated into strategic planning for urban energy transitions. Paper I demonstrated integration of modelling with participatory strategic planning for the case of Niš, Serbia. Papers II and IV provided examples of how analytic and participatory processes were integrated in the case of Stockholm, Sweden.

Paper I presented a scheme of integration of urban energy modelling in a participatory backcasting (PB) project conducted in Niš in 2014–2015. Five scenarios for transformation of the heating system by 2030 were developed by local stakeholders during three co-creation workshops (Figure 7).

Figure 7. Co-creation work by the stakeholders during participatory activities in Niš.

These scenarios, together with the business-as-usual (BAU) scenario, were then analysed in terms of decarbonisation, energy security and energy efficiency using LEAP (Heaps, 2018). The scheme followed an integration of the energy modelling conducted in LEAP with the participatory strategic planning project is shown in Figure 8. Such integration made it possible to utilise advantages of both ‘worlds’ in the scenario analysis. Quantitative modelling was beneficial to represent the system complexity and to provide more formal assessment of alternatives. Participatory methods enriched the analysis with a wider range of perspectives on a system and enabled further acceptance and ownership of the modelling outputs by stakeholders.

Visualisation of scenarios and underlying modelling played an important role for active involvement of a broad range of stakeholders in joint knowledge and critical analysis of quantitative results. Due to the limited interactivity of the tools used (LEAP, MS Excel), multiple visualisations were prepared beforehand to support workshop discussions. Figure 9 provides an example of a visualisation used to explain the interplay of retrofitting solutions (heat pump and insulation of façade) applied to the typical multi-family residential building in Serbia.

Figure 8. Integration of urban energy modelling based on LEAP into the strategic planning process based on modular participatory backcasting (mPB) in the case of Niš (reproduced from Paper I).

Transdisciplinarity proved to be an important research design principle in ensuring the impact of participatory modelling on urban sustainability transitions, and hence it was utilised further in the Stockholm case. Papers II and IV present the urban building energy modelling conducted in 2015-2018 to support strategic planning of building retrofitting in Stockholm. The project was based on collaboration organised on two levels: (1) an interdisciplinary group of researchers meeting regularly to coordinate modelling efforts, and (2) a reference group of societal partners involved more rarely to set up initial requirements to the modelling outputs and give feedback to intermediary results later in the process (Figure 10).

Example. Installation of the ground source heat pump and insulation in a typical residential building

Стамбена слободностојећа зграда

A. Heat pump
only

B. Heat pump
+ insulation

SLIDE 1

SLIDE 2

A. Heating consumption without insulation

B. Heating consumption with insulation

Figure 9. Sample visualisation from a stakeholder workshop in Niš. Two presentation slides provide problem formulation (slide 1) and modelling results (slide 2) for comparison of the effect on heat consumption in a typical residential building of two retrofitting packages (A – heat pump, B – heat pump and insulation). Data: Volodymyr Voloshchuk, my visualisation.

Figure 10. Co-creation work by the stakeholders during participatory activities in Stockholm.

Paper II presented the results of urban building energy modelling for Stockholm that were co-created with societal stakeholders. Stakeholders were involved in defining the scope of the study, securing the required data, choice of modelling principles and target indicators, validation and discussion of modelling results. Similarly to the Niš case, visualisation was found to be an important technique to communicate analytical results and support further constructive and trustful dialogue among research collaborators and societal partners. For instance, Figure 11 reflects the compromise achieved in a debate on selecting the appropriate emission allocation scheme for accounting for environmental consequences of various retrofitting packages (for in-depth description of this figure see Paper II).

Figure 11. Emissions changes for the three retrofitting packages (S1-S3). a) Projections for 2025 obtained using Minerva, a physical model of district heating (DH) production after phase-out of coal-based combined heat and power in 2022 and introduction of new production facilities, and b) comparison of estimated changes in CO₂ emissions in 2025 from Minerva (local and global) and the current system (2016), obtained using emissions factors for the various allocation schemes (reproduced from Paper II).

