Perspectives on Modeling and Simulation of Urban Systems with Multiple Actors and Subsystems

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Abstract

Cities are the spaces of the interaction between social, physical, political, and economic entities, which makes planning and intervening in such systems difficult. Urban systems are complex adaptive systems in that their behaviours are often the result of the interaction of their components. The growth of urban systems is driven by mass urbanization. Their complexity is the result of interactions between its constituent systems and components.

Simulations and models as tools of exploration of urban systems face many challenges to be useful tools for intervening. Throughout the past decades, the use of simulation models focused on providing tools for managing functions and systems within metropolitan and urban environments. The cognizance of the complexity of these environments and the maturity of complexity science as a field of studying complex systems allow for the application of complexity science methods to study urban systems not only as physical systems but as social systems too.

As learning from simulations and models can occur both at their construction and their use, this thesis focused on model and simulation building, running, and final use. The thesis takes into account two main aspects of urban systems. First, urban systems are often multi-stakeholder, that is systems where multiple stakeholders are intervening at the same time, and sometimes without clear boundaries and agency over sub-parts of the system. Second, urban systems can have a multi-subsystem structure, where each subsystem often have their objectives and affecting the rest of the system in unfamiliar ways.

The thesis investigates through a multicase study, with three case studies, five main themes in simulation modeling that relate to increasing validity and usefulness of models for urban complex systems. Those themes are as follows; (1) the ability of simulation to be tools that capture complexity in ways that are similar to the real target systems, (2) the effects of the inclusion of experts in simulation models construction on the models, (3) the ways quantitative and qualitative ways of modeling can together make simulations and models more useful, (4) the value of simulation modeling to study connections in systems that are multi-system and multi-stakeholder, and (5) the ability to learn from models under the model building journey.

The study cases included are modeling of a city pedestrian network, a metropolitan emergency care provision, and urban mental health dynamics. The case studies provided a diversity of system granularity. The methods used for each of the case studies have also been different in able to study different levels of inclusion of expert knowledge, data, and theoretical models.

Besides its contribution to each of the case studies, with new models and simulation approaches, the thesis contributes to the five themes it investigated. It showed simulation modeling to be able to exhibit multiple elements of complexity. It also showed the ability of expert knowledge to help models become more useful and valid either by increasing their realism or level of representation. This result is achieved by the contextualization of the expert knowledge in the case of pedestrian modeling, and its full exploration in the mental health modeling. Furthermore, the thesis shows ways in which simulation and modeling can find and investigate bridges between urban subsystems.

The outcomes suggest that simulation modeling can be a useful tool for exploring different kinds of complexity in urban systems as multi-actor and multi-system systems. Models can mirror the complexity of urban systems in their structure. They can also be ways of exploring non-intuitive behaviors and dynamics. Expert knowledge, in particular, is shown throughout the thesis to be able to help simulations achieve more validity and usefulness.

Keywords: Simulation & Modeling, Urban Systems, Expert Knowledge, Complexity Science, Mathematical Modeling, Second Order Effects.

Sammanfattning

Städer är platser för samspel mellan sociala, fysiska, politiska och ekonomiska enheter, detta gör planering i dessa system svårt. Urbana system är komplexa adaptiva system i och med att systemens beteende ofta är ett resultat av interaktion mellan deras komponenter. Tillväxten av urbana system drivs av massurbanisering. Deras komplexitet är resultatet av interaktioner mellan dess beståndsdelar och komponenter.

Simuleringar och modeller som verktyg för utforskning av stadssystem står inför många utmaningar för att bli användbara verktyg för att skapa åtgärder. Under de senaste decennierna, var inriktningen för användningen av simuleringsmodeller att tillhandahålla verktyg för att hantera och optimera funktioner och system inom storstads- och stadsmiljöer. Kunskapen om komplexiteten i dessa miljöer och mognaden för komplexitetsvetenskap som ett område för att studera komplexa system möjliggör tillämpning av komplexitetsvetenskapliga metoder för att studera stadssystem inte bara som fysiska system utan också som sociala system.

Eftersom lärande från simuleringar och modeller kan förekomma både vid deras uppbyggnad och deras användning, fokuserade denna avhandling på modell- och simuleringsbyggande, testande och slutanvändning. Avhandlingen tar hänsyn till två huvudaspekter av urbana system. För det första innehåller urbana system ofta flera flerparts-aktörer, det vill säga ett system där flera aktörer samverkar samtidigt, och ibland utan tydliga gränser och instanser för underdelar av systemet. För det andra kan urbana system ha en struktur med flera delsystem, där varje delsystem ofta har sina mål och påverkar resten av systemet på okända sätt.

Avhandlingen undersöker genom en flerfallsstudie, med tre fallstudier, fem huvudteman i simuleringsmodellering som relaterar till ökad validitet och användbarhet av modeller för urban komplexa system. Dessa teman är följande; (1) simuleringens förmåga att vara verktyg som fångar upp komplexitet på sätt som liknar de verkliga målsystemen undersöktes, (2) effekterna av att experter inkluderas i konstruktionen av simuleringsmodeller på modellerna studeras, (3) hur kvantitativa och kvalitativa sätt att modellera tillsammans kan göra simuleringar och modeller mer användbara studeras, (4) värdet av simuleringsmodellering för att studera anslutningar i system som är multisystem och består av flerparts-aktörer, och (5) förmågan att lära av modeller under arbetet med konstruktionen av modellen.

De fallstudier som studerats är en modellering av ett nätverk för gående i staden, en akutvårds nätverk inom en storstad, och dynamisk stads mentalhälsovård. Fallstudierna tillhandahöll en mångfald av bildning. Metoderna som använts för var och en av fallstudierna har också varit olika för att kunna studera olika nivåer av inkludering av expertkunskap, data och teoretiska modeller.

Förutom dess bidrag till var och en av fallstudierna, med nya modeller och simuleringsmetoder, bidrar avhandlingen till de fem teman som den undersökte. Avhandlingen visade att simuleringsmodellering kunde visa flera element av komplexitet. Avhandlingen visade också effekten av expertkunskap, vilken var att bidra till att modeller blir mer användbara och tillförlitliga antingen genom att öka deras realism eller representationsnivå. Detta resultat uppnås genom kontextualisering av expertkunskapen (första fallstudien) och dess fullständiga undersökningen i modelleringen av psykisk hälsa. Vidare visar avhandlingen sätt på vilka simulering och modellering kan hitta och undersöka broar mellan urbana delsystem.

Resultaten tyder på att simuleringsmodellering kan vara ett användbart verktyg för att utforska olika typer av komplexitet i urbana system genom att de är flera aktörer och multisystem. Modeller kan spegla komplexiteten i urbana system i deras struktur. De kan också vara sätt att utforska icke-intuitivt beteende och dynamik. Särskilt expertkunskap visas i hela avhandlingen kunna bidra till att simuleringar uppnår högre validitet och användbarhet.

Nyckelord: Simulering och modellering, urbana system, expertkunskap, Komplexitetsvetenskap, matematisk modellering, andra graden effekt

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Elhabib Moustaid,
Stockholm, 2019

Preface and Appended Papers

The following papers are attached to the thesis.

Appended Papers

Paper I- E. Moustaid and G. Flötteröd: Macroscopic Modelling of Complex Multidirectional Pedestrian Intersections. Manuscript Under Review at *Transport Research Part B: Methodological*. 2019.