The identified need for visualisations of a certain type triggered the further expansion of input data. For instance, after numerous manual check-ups of modelled buildings by an address search in Google Maps, in order to validate the input and output data for the UBE, the EPC data were enriched with geographical coordinates through geocoding using Google Maps API. Furthermore, the pressure of scale (e.g. around 3500 buildings for simultaneous analysis in Paper II) resulted in a need to shorten the time and human efforts needed for each analysis session, which was achieved through developing more automated and interactive visual exploration tools used further for rapid prototyping. Figure 12 presents a screenshot of an early version of Oden — the urban building energy dashboard that was initially created for fast validation of modelling results using dashboards and visualisation in Tableau software. Oden uses the EPC dataset as its main data source, combined with Google Street View API to retrieve single building images. The dashboard makes it possible to filter into any specific set of buildings in Stockholm and aggregate building characteristics that are used as inputs or as validation values in the UBE. Oden was widely discussed, since it was first demonstrated to societal partners. In particular, this early prototype served an important role in fostering further discussions about a wider range of interactive data-intensive decision-support tools that can be developed for urban energy strategic planning.

Figure 12. Early prototype of Oden — urban building energy dashboard (March 2018).

Paper IV contributed to Objective 3 through the case of estimation of power grid capacity required for electric heating. This case was not present in the

initial research agenda, but has been a high priority for core societal partners (Stockholm Stad, AB Stockholm Exergi) since 2018, when capacity deficit of local power distribution grids became an urgent issue that could not be ignored any longer. Thus, a need emerged to obtain quantitative estimates for all main constituents of the local electric power demand, especially those that grow in size and have certain flexibility potential, such as electric heating systems.

The capacity case is noteworthy due to the dominant role played by societal partners in the modelling, corresponding to the highest levels of stakeholder involvement²⁰. Most of the data analysis stages, i.e. problem definition and formulation of research questions, clarification and adjustment of modelling approaches, validation and review of obtained results, were performed jointly with problem owners. This study to a great extent exploited data and modelling routines developed for the retrofitting analysis (Section 4.1), and hence it was not very complex from a computational perspective. However, making the calculated results relevant and usable to practitioners and decision-makers was a challenging task. The segmentation scheme for Stockholm building stock used to characterise the problem (Figure 6) evolved from a number of iterations. Visualising the structure of the urban heat demand in various ways (Figure 13) played a crucial role for better understanding the phenomenon and finding the most optimal way to structure it in further analysis (for in-depth description of this figure see Paper IV).

Paper IV demonstrated that well-established urban analytics infrastructure — curated and integrated datasets coupled with earlier developed models and tools for fast data exploration and aggregation — could be used to support strategic planning in an efficient way. The results of the data analysis conducted in Papers II and IV have since been used by societal partners in strategic planning processes outside this research project (e.g. Bondemark et al., 2018). However, such strategic planning support would scarcely be possible without earlier experience of collaboration between researchers and societal partners, leading to: a) mutual trust and understanding; b) secured data collaboration allowing for access to data to address societal issues unless it did not violate access conditions; and c) knowledge accumulated by stakeholders about data, methods and tools available for analysis. Hence, while urban analytics is traditionally associated with a pure technological stack of practices related to urban data, methods and tools, this thesis highlighted the role of stakeholders in these practices and the need for explicit inclusion of stakeholders in analysis of urban analytics frameworks (Figure 14).

²⁰ ‘Collaboration’ and ‘empowerment’ levels from taxonomy by Brandt et al. (2013) are meant.

SECTION 4.3. INTEGRATION OF URBAN ANALYTICS INTO DECISION-MAKING FOR ENERGY TRANSITIONS IN CITIES (PAPERS I, II AND IV)

Figure 13. (a) Simplified and (b) detailed structure of the heat demand in Stockholm building stock by combinations of heat sources according to EPC data. Colours corresponds to scheme H3. Buildings using district heating (blue) are provided with the measured data. Buildings using electricity for heating (red) were the focus of this thesis. Buildings using fossil and biofuels are marked in brown²¹ (reproduced from Paper IV).

²¹The upper graph in section (b), visualising the intersection of atomic sets from H6, is called an 'upset plot' (Lex et al., 2014).

Figure 14. Conceptual scheme of the urban analytics addressed in this thesis.

Both Niš (Paper I) and Stockholm (Papers II, IV) cases can be characterised by active involvement and interest of stakeholders towards advancement of their strategic planning practices. This can be seen as an important factor for success in these transdisciplinary studies. Reducing the *gap between analytical and participatory processes* was found to be the key challenge to enabling integration of urban analytics in strategic planning in both cases. Visualisation was one of the actively used solutions to address the abovementioned gap. However, it alone would not be sufficient, as it can only assist in direction ‘analytics → participation’ (A→P), while input and feedback from stakeholders back into analytics (‘participation → analytics’, P→A) must be secured by other means.