Paper II- E. Moustaid and S. Meijer: A hybrid approach for building models and simulations for smart cities: Expert knowledge and low dimensionality. In *Proceedings of the 2017 Winter Simulation Conference*. p(1551-62). 2017. IEEE.

Paper III- E. Moustaid, R. Richard, and S. Meijer: Agent-Based Modeling of a Network of Emergency Departments in Urban Environments. In *The Proceedings of the 2018 Computational Science and Computational Intelligence Conference*. p(697-702) 2018. IEEE.

Paper IV- E. Moustaid and S. Meijer: A System Approach to Study Waiting Times at Emergency Departments in Metropolitan Environments. In *Proceedings of the 2019 Winter Simulation Conference*. Upcoming. 2019. IEEE.

Paper V- E. Moustaid and S. Meijer: A Simulation Study of the Effect of Information on Waiting Times and Quality of Care in Major Emergency Departments in the Stockholm Region. Submitted Manuscript to *PLOS One Journal*. 2019.

Paper VI- E. Moustaid, M. Kornevs, F. Lindencrona, and S. Mejier: A System of Systems of Mental Health in Cities : Digging Deep into the Origins of Complexity. Revised Manuscript at *Administration and Policy in Mental Health and Mental Health Services Research*. 2019.

Paper VII- E. Moustaid, M. Kornevs, S. Meijer: Sensitivity Analysis of Policy Options for Urban Mental Health using System Dynamics and Fuzzy Cognitive Maps. In *Proceedings of the 2019 Winter Simulation Conference*. Upcoming. 2019. IEEE.

List of E. Moustaid Contributions

E. Moustaid is the corresponding author of all the papers appended to this thesis. E. Moustaid the main contributor in writing the papers. The division of the rest of the work is as follows.

Paper I- E. Moustaid formulated and implemented the models, designed and analyzed the experiments. G. Flötteröd contributed in the models formalization, parts of the writing, and contributed to experiments design.

Paper II- E. Moustaid designed and implemented the simulation platform, he contributed to the methodology, moderated parts of the validation workshops and analyzed the experiments. S. Meijer contributed to the approach, and wrote parts of the article.

Paper III- E. Moustaid designed the experiments, he contributed to the methodology, and he analyzed the experiments. R. Richard implemented the simulation and extracted data. S. Meijer contributed to the methodology and the experiments.

Paper IV- E. Moustaid designed the experiments, implemented the simulation, he contributed to the methodology, and he designed and analyzed the experiments. S. Meijer contributed to the methodology and the experiments.

Paper V- E. Moustaid contributed to the design the experiments, he contributed to the methodology, and he analyzed the outcomes experiments. S. Meijer contributed to the methodology and the design of the experiments.

Paper VI- E. Moustaid co-designed and co-moderated the model building workshops. He conducted part of the validation interviews, implemented the model and performed the quantitative analysis. M. Kornevs contributed to writing, moderating workshops, validation interviews and model analysis. F. Lindencrona contributed with moderating the workshop, getting participants, reviewing the results and the manuscript. S. Meijer contibuted with the methodology, revising the manuscript and moderating the workshop.

Paper VII- E. Moustaid was the main contributor in the formalisation of the model and the experiments. M. Kornevs and S. Meijer contributed to the methodology and the analysis. M. Kornevs contributed to parts of the writing.

Other Academic and Project Contributions

These academic and project contribution are performed under the time of the thesis but are not included in the thesis.

VIII- J. Raghothama, E. Moustaid, V.M. Shreenath, and S. Meijer: Bridging Borders: Integrating Data Analytics, Modeling, Simulation, and Gaming for Interdisciplinary Assessment of Health Aspects in City Networks. In *Collaboration and Planning for Health and Sustainability*. A. Karakitsiou, A. Migdalas, S. T. Rassia, and P.M. Pardalos, eds. 135-155. Springer International Publishing. 2017.

IX- V.M. Shreenath, E. Moustaid , and S. Meijer: A Methodology to Assess Changes in Healthcare Infrastructure in Stockholm. In *Infrahealth 2017-Proceedings of the 6th International Workshop on Infrastructure in Healthcare*. 2017.

X- J. Hauge, E.Moustaid, and L.B. Zomer: Validated gaming simulation environment. Project Deliverable, Personal Travel Advisory Platform, European FP7 funded Project. 2016.

XI- M. Nanni, R. Trasarti, V. Romano, and E. Moustaid: The simulation framework for Crowd mobility Behaviour. Project Deliverable, Personal Travel Advisory Platform, European FP7 funded Project. 2016.

XII- L.B. Zomer, E. Moustaid, and S.Meijer: A meta-model for including social behavior and data into smart city management simulations. In *Proceedings of the 2015 Winter Simulation Conference.* p 1705-1716. 2015. IEEE.

XIII- E. Moustaid and G. Flötterod: Macroscopic modeling of multi-directional point-like pedestrian intersections. Extended Abstract Presentation. In *the 4th symposium arranged by European Association for Research in Transportation*. 2015.

XIV- E. Moustaid and G. Flötterod: Analytical modeling of bidirectional pedestrian network flows. Abstract Presentation. In *National Conference in Transport Science.* 2014.

Contents

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List of Acronyms

ABM	Agent-Based Model
ABS	Agent-Based Simulation
CA	Cellular Automata
CAS	Complex Adaptive System
CTM	Cell Transmission Model
EC	Emergency Care
ED	Emergency Department
DES	Discrete Event Simulation
FCM	Fuzzy Cognitive Map
FD	Fundamental Diagram
KWM	Kinetic Wave Model
MH	Mental Health
SD	System Dynamics

Chapter 1

Introduction

'Do not say a little in many words but a great deal in a few'
Pythagoras

The mass urbanization that took place over the past seven decades saw the rise of the urban population from 33% in the year 1960, 40% in the year 2000, to 53% in 2014 (World Health Organization, 2014; World Bank, 2019). It posed and continues to pose challenges to planners to design and provide the services required by city populations efficiently. Urban and metropolitan environments are attractive for they provide possibilities for employment, healthcare, and education, for example. The population growth saw the increase of demand for services to satisfy the needs of populations for healthcare, transportation, sanitation, schools, education, to name only a few (World Health Organization, 2017).

For this thesis, *urban systems* are defined as systems that are part of an englobing urban or metropolitan environment. A system is 'a complex whole; a set of things working together as a mechanism or an interconnecting network' (Oxford Dictionaries, 2010). Urban systems are hence defined as a set of components, subsystems, agent systems, that through their interactions in urban environments, form a complex whole. The complex whole includes city populations, service providers, planners, and other relevant stakeholders. The design, operations, and the constant improvements of such systems are challenging due to the very nature of urban systems as being complex adaptive systems (CAS) (Batty, 2013). Complex adaptive systems are systems with many components, interacting non-linearly, self-organizing, and constantly reacting to their environments (Portugali, 2006). CAS are ever-evolving systems making them hard to operate, manage, or predict.

Today's cities and urban systems are more connected than ever before. They are also subject to disruptions that are both technological and social. Urban systems affect each other in many ways and often deal with a world that is evolving fast. Cities are the place of the interaction of numerous social, physical, economic, and political entities. They are forming systems and structures that often deal with functions and processes within the same space and time hence affecting each other in complex ways (Allen, 1997). The interconnection between different systems calls for new methods to understand the effects that propagate between and across systems (Allen, 1997). The planners of these systems deal with problems that are often ill-defined, lacking, or changing objectives, dealing with high levels of uncertainty and situations with incomplete knowledge. Scholars and planners are in a constant quest to find new ways of dealing with the inherent complexity of urban systems.

Mathematical modeling in the form of optimization, operations research, simulation, and data analysis helped planning in cities for multiple decades (Larson and Odoni, 1981; Wegener, 1994; Thakuriah et al., 2017). These models were often successful at optimizing functions within city physical systems. However, they often faced challenges when dealing with the scale or the social complexity of these systems (Lee, 1973, 1994). Despite the subsequent development in technology and the improvements in modeling techniques, simulation and modeling applications faced their challenges over the past decades in proofing themselves valid and useful for planning in urban systems (Batty and Torrens, 2005). These methods that originate from the natural sciences often faced challenges to be valid and useful in systems that are inherently social and complex (Batty, 2016).

Modeling is a bridge between the theory and the real-world (Morgan and Morrison, 1999), a tool of exploration of both theories and the world they aim to represent. For simulation modeling to be a practical tool of investigation of the complexity of urban systems, it behooves modelers to take into account the origins and characteristics of complexity in these systems. Urban systems are systems that are multi-actor and multi-system. The multiplicity of actors makes the knowledge over these systems distributed (Lemon and Oxley, 1999; Jeffrey et al., 1999). The multiplicity of systems makes urban environments spaces where effects propagate in ways that are hard to understand (Batty, 2013; Lemon and Oxley, 1999). These elements are fundamental to the structure of urban systems. Modeling and simulation are yet to live up to the challenges posed by such complexity.

A neglected aspect of formal methods in modeling is the inclusion of planners and operators in the building of models. While using experts, planners, politicians, to build models has been in practice since the late 70s in social sciences (Axelrod, 1976), those methods often stayed at a conceptual level. The fields of participatory simulations and simulation gaming provide areas of inquiry of the uses of simulations in planning (Vedung, 2000; Meijer, 2015). These methods often used experts and planners to interact with a simulation or a game through specific rules and provided the advantage of dealing as well with the complexity of decision-making using simulation-based exercises. The combination of expert knowledge with quantitative models, at the building and running of simulation, is yet still a developing field.

1.1 Thesis Objective

The objective of this thesis is to investigate the capacity of simulation modeling to be a valid and useful instrument to support the design of interventions in urban systems. The use of simulation modeling for intervention means interactions with simulation and models in ways that can lead to formulating or understanding new policies, managerial, or operational measures. The thesis intends explicitly to investigate these interactions throughout the model building journey. That is, the building, running, and analysis of simulations and models.

Taking into account that learning from models and simulation takes place both at the construction of these models, as well as the running and the analysis simulations (Morgan and Morrison, 1999; Morgan, 1999), the value of simulation modeling is investigated at all these steps. In doing that, the thesis uncovers the values and the implications of building models using different involvement of theory, data, and expert knowledge. Through the running and the analysis of the simulation models, the thesis shows precisely ways simulations can help planning in systems with multiple subsystems and actors.

1.2 Research Questions

The thesis asks the following central research question.

Central Research Question. **What makes models and simulations a valid and useful instrument to design interventions in multi-stakeholder and multi-subsystem urban systems?**

The goal of the general research question is to find ways in which simulation and modeling can be useful to find and understand intervention measures in urban systems in that these systems are multi-stakeholder and multi-system. The complex dynamics and the structures of urban systems make the design of interventions in such systems rather tricky. The thesis sees models as mediators between theory, expert knowledge, and the real-world. Through that triadic relationship, the quest to answer this research question digs into ways the use of expert knowledge, theory, data, or their combinations in building models that achieve validity and usefulness to design and test interventions. The journey to answering this question goes through the answer to the following related questions.

Research Question I. **What elements of complexity in urban systems are simulations capable of capturing?**

There is a need to address the faculty of simulation modeling to explore urban complex systems. This question looks into the ability of simulation modeling to capture complex behaviors and structures in urban environments and the ways it does that. The question verifies if simulation approaches can (1) capture the bottom-up mechanisms that generate complex behaviors and (2) help the top-down approaches that try to influence these behaviors.

Research Question II. **How can quantitative and qualitative methods assist each other in achieving usefulness of models for urban systems?**

The knowledge of experts in urban systems both in planning and operating these systems is fundamental to interventions that take place in city systems. Model building and execution often relied on two aspects; theory and empirical evidence, and neglected the tacit or explicit knowledge of planners. There is a need to understand which ways theory and expert knowledge can interact to build models.

This question investigates ways of combining qualitative methods that elicit the knowledge of experts, with quantitative methods relying on theory and mathematical modeling. Specifically, the question wonders in which ways these methods can assist each other to become useful for urban systems.

Research Question III. **What does the the inclusion of experts in building and running simulation models imply on the validity of models?**

As a continuation of the research questions II, the inclusion of experts in model building, running, or execution can affect the model building and the theory applications. This question identifies the implications, if any, of including experts in the process on the models and their validity.

This question is essential as the mathematical modeling often sought formalism and rigor, while models relying on expert knowledge are often 'softer'. The implication of expert knowledge hence requires some trade-offs.

Research Question IV. **In which ways can simulation assist planning in systems with multiple interconnected subsystems?**

Models and simulation value of being simpler than reality is confronted with a reality that grows complex every day. In the face of high connectivity, and unclear effects of interventions, there is a need for models to be useful in new ways. This question investigates new ways in which simulation models can be useful to assist in designing interventions in urban systems with multiple subsystems and to understand their potential effects.

Through the question, the thesis investigates ways to create intervention bridges between multiple systems and ways to evaluate those bridges. Intervention bridges are connections between multiple systems, and which aim is to intervene in a way that improves aspects of the systems.

Research Question V. **What can be learned about intervention measures in urban systems under the process of building models for such systems?**

Learning from models and simulations also happens at the constructions of these models. This question focuses on which learnings occurring the model building stage help the design of intervention measures.

1.3 Thesis Structure

This thesis is structured as follows. This chapter provided a general introduction of the thesis, its research questions, and its limitations. Chapter 2 provides a background for the work done in this thesis. The background is further detailed into three sections. A scientific background details the theories and frameworks of complexity science used in the thesis. A methodological background formalizes the use of simulations in this thesis. A contextual background studies the advances in modeling and simulation for urban systems and exhibits further the research gap this thesis aims to fill. Chapter 3 details the methodology and the case studies used to answer the research questions. Chapter 4 shows the contributions to each of the research questions in this thesis, as well as to the central research question. Chapter 5 shares the conclusion of this work.

1.4 Limitations

This thesis follows a multicase research methodology. The thesis only uses three cases. The results could be corroborated or challenged, with more cases providing additional evidence. The thesis investigates multiple systems or subsystems at once, or multiple stakeholders at once, given the difficulty of accessing such stakeholders, or getting data on time within the scope and the time frame of a doctoral thesis, the scope was limited.

Ethical Considerations

The thesis uses participants in focus groups and participatory methods. The basis for selecting participants was the relevance of their expertise, and sometimes occupation to the research objectives. No consideration was given to their age, gender, religion, race, disability or other discrimination forms.

The thesis also uses data that is either publicly available from verified sources, or made available through projects. The thesis did not collect any data on individuals.