In the case of Niš, this P→A linkage was provided using a wide range of group participation techniques facilitated by a large group of researchers to collect qualitative assumptions of stakeholders that were further translated into model inputs. This proved to be a working approach to capture stakeholder knowledge required for the analytics and to successfully support strategic planning. In Stockholm case the P→A linkage was supported with the use of more automated and interactive urban analytic tools. Automation allowed to reduce the average length of one iteration between researchers and stakeholders (full P→A→P cycle). Interactivity of tools has allowed rapid prototyping and orientation of final tools towards stakeholder needs. In both cases researchers played an important role, serving both as translators and mediators.

Active involvement of stakeholder representatives in the framing of the expected outcomes for urban analytics being created, and early feedback to researchers, allowed the final analytical products to be shaped in the way they were most relevant for addressed problems. Hence, this approach can help

to make underlying data and models 'closer' to stakeholders on a permanent basis and increases their potential to be integrated in regular strategic planning practices. In the long run, development of such city-as-interface tools can noticeably improve the quality of decision making through availability of instant analysis from multiple perspectives for all typical urban energy interventions. However, this would require further improvement of quality for utilised data sources, development of more automated and integrated models and, not least, readiness of key actors to extend data collaboration around these data.

5 Critical reflections

“Your assumptions are your windows on the world.
Scrub them off every once in a while, or the light won't come in.”

Isaac Asimov

Conducting my PhD studies in the emerging domain of urban energy data analytics using a transdisciplinary research design allowed me to develop a number of process-based observations and reflections. I feel it is important to share those here, in order to reflect the nature of my research process and its underlying choices and assumptions. This thesis work can be characterised as a trial and error process repeated in multiple iterations, starting with trivial single building models and tools that were further complexified. The sections below provide critical reflections grouped by the three main topics: data, modelling and transdisciplinarity.

5.1 Role of data

Collection of data and reshaping the data for further modelling does not appear so complicated now, after five years of work with the same datasets, but was an intricate and time-consuming process in the early stages of this research. First of all, it took me a certain time just to build up some basic *understanding* of the data I was working with. That was achieved through building lots of (often meaningless) graphs and tables, translating variable names and relevant documentation from Swedish, discovering the errors and inconsistencies which later resulted in Objective 2 and Paper III (Section 4.2) and, not least, discussing it with my colleagues. Even though I have never felt comfortable categorising the data analysed as ‘big data’, some big-data traits were clearly apparent to me and my colleagues. In particular, we had to move away from thinking and modelling using conventional ways and tools in the building energy domain. For me, that meant regular exercises in thinking in terms of *scale*. We started with calculations for single buildings, but these soon had to be accompanied by rapid statistical summaries for much larger numbers of buildings. As most conventional manual checks for the modelling outputs could not be conducted, a number of automatic error and consistency checks had to be developed. That alone later led to the development of the very first prototype of Oden as an information system for fast checks of model results with the help of statistical reports for the analysed building stock, paving the way for Objective 3 (Section 4.3).

Speed of *computation* was clearly another issue to solve in the early modelling stages. It took around 40 hours to make a full run of the first version of the UBEM (in the state it was published in Paper II), while my later crusade for speed through refactoring and optimisation of the code²², as well as acquiring a more powerful laptop, resulted in around 15 minutes of total calculation time for the same task. Finally, as the first modelling results appeared, the question of *data consistency* became quite crucial for validation of these results. At the time when Paper II was written, *EPC data* and *measured data* were used as independent inputs to the model. While *measured data* provided an important advantage of high resolution for the building performance, they lacked the level of detail required for proper segmentation and characterisation of building archetypes²³. At the same time, we were quite limited in using *EPC data* to inform these processes, due to the anonymisation of *measured data*. This issue was properly addressed only after the linkage between *EPC* and *measured data* was established (Paper III, Section 4.2). Hence, the case of retrofitting in Paper IV (Section 4.3) was about further development of the same UBEM, demonstrated for two more archetypes but with much better control on data consistency and the quality of the outputs produced.