Chapter 2

Background

This chapter consists of two parts. The first section presents the scientific and the theoretical background of the thesis. It consists of a short introduction of complexity science, simulations and models, and the concepts that the next chapters treat. The second section presents a contextual background. The contextual background puts the research questions posed by this thesis in their context in the body of relevant literature and identifies gaps that are treated later on in the thesis.

2.1 Scientific and Theoretical Background

This section details the theoretical and scientific background of the thesis. First, the definitions of complexity science and complex systems are elaborated. Second, simulation modeling is formalized for its future use in the thesis.

2.1.1 Complex Systems and Complexity Science

Complexity science is a body of theories concerned with the study of complex systems. Complexity science provides a body of theory-driven driven methods initially to study complex systems in natural sciences. The applications of these theories in the study of social systems have also grown throughout the past years (Portugali, 2006; Byrne and Callaghan, 2013; Batty, 2016). Complex systems are systems whose behavior is dependent on the interaction of their components. Complex systems are characterized by a set of proprieties that are defined inline with Byrne and Callaghan (2013) as follows:

- **Emergence:** Emergence refers to the forming of particular structures, patterns, or behaviors from the elementary interactions in a system. Emergence can be observed, for example, through the forming of an order at the system level, sudden and abrupt changes, or the formation of states between which the system alternate.

- **Non-Linearity:** Non-linearity refers to dynamics that occur in a non-linear way, where the system as a whole is not just the sum of a linear combination of its part. Non-linearity also means that effects that take place at the system are not necessarily proportional to the changes in the elements that cause these effects.

- **Non-Equilibrium:** Non-Equilibrium refers to the absence of steady states in which systems evolve permanently.
- **States Space:** States Space refers to the space of states at which the system can be.
- **Attractors:** Attractor States refer to states that systems are more inclined to gravitate around until the occurrence of a disturbance that takes it away to a different attractor.
- **Boundaries and Bridges:** Boundaries refer to the scope of a system (or subsystem) and differentiate that system for other systems (or subsystems). Bridges refer to links between those systems, where they affect each other.
- **Feedback Loops:** Feedback loops refer to the cases where the outputs of a part of a system propagate in such a way that they are routed back to the origin, forming a circle or a loop of causes and effects.

The list of proprieties described above are the elements that this thesis investigates in the first research question. In particular, the ability of modeling and simulation to exhibit these proprieties in urban systems is studied. Furthermore, the relevance of these proprieties for designing interventions in urban systems is put forward.

2.1.2 Simulation for Complex Systems

Models and simulations are a representation of a target that can be an object, a system, or phenomena. Models can be abstract or physical and are static by nature. Simulations are dynamic and continuous representations. The difference between a model and a simulation is mainly in their dynamism. The first is static by nature. The latter is dynamic (Wright-Maley, 2015). The uses of the words simulations and models in this thesis refer to them being representations of systems. The relationship between a model and simulation is expressed best by Bratley et al. (1987) as follows, 'Simulation means driving a model of a system with suitable inputs and observing the corresponding outputs'.

Models and simulations represent a medium of exploration. Scientifically, models and simulations are a way of scientific inquiry that is distinct from theory or experiments (Grüne-Yanoff and Weirich, 2010). In practice, models and simulations are a way to overcome the limitations and the burdens of a costly reality, thus providing an alternative way of testing strategies and exploring complex systems (Elgood, 1996).

A simulation level of representation is a continuous discussion between scholars for decades already. Realistic models often try to reach a high level of validity through a maximal representation of their targets. On the other hand, 'toy models', which are constructed to be rather a very simplified version of reality, aim through simplification to isolate effects in real systems, hence enabling understanding complex phenomena through simple models. The right level of idealisation and simplifications of a simulation model is often hard to determine (Sugden, 2000; Grüne-Yanoff and Weirich, 2010; Meijer, 2015).

In an attempt to generalize, simulation models aiming for the representation of the world are characterized by their logic, the theory behind them, their data inputs, the control inputs, and the outputs.

- The logic and theory refer to rules that the simulation components follow in their interactions (and their decision making if applicable). Logical rules are simple rules that originate from the understanding of the modelers of the target of the model (Wolfram, 2002). Theoretical models are equation-based. They rely on the mathematical formulation of the relationship between some or all of the simulation variables (Byrne and Callaghan, 2013).

- Input data refers to the input the simulation gets in order to run. Input data can realistic to represent realistic scenarios or fictive to represent scenarios of interest.

- Control refers to control that the simulation user is manipulating to explore the simulation or to achieve specifically desired results.

- Outputs are measures of interest that are drawn for the simulations.

To draw a generalization, let F be the simulation function, representing all the interactions, the logic, the calculation, and the computations that originate from a simulation model. Let X be the vector of all variables taken in the simulation, D the input data in the simulation, and C be the control data. The state of a simulation at the simulation time-step i can then be represented by the values of the vector X at the time-step i, denoted $X(i)$. Similarly, let $D(i)$ and $C(i)$ be the control data at time i. A simulation iteration is analytically expressed by Equation 2.1 and graphically shown by Figure 2.1.

$$(Y(i), X(i+1)) = F(X(i), D(i), C(i)) \tag{2.1}$$

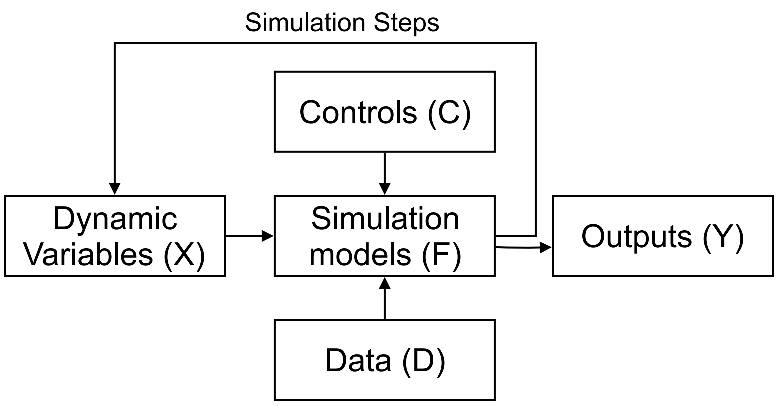

Figure 2.1: Simulation in General

The Markovian representation in Equation 2.1 describes the way simulation mimics the dynamics of the world. The relationship between the components of the simulation at a time i, the data, and the controls determine the next states. A simulation state at time i is the value of its variables at that time step. At every time step i, the state of the simulation in the next step $(i+1)$ is determined through a deterministic or a probabilistic mechanism. Deterministic simulation models do not rely on any randomization, i.e., a fixed input will result in the same outputs. Probabilistic models rely on stochasticity that makes the simulation able to provide different outputs for similar inputs.

In this representation, the system state at time i is entirely determined by $X(i)$. Values of X are analyzed through visualization of patterns, analysis of a set of variables to understand the dynamics of the simulation. The control parameters are means to either move the system to a different state that is deemed better or to maintain an already 'good' state. The manipulation of simulation control parameters is meant to identify, under simulation state $(X(i))$ and the conditions specified by D, the controls that make the system evolve to an attractor state X^*, or an attractor space M of states that are better than the current status. In this representation, the problems often faced by simulation are similar to general system engineering and optimal control problems, where the problem becomes finding the optimal control parameters to drag a system from a state X_i to a state X_j supposedly better. However, urban systems are not only physical but also social, posing challenges at representing these systems in ways that are sufficient to get useful results from simulations.