Availability and quality of the data noticeably affected the directionality and the possibilities for validation of this research. Having a solid starting data collection system, with hourly measurements of heat energy use and EPCs for Stockholm before the study, was a critical advantage for its initiation and funding. This allowed a greater focus on development of a base modelling approach in the first years of the study, but evidently posed some risk of a streetlight effect²⁴, which I sought to mitigate through more question-driven data analysis (Leek and Peng, 2015) in the later stages of my studies. However, while having data is indeed a core requirement, it is not always easy to fulfil. For example, to create one more small table setting a linkage between the two main data sources, it took us another 1.5 years to get through the burden of legal negotiations. This would certainly not have been successful without the persistence of my co-supervisors and the goodwill of our corporate partner. Luckily, the time and efforts spent proved to be worthwhile — the high granularity of the integrated dataset obtained allowed us to conduct the EPC data quality assessment (Paper III); to improve the precision of

²²At the end, the main drivers of performance improvement of the R code were vectorisation, parallelisation and caching.

²³This is evident from the disproportionately wide period of 1946-1975 used for archetype A1, which corresponded to the smallest time granularity available from the measured data (without its linkage to EPC data).

²⁴A type of observational bias when the search for something happens where it is easiest to look (Battaglia and Atkinson, 2015; Hendrix, 2017).

building segmentation and advance the retrofitting analysis (Case 1, Paper IV); and to utilise the data on actual energy use for estimation of the power demand from electric heating (Case 2, Paper IV). All these studies made the drawback of incompleteness (incomplete coverage of the whole building population), shared by both DH and EPC data, quite obvious (especially for a large urban form such as Stockholm). A further logical solution to this was adding cadastre data²⁵ as another core data source, but that was implemented much later, beyond the period of this PhD work. All this experience led me to conclude that, even in Sweden where the availability and quality of the urban energy data is much better than in most other countries around the globe, the possibility of such research and its replicability remains quite low, mainly due to the limitations in data access. Without doubts, publishing my scripts and derivative data in open access would be beneficial for the community. Despite there remains a number of institutional barriers that restrained it at the moment of my PhD study, I still view this as an important type of contribution for better transparency and impact of this research to be enabled in the future.

5.2 Modelling choices

Striking a balance between *holistic* and *system* modes of thinking was another important dimension in development of the UBE framework. Having the city level as the main focus for analysis involved certain requirements to consider the objects of analysis as a whole. At the same time, aiming for models that include all important aspects of study objects is inherent in much research, as could be sensed during the review process for all papers included in this thesis. Given the amount of ambiguities embedded in urban energy systems, meeting both criteria to the full extent was recognised as a ‘mission impossible’ from the very beginning. Therefore the research design evolved from the opposite principle, by focusing each time on those aspects of the model that were seen as most critical, bringing most improvement at that moment, as proposed by Box (1976).

Stakeholder opinions played a vital role in defining the agenda and priority list for UBE framework development. For example, introducing multiple accounting perspectives (energy, emissions, costs) on the effects of retrofitting was the aim from the very first meetings of the project consortium. As diversity of stakeholder viewpoints and priorities is essential for urban building energy domain (Späth and Rohrer, 2015), it was especially important to take these

²⁵The Swedish property register is called Fastighetsregistret and is maintained by Lantmäteriet, <https://www.lantmateriet.se>.

into account starting from early design stages for the modelling framework developed.

Aiming for *objectivity* and *neutrality* of the model resulted in further developments, e.g. comparing average and marginal perspectives for environmental consequences, and investigating effects of large-scale interventions on the DH supply. At the same time, some aspects (such as life cycle perspective for ECMs introduced or explicit accounting for impacts of human behaviour in modelling of building energy performance) were kept out of the scope. This does not mean that they were viewed as unimportant, but rather that they were beyond my personal capacity and/or the primary needs of societal actors. Furthermore, UBEMs by their nature involve quite a radical *simplification* of the building stock modelled, which always leads to lower average quality of modelling results compared with standard per-building simulations. However, this is still seen as a reasonable compromise for modelling building energy on the city scale and has proved to be relevant for application in Stockholm case.

5.3 Effects of transdisciplinarity

A *transdisciplinary* design proved to work well in research on the societally relevant issue of data-driven urban energy planning. Despite being time-consuming, academia-society collaboration is crucial for the success of applied research projects such as this PhD work. Many important research questions were framed jointly by representatives of the city, energy utility, energy service company, local neighbourhood and researchers, in a co-creation mode via live participatory workshops, bilateral meetings or digital mailings. This allowed early testing and follow-up to the modelling results and ensured their later applicability and impact.