2.1.3 Usefulness and Validity of Simulations

Simulation validation is and has always been a subject of discussion between scholars. The existence of multiple ways of validation definitions and techniques often makes it hard to just define the term validation (Roungas et al., 2017; Sargent and Balci, 2017). Methods of validation are either quantitative, qualitative, or mixed (Kleindorfer et al., 1998). The quantitative methods of validation often relied on comparing simulation outputs with realistic outputs, i.e., given a realistic input, simulation outputs should be similar to realistic observed data. This relied on statistical methods of verification, graphical visualizations, and other data analysis methods. Qualitative methods relied on subjective methods of analysing simulation outputs such as face validation. Face validation is a validation in which experts evaluate whether the simulation outputs are within the range of possibility (Gigerenzer, 2008).

Validation is not only a matter of reproducing outputs, but also a matter or representation and duplication of dynamics (Balci, 1986; Sargent, 2005). Making a simulation capable of duplicating systems behaviors is often difficult, even impossible in systems that are predominately social and complex (Kleindorfer et al., 1998). Furthermore, validations are not proof of the truth of models. Models as simplification of reality are inherently incapable of claiming truth. Hence, simulations validation is often from the perspective of whether they are providing results that allow for understanding of real-systems. Validation is studied alongside to usefulness. Models as tools of understanding and learning about the world should also be useful. This makes models validation value-dependent.

A useful model is a model that allows to understand or acquire new knowledge about systems. Toy models, which are often very simplified, and hence do not have the quantitative validation are for example useful to decision-making as they allow to uncover parts of systems that are not strictly quantitative (Meijer, 2015). Toy-models or simplified models, also have the ability to provide insights through the power of isolation (Grüne-Yanoff and Weirich, 2010).

For the scope of this thesis, the validity is regarded as the degree of verisimilitude of the models against the real-world. The thesis uses different validation methods to evaluate different aspects of validity in simulations, i.e., level of representation, dynamism, and outputs.

Besides verisimilitude, the thesis looks into the value of simulation to engage relevant actors in urban systems. An engaging simulation or model is one that is rich enough, and simple enough to draw users to use it and rely on it (Arnold, 1998; Wright-Maley, 2015).

2.1.4 Simulation in the Face of Actors Multiplicity

The representation Figure 2.1 (or Equation 2.1) is one that requires to take into account the requirements of systems with distributed agency and knowledge, as well as the multitude of objectives different stakeholders can have, based on their values, and experiences (Jeffrey et al., 1999). Controlling complex adaptive systems is hence not a matter of engineering (at least not engineering only), but a matter of understanding the complexity that stems from the distribution of agency between multiple actors often in control of different systems. These actors can have either contradicting objectives. They can also affect each other in ways that are not intuitive (Goodspeed, 2016; Raghothama, 2017).

The multiplicity of actors poses challenges to simulation in two main ways, at their construction and their use. When it comes to their construction, simulation models need to take into account the multiplicity of systems and the extensive and distributed knowledge about these systems. Models need to have 'representations that incorporate the different perspectives of those who are making decisions which impact upon that landscape' (Lemon and Oxley, 1999).

As for the use of simulation, participatory and gaming simulation are (new) methods that are responding to the challenges of the multiplicity of actors (Duke and Geurts, 2004). These methods use simulation as the basis of group and social exercises and experiments. They allow multiple actors to act simultaneously and collectively see the possible outcomes of a strategy on an overall system, or on parts of the systems. These methods open up for new use of simulations as they also allow the investigation of the complexity of the decision making in such systems.

The contextual background develops further the challenges posed by the multiplicity of stakeholders and subsystems in relation to the advances in simulation modeling for urban systems.

2.2 Contextual Background

This section intends to provide a body of relevant literature to position this thesis in its research context. Furthermore, the specific challenges of simulation in regards to urban and metropolitan challenges are further explained in order to contextualise the research questions posed in Section 1.2.

2.2.1 The Complexity of Urban systems

Cities are complex adaptive systems as they are the space of the interaction of a large number of components of social and physical nature (Barthelemy et al., 2013). The interactions of such agents often lead to dynamics that are difficult to understand. The study of cities, their growth, and their constituent systems is one that has been part of multiple research disciplines such as sociology, operations research, policy-making, economy, physics, health, and engineering (Glaeser, 2011; Makse et al., 1995; Bettencourt et al., 2007; Bally and Marshall, 2009). The realization that cities are dynamic networks of people and information rather than a mere physical environment is shifting the focus of planning for cities from just a 'place' to a space of interactions of networks and systems with different morphologies (Raghothama et al., 2017; Portugali, 2006). The view of cities and their subsystems as complex systems characterized by non-linear relationships, self-organization, emergence, and ever-changing dynamics, has allowed for the emergence of a new science of cities (Batty, 2013; Portugali, 2012).

The evolving nature of cities makes them dynamic and ever-changing. Policies are often challenged by the interconnection between the constituent subsystems of the urban systems. The effects of changes in one subsystem are often propagating beyond its boundaries. This makes city subsystems and aspect systems rather hard to plan and design. Stakeholders, often planning from the perspective of a subsystem and trying to reach their objectives, are often acting in an environment where other stakeholders have different objectives, values, and experiences (Lemon and Oxley, 1999). The non-uniformity of incentives of stakeholders, their values, and their objectives make planning in cities even a more laborious task.

Furthermore, top-down approaches of planning have often failed as cities, and their constituent systems are rather self-organizing, reacting to new information rather than being planned from the top-down (Batty, 2013; Portugali, 2012; Barthelemy et al., 2013). Cities today are not isolated as populations and city systems can react to national or international trends (such as climate, economic growth, political situations, migration, effects of technology) (Glaeser, 2011). Planning and designing services in cities to have new approaches for policy design.

2.2.2 Modeling and Simulation for Urban Systems

Simulations and models are among the tools used to study cities and urban systems. From the early 1950s, there were attempts to build new theories and models useful for operations and planning, hence bringing domains of science to the policy-making processes (Morse, 1967). Similarly to natural sciences approaches, modeling attempted to represent systems, phenomena, and processes in cities through sets of mathematical equations, often using analogies and established theories. This was driven by the belief of scholars in the possibility of predicting these systems in the future using such analytical methods (Weiss, 1961; Wheaton, 1963). These Operations research, combinatorial optimization, and mathematical modeling generally aimed at describing the city subsystems such as public transportation, logistics, or land-use with sets of mathematical equations (Barnhart, 1970). The use of simulation of models was often done to investigate specific systems and services in cities and perform cost benefit analysis of interventions (Weiss, 1961). An example of the early models for land-use, for example, was the four-step model was one of the first models that focused on transportation and land-use (McNally, 2008). The model was a tool to assess the benefits and costs of land-use strategies. The model combines four sub-models in series (trip generation, trip distribution, mode choice, and route assignment) and uses a land-use forecast. Then across several regions, this model shows the costs and benefits of policies. Most models developed around this period (the 60s and 70s) focused on simulation and optimization of functions within cities such as transit, water supply, labor, energy supply, and urban activity (Holroyd, 1967; Hanke and Flack, 1968; Herbert and Stevens, 1960; Baroyan et al., 1971). These approaches often focused on showing planners ways public policy can be assisted with operations research methodologies (Morse, 1967).