As with most new fields, urban energy data analytics is emerging at the intersection of several early established domains and requires the establishment of new methods and research approaches. Thus, I devoted much effort to creating a modelling framework that permitted reasonable integration of knowledge from building physics, statistics and machine learning, urban sustainability, database management, investment analysis etc. This allowed me to learn more from all of these domains and develop an understanding of how they can (or cannot) work together. However, setting up cross-domain collaboration proved challenging, as it required the creation of a shared vocabulary and understanding of the problem, time to align different research styles etc. For me personally, this cross-domain experience triggered imposter syndrome from time to time. However, I believe that this

was an acceptable price to pay for the opportunity of being part of development in the novel research domain of urban energy data analytics.

Finally, the transdisciplinary setting was fruitful for my understanding of the roles that urban analytics can play in urban energy transitions. Energy data can be seen as a disruptive innovation that could trigger new forms of urban governance and rearrangement of existing actor constellations. For instance, during my PhD studies, I observed the emergence of data collector roles for energy utilities, creation of new digital services and structuring of dialogue regarding shared data exchange formats and open energy data. I also saw the challenges that slow the pace of transition, for example, lack and fragmentation of competences, fear and resistance among certain actors to substantial changes, the long time required to build up a shared understanding of new emerging issues. Transdisciplinary research projects can contribute in addressing these challenges and support for urban sustainability transitions. If successful, they can also have a marked societal impact and, equally important, can gain significant support in further research by societal partners.

6 Conclusions

“The real act of discovery
consists not in finding new lands
but in seeing with new eyes.”

Marcel Proust

Urban analytics is an emerging field at the intersection of dedicated domain modelling and operations research, data science and visualisation, decision-making and strategic planning. Urban energy data provide new opportunities for development of different models and tools to support decision making and strategic planning for energy transition in cities.

With regard to Objective 1 (*Develop and demonstrate an urban building energy modelling (UBEM) framework for strategic planning of building energy retrofitting*), a new method for strategic planning of building energy retrofitting was developed (Paper II). The method utilises high-resolution metered energy use and energy performance certificate (EPC) data to construct a UBEM that combines physical and statistical approaches. The model makes it possible to identify buildings and retrofitting measures with the highest potential, to assess the change in total energy demand from large-scale retrofitting and to explore its impact on the supply side. The method was empirically tested for the case of Stockholm (Papers II and IV). It allows the benefits and drawbacks of each retrofitting measure to be analysed from multiple perspectives and strategic decisions to be made based on information about related trade-offs. Furthermore, the novel archotyping technique in the UBEM can be used to address other urban energy challenges, as demonstrated for the case of electric heating (Paper IV).

With regard to Objective 2 (*Investigate the interconnection between quality and applications of urban building energy data*), the quality and applications of EPC data were analysed (Paper III). Through systematic mapping of 79 papers, existing current EPC data applications were characterised. The mapping also revealed that EPC data have a much wider range of applications than was envisaged by the initial data collection design. It was found that the amount and complexity of data applications are positively reinforced by the quality of data. A larger number of applications in turn imposes higher requirements on the quality of the data. The quality assessment framework proposed for EPC data and its demonstration for the Stockholm case showed the value of linked urban energy data for strategic planning. Hence, data

enrichment from linkage of several data sources enabled more advanced quality assessment (Paper II) and development of a novel data application compensating for scarcity of other data sources (Paper IV).

With regard to Objective 3 (*Explore how urban analytics can be integrated into decision-making for energy transitions in cities*), integration of urban analytics into decision-making processes was analysed for the cases of Niš (Paper I) and Stockholm (Papers II and IV). In both cases, a participatory modelling approach was used to address the gap between urban analytics and decision-making processes. In Niš, the analytical process was included through facilitation and visualisation techniques (Paper I). The Stockholm case showed that continuity of data collaborations and interactivity of developed analytical tools can provide a higher level of stakeholder involvement in urban analytics, and consequently better integration of urban analytics into decision-making process (Papers II and IV).

Urban analytics can affect how cities are governed, through changing the availability of the information to stakeholders, expanding their default capacity for decision analysis through more automation and built-in intelligence. Sample applications of urban energy data for strategic planning in Stockholm demonstrated that urban data can have a significant impact on the current mode of urban governance. The growing number of energy data applications showed great potential to affect existing business models and markets. Therefore, urban analytics can be recognised as a disruptive innovation that should be researched further.

7 Further research

“What of the future? ...

That remains to us, to our willingness to take up the rocky road of real problems in preference to the smooth road of unreal assumptions, arbitrary criteria, and abstract results without real attachments.”

John W. Tukey (1962)

This thesis work demonstrated the increasing potential of urban energy data for urban governance. However, there are plenty more open questions raised in this thesis that should be investigated further. These issues can be divided into two main categories — *analytics*, i.e. how the data are instrumentalised, and *transitions*, i.e. how data can be used to foster urban transformation.

7.1 Analytics

There is clear evidence of a further exponential increase in the amount of data relevant for urban climate governance. However, this does not mean automatic improvement of data quality, especially data interoperability and consistency. To secure the application potential of data, more attention should be dedicated to the development of data standards, quality assurance frameworks and tools, aiming for linked open data (Berners-Lee, 2006) and machine-to-machine (M2M) interoperability of data. The urban scale of data applications means that, as a rule, data in their raw generated form would never be usable, due to storage costs, privacy limitations and computational complexity. However, the utility of secondary data derived after excessive data compression and anonymisation conducted by data holders is similarly questionable. Hence, it is critically important to acknowledge the difference in data requirements for data collected for purely operational and more long-term decision-support purposes, and to develop more structured and application-oriented approaches to the design of data requirements for urban energy analytics.

The fusion of novel data science techniques with traditional energy modelling provides good scope for further reduction of modelling costs and simultaneous improvement of quality for modelling outcomes, especially for urban-scale applications. Further development of integrated urban energy

data-lakes (Monteiro et al., 2018) would allow implementation and validation of more machine-learning techniques in urban building energy modelling (Grillone et al., 2020). Data-driven models clearly have potential for more accurate and computationally efficient estimation of energy performance than detailed physical models (Kontokosta and Tull, 2017). However, they cannot be expected to become a ‘silver bullet’ for the urban energy domain, and should instead be developed as a complement to physical models (Nageler et al., 2018). Hence, a number of challenges remain to be addressed, including automated generation of models (Dogan and Reinhart, 2017), integration of various dedicated models (simulations of building energy performance, thermal networks and power grids, urban climate, life cycle analysis) (Zhang et al., 2018) and associated issues of complexity reduction (Remmen et al., 2016), calibration (Nagpal et al., 2018) and co-simulation (Arnaudo et al., 2019).

The emergence of structured data and data-driven urban models creates new opportunities for scaling out decision-support tools, developed earlier for individual buildings (Mjörnell et al., 2014), for urban-level applications. Beside simultaneous analysis of certain portfolios of buildings or particular districts, these tools could allow for data-based studies of system effects induced by large-scale energy interventions (e.g. Romanchenko et al., 2018). However, the main challenge that must be addressed in order for decision-support tools to have an impact is the gap between analytics and stakeholders. Hence, visualisation and interaction capabilities of developed tools should be more critically assessed, using both theoretical (e.g. human computer interaction) and practical (stakeholder) perspectives (Hasselqvist et al., 2016).

7.2 Transitions

Urban energy data and derived analytics do not exist per se. Recognising them as constituents of a more complex data assemblage can be useful when investigating socio-technical drivers and consequences of data-driven development (Kitchin and Lauriault, 2014). Following on from this PhD work, stakeholder perspectives on urban energy analytics can be seen as a particularly interesting subject for further studies. First, stakeholder needs analysis can be helpful in guiding development of analytics. Second, better understanding of current and possible future stakeholder roles and related system configurations can allow us to identify existing barriers and potential lock-ins for further emergence of urban analytics as a niche form of urban governance. Finally, such analysis would support early assessment of changing governance practices and emerging business models induced by data-driven

developments in the urban energy domain. This can be seen as the most important aspect of such studies, as it is related not only to success of these innovations, but also their societal consequences.

Stakeholder involvement is vital for further prospects of urban analytics research. Understanding the possible formats for data collaboration and non-technological prerequisites for such collaborations is key to creation of a successful urban energy data ecosystem. This includes elaboration of common data standards and protocols, establishment of data marketplaces, creation of shared tools, and supporting third-party innovations. While all stakeholders can and should contribute to this development, it is the particular societal responsibility of public authorities and researchers to ensure that it happens for the public good.

Finally, diffusion of data-intensive methods in energy research can only be successful if the ongoing alteration to conventional modelling workflows is recognised and supported by research ecosystems. Urban energy research should be more generous in sharing open data samples, well-documented data-processing scripts and community-driven tools that could enhance the replicability of results and allow for more efficient advancement of frontiers by the next generation of researchers.

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