Equation-based models represented a theory-based approach to modeling. It aimed at representing real-world systems through abstraction into mathematical models (Larson and Odoni, 1981). They generally aimed to optimize clearly defined objective functions and often assumed the existence of steady states (Batty and Torrens, 2005). The existence of steady-states in city systems was not only an assumption on the nature of these systems but an essential requirement on models to be useful for analysis. Consequently, modelers often focused on mathematical formalism, rigor, and theoretical validity (Wolfram, 2002). In doing that, they often made unrealistic assumptions to be able to reach valid mathematical models of systems they represent. Models also used heuristics to tackle problems of the hardness of modeling or unfeasibility of solving the subsequent mathematical or theoretical representations of the world they are modeling. Mathematical models, while often theoretically rigorous, have either oversimplified the world they represent, or lost the link to real-world objectives as they were faithful to theory at the expense of fidelity to representing real-world targets. Consequently, models from the 50s and 60s faced criticism for often failing at reaching the objectives as they neglected the complex and social nature of the systems they are representing and the requirements of those models to be used in practice (Lee, 1973; Barnhart, 1970).

Over the next decades, modeling techniques improvements and the shift in paradigms in the views of the nature of city systems as complex and predominantly social and connected brought new waves of models and simulation (Barnhart, 1970). In the 1970s, methods such as system dynamics (SD) and discrete event simulation (DES) were used to explore the dynamics of systems. SD models relied on differential equations to build models that did not intend to provide exact answers to real-world questions but instead provide tools of investigation and exploration of complex systems dynamics and explore 'non-intuitive' behaviors in these systems (Forrester, 1971). The focus on feedback loops aimed mainly at detecting dominant non-intuitive loops that determine or affect the evolution of systems overtime (Sterman, 2002).

Growing computational powers allowed for another wave of bottom-up approaches in modeling and simulating such as Cellular Automata (CA) or Agent-Based Models (ABM). The shift from macroscopic to microscopic simulation and modeling is similar to the one experienced in economics. Modeling and simulating markets were done both at a macro-level, as well as a micro one (Grüne-Yanoff, 2009). CA often relied on representing spaces as grids of cells. Those grids have proprieties that evolve depending on their neighboring cells (Wolfram, 2002). ABM relied on modeling systems as the interaction of its constituent agents (Bonabeau, 2002). Agents can be people, institutions, or organizations with an agency. ABMs represented tools to explore systems from their relational aspects (Macy and Willer, 2002). Hence models, instead of focusing on representing systems at aggregate levels, represent the elementary level of these systems and the interactions of these elements through the use of simple rules (Mikler et al., 2005). The bottom-up approaches of modeling provide the advantage of being more intuitive and take into account the very nature of the systems they represent. ABM and CA allow for modeling complex behaviors taking into account non-linear interactions and are capable of mimicking complex emergent behaviors. These models often require vast amounts of data to run or to assess their validity creating mismatches between models and their intended use. These models were used for city systems such as traffic simulations, epidemiology, and the spread of diseases, land-use, or hospital processes and health decision making. (Mikler et al., 2005; Giesen et al., 2015).

Furthermore, alongside advances in computational powers, there were also advances in other technologies such as sensing technologies, the Internet of Things, and data storage capacities. Such developments allowed for the use of models based only on data for visualization and prediction. They are using machine learning techniques for both reinforced and unsupervised learning and techniques such as regression, clustering, or classification to identify patterns. Data mining and data-based models are often better than simulations at finding patterns in the past but are also confronted with the challenges that self-organization and non-linearity pose. Changing infrastructure and social norms are often hard at depicting using these methods (Thakuriah et al., 2017).

The availability of vast amounts of data and the development of modeling techniques, combined with a tendency to see city systems as complex, saw the rise of hybrid approaches in simulation. Hybrid approaches consist of the coupling of different simulation approaches to represent different aspects of complex systems. The combination of simulations often relied on output-input structures where the output of a simulation is linked as an input of another one (Chahal and Eldabi, 2008; Martinez-Moyano and Macal, 2016; Djanatliev and German, 2013; Mustafee et al., 2010). Hybrid approaches also extend to the combination of simulation and models with other methods such as data analytics or gaming, allowing simulations to be enriched with other scientific methods (Duke and Geurts, 2004; Zomer et al., 2015; Marshall et al., 2016).

2.2.3 Expert Knowledge, Planners, and Simulations

Expert knowledge refers to the knowledge gained by a person through working on a subject practically or academically. Experts' relationship to models and simulations can be beneficial for both experts and the models. Experts and planners can rely on simulations and models to enrich their learning about the world. However, they can also decide on the virtues needed on simulation models to be useful tools.

Simulation models have multiple virtues that allow learning from them. As such models are themselves objects (artifacts) that are independent both from theory and the real-world (Morgan and Morrison, 1999). Interactions with simulation come in multiple forms. Participatory and gaming simulations are social exercises that studied the use of simulations to benefit planning in multi-actor environments (Duke and Geurts, 2004; Meijer, 2015). These methods rely on simulations to bring stakeholders and planners to interact with simulations and with each other. The interactions happen through collectively manipulating simulation controls or analyzing the dynamics of a simulation model or its outputs. Gaming makes the possibility for planners to be part of the simulation, and these methods are a growing body of scientific literature that deals with simulations as artifacts (Devisch, 2008). The widening application of these methods is partly due to the complexity of decision-making processes that originate from the multi-stakeholder nature of these systems. Furthermore, these systems and their stakeholders are not separable. Stakeholders are part of the system as well (Portugali, 2012). Including actors in such ways was able to bring the inherent uncertainties of planning and to operate complex systems to simulation studies (Raghothama, 2017).

The involvement of experts, planners, operators, and other relevant stakeholders in simulation and modeling does not only happen at the use of these models. It can also occur at the construction of simulation models (Axelrod, 1976). This often relied on graphical ways of building conceptual mental models with experts and planners. The inclusion of experts and stakeholders comes from the need to take into account multiple perspectives in model and simulation building and use (Axelrod, 1997). These models stayed, however, very informal despite their practicality and capacity to generate knowledge on systems of interest.

2.3 Summary of the Background: Contextualisation of the Research Questions

The contextual background shows that the challenges on simulation and models can be seen from two perspectives. First, on the simulations themselves as technological artefacts that need to be useful for their intended use, without them being over-suggestive or over-simplified. Second, on the nature of urban system as complex and dynamic systems.

On simulations, the challenge is on how to make simulation reach the trade-off between complexity and simplicity to make them relevant and valid. Over the past decades, reaching mathematical rigor alone proved to be insufficient as it tends to either oversimplify reality for the sake of consistency with a core body of theories or to develop models that are over-complicated for policy makers. On the other hand approaches to simulations that are over-detailed trying to maximize their representation of a complex reality often fail to reach their objectives of representation or validity, due to the hardness of the modeling task, or the non-existence or lack of data that can support those models claims. Microscopic models can also suffer over-inclusiveness making them hard to understand as they overburden themselves with unnecessary representation.

On the nature of urban systems, the challenge lies in the fact that cities are spaces where knowledge is distributed amongst different actors, where operational measures and policies can have unforeseen second order effects. Furthermore, today's cities are more populous, more connected, more challenged with disruptive technologies and constantly changing social norms and physical infrastructure. Simulations are yet live up to the challenges that such complexity presents. Simulations can take advantage of the understanding of the complex aspects of operating, managing, and policy-making for complex systems on one hand and on the constant advances in theory, computing powers, and data storing technologies on the other hand hand.

To live up to those challenges, new ways of making models and simulations valid and useful tools are needed. Simulations and models need to be capable of exploring urban systems while taking into account their complex nature. As simulations learning takes place both when the models are built and when their outputs and dynamics are analyzed, the exploration of both their construction and their use is needed.

Modeling and building simulations is a modeler's profession. It is also a matter of art. If there is no recipe for building model, the ingredients are known. The ingredients - theories, empirical data, and expert knowledge - need to be explored to make building and using models and simulations relevant for urban planning. The degree of representation of models and the idealizations to make is often determined by a modeler. There are no specific methods to build models or objective methods to measure the level of their representation. Modelers face often the hard task of choosing on the dimensions to include, the theories to use in model and simulation building. The ultimate goal of simulations and models being useful poses a lot of challenges on the ways these artifacts are built and used (Batty, 2015).

This thesis hence focuses on two main aspects of modeling urban systems.

- Exploring the capability of simulation modeling to be a tool that can capture some of the complexity of urban systems and to be useful in providing the tools for design of interventions.

- Exploring ways in which experts, and consequently expert knowledge, can assist theory and data in building and executing models.

The scope of the thesis is hence limited to systems that exhibit these proprieties. That is, systems that characteristically have a multitude of systems or a multitude of actors. However, the scope expands throughout the simulations building journeys. This is crucial to understanding how the model building can be done to reach modeling objectives while taking into account the complexity of the systems, and their resources in terms of expert knowledge, data available, as well as, known theories.

Chapter 3

Methodology

The general methodology of this thesis is a *multicase method*. Multicase methods are research methodologies often used in social science studies and detailed by Stake (2005). The method is characterized by the focus on a common objective of multiple case studies. The objective is referred to as the *quintain* by Stake (2005). The quintain, and hence the objective of the research, can be only reached through the study of multiple cases that exhibit both similarities and differences in their characteristics and objectives, while relevant to the main objective. Those similarities and differences are essential to enrich the knowledge about the global objective (quintain) of the multicase study. This method, compared to other cross-analysis methods, has the advantage of exploring all the cases in great detail and explore the similarities between the cases as well as the differences to learn on the objectives (Khan and VanWynsberghe, 2008).

The answers to the research questions rely on three case studies of simulation modeling in urban systems. The answers rely both on within-case studies as well as cross-case analysis. The objective (quintain) is the inquiry of the role of simulation modeling as a valid medium to study and intervene in urban complex systems. This objective is further reduced to sub-objectives, which are finding answers to the questions I-V.

In order to answer the main research question and the subsequent research questions, the three cases had to satisfy the same inclusion criteria. The inclusion criteria ensure the relevance of the case studies to some or all of the research objectives (I-V). The criteria for the inclusion of these cases are as follows.

- The study case represents a system within cities, urban or metropolitan environments.
- The study case represents a system that is complex adaptive in that they have a multi-stakeholder or multi-subsystem structure.
- The study case provides access to one or multiple stakeholders at least at one point of the simulation model development. This provides a link to a real-world challenge.

Besides, the studies included in this thesis follow a generic framework for the development and analysis of the simulation models. The framework represents a high-level description of the modeling process, which starts from a target, builds a model/simulation, analyze it, and refer back to the original target. This process is not new, and the attempts to formalize it can be seen in other scholarly work in the field of simulation modeling and related fields (Sargent, 1984; Maria, 1997).

1. Determining the objectives and scope of the simulation model.
2. Investigation of the resources for the simulation model. This step investigates the available data, theory, and expert knowledge on the systems investigated, the phenomenon, and/or the process modeled.
3. Choice, building, and development of the simulation models.
4. Verification and validation of the simulation models.
5. Analysis and manipulation of the simulation models.
6. Inference and learning on the real target systems.

The analysis method for answering the research questions of the thesis are detailed in the Chapter 4 (Contributions). The analysis method relies on Stake (2005)'s frameworks for within and cross study case analysis.

The three case studies represent three different systems in urban or metropolitan environments. All cases deal with uncertainty in intervening in systems within urban environments, and these systems are viewed as complex adaptive systems. In order to be able to answer the questions in different settings and areas, the three systems provide three different system compositions discussed upon the description of each of the cases.

Figure 3.1 shows a summary of the methodology that is used for this thesis.

3.1 Study Case I: The Venice Pedestrian Simulation

Background and Investigation of the Goals

Venice is one of the major tourist attractions in Italy. It faced over the past decades an increasing number of tourists, which led to the incapacity of the city to provide tourists with enjoyable experiences and to the local population to move comfortably (Canestrelli and Costa, 1991; Borg and Costa, 1993; Mamoli et al., 2012; Massiani and Santoro, 2012). Venice is mainly a pedestrian network built over small connected islands connected to the mainland through one single bridge (see Figure 3.2). As a cultural heritage, Venice has many attractions spread throughout the islands. Venice has a water public transit system connecting the islands. The water bus stations represent other entry points to the pedestrian network (see Figure 3.2).

Investigating Venice requirements on a simulation followed a series of interviews with the agency mobility of Venice. It elicited the sought role of the simulation. It also checked resources of Venice in terms of data and the knowledge over the city issues and its pedestrian and public transportation network.

The result of this step showed that operators had extensive knowledge of the city and its dynamics. They also know most of the problems faced in the city transit system and

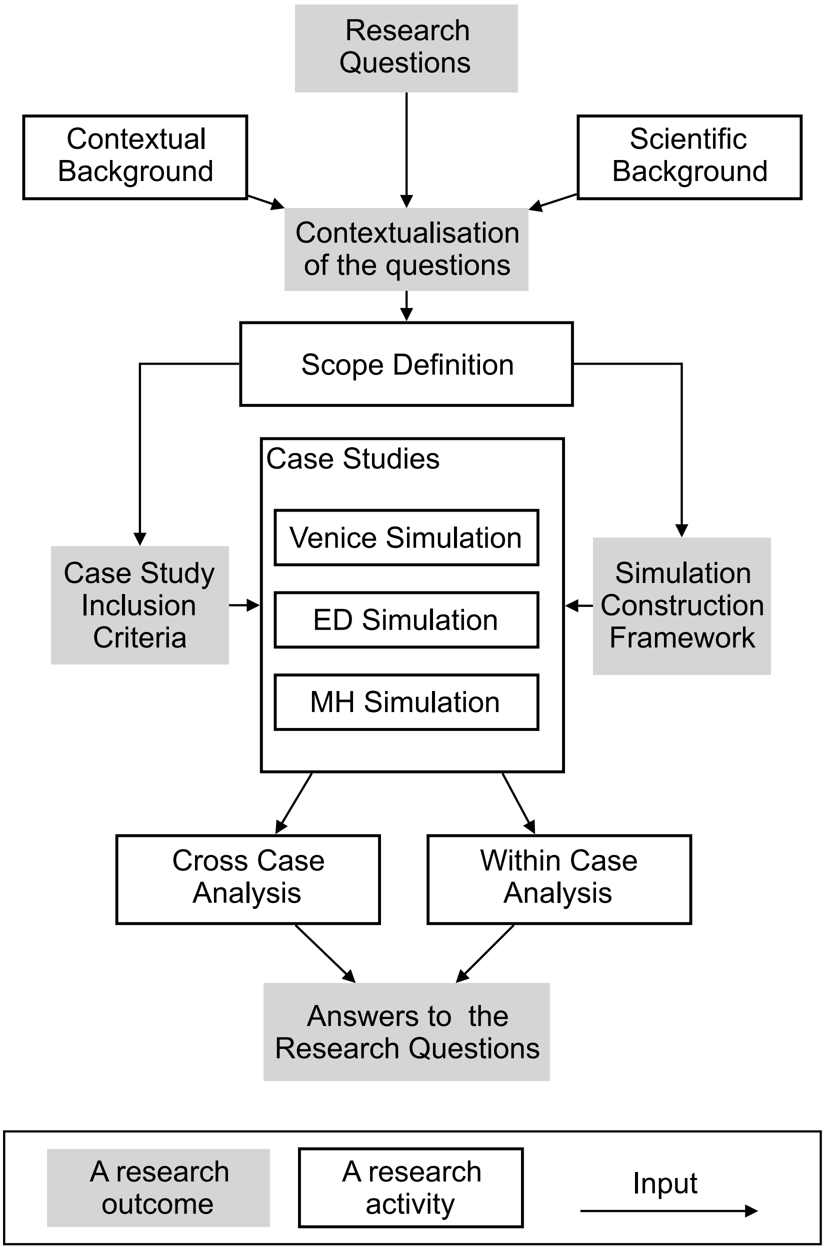

Figure 3.1: Methodology

pedestrian networks, since those were known for decades already. The variables that were monitored were crowdedness (densities), and travel times across the pedestrian network.

The use of simulation modeling, in this case, was twofold. The first objective was to provide public transport operators, together with other relevant agencies, the tools to explore solutions to the crowdedness in some areas in Venice. The simulation also is intended to provide operational measures to respond to scenarios of disruption of public

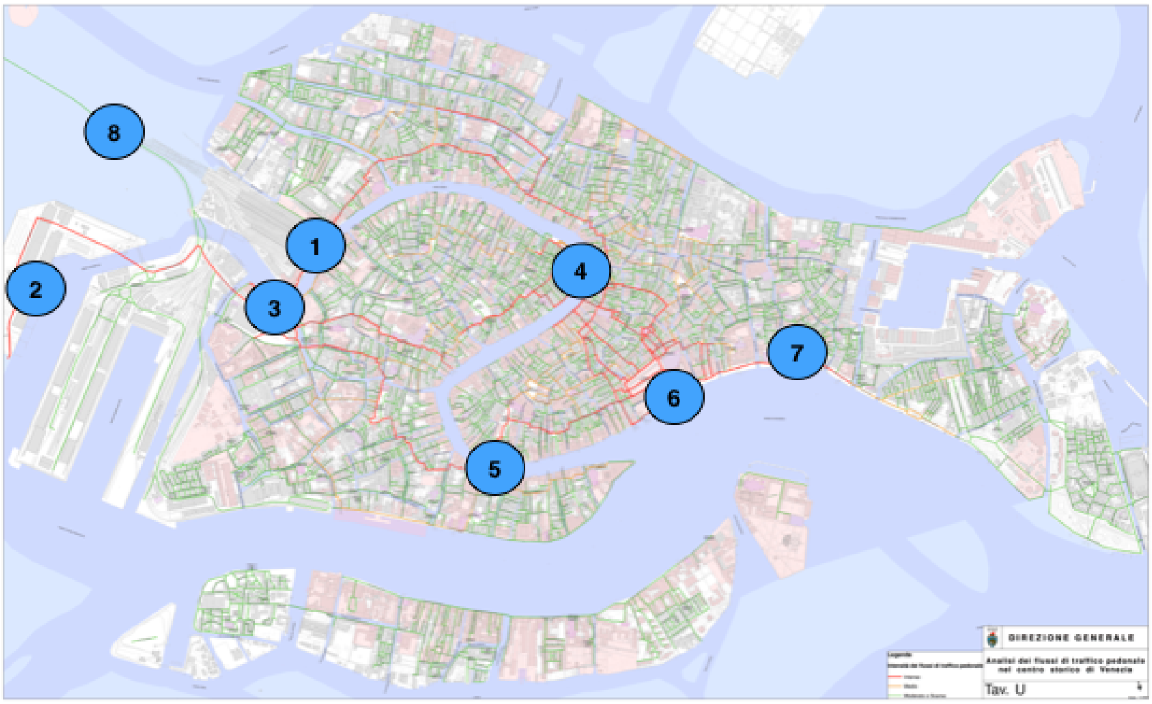

Figure 3.2: A Map of Venice and Important Access Points and Attraction in the City (Moustaid and Meijer, 2017).

transport and cultural events. Second, computing dynamic travel times between main attractions given levels of crowdedness. The goal was building a simulation that can allow its users to explore options such as changing, building new water bus stations, closing, and opening pedestrian links, or diverting pedestrians to different paths. The available data to achieve these goals were was very limited and sometimes lacks precision.

- The geographic data of Venice in the form of maps including locations of the main attractions in the city.
- The water transportation data in the form of the number of pedestrians taking water transportation from which stations.
- Data of individual trips in the pedestrian network with the time they occur.

Simulation Building

The lack of highly granular data and the existence of vast knowledge on the city and its patterns resulted in the need for the development of a low-dimensional simulation model. Besides the fact that low-dimensional models are often easier to validate (Batty, 2015), the modeling approach intended to use expert knowledge as a direct input to the simulation model to see whether it can make it more realistic.

A literature review of pedestrian modeling showed that most pedestrian modeling often relied on high granular models using CA models (Blue and Adler, 2001; Burstedde et al., 2001; Dias and Lovreglio, 2018), microscopic ABM (Helbing and Molnár, 1995; Chraibi et al., 2010; Chen et al., 2018) empirical studies that drove fundamental diagrams from experiments with pedestrians walking in corridors, or T-junctions (Schelhorn et al., 1999; Hussein and Sayed, 2017).

Most pedestrian modeling focused on fundamental diagrams. A fundamental diagram (FD) is a relationship between the three variables often investigated in transport flows; density, flow, and velocity.

- Density is the measure of the number of pedestrian per space unit.
- Velocity is the measure of the speed of a pedestrian group.
- Flow is the measure of the number of pedestrian crossing a space per unit of time.

The simulation in order to take into account the particularity of the Venice case generalized an existing analytical FD that expressed flows as functions of densities on a corridor (Flötteröd and Lämmel, 2015). Flötteröd and Lämmel (2015)'s model is fit to be applied as it expresses bi-directional flows relying only on a few measurable parameters without the need for highly granular-data. It also showed a good fit against real-data and other models validated and calibrated against data.

Flötteröd and Lämmel (2015)'s model was generalized to compute flows at the level of pedestrian intersections and interfaces, as shown in Figure 3.3. The generalization is the subject of the appended Paper I (Moustaid and Flötteröd, 2019). The generalized model expresses flows as a function of densities in addition to four measurable parameters, (1) maximum pedestrian velocity, (2) maximum density, (3) avoidance parameter representing the amount of time a pedestrian loses when encountering another pedestrian, and (4) a fraction matrix for intersection representing the way flows break at the level of intersections.

The generalized model relies on established theories in urban traffic flow and shows how those can be used for pedestrian modeling. Such theories include the use of the analogy to Kinetic Wave Model (KWM) to study traffic and the numerical schemes (Godunov) used to solve the Kinetic Wave Model (Lebacque, 1996; Daganzo, 2006; Flötteröd and Rohde, 2011). The simulation model is a cell-transmission model (CTM), where the cells exchange flows given their densities. The generalized FD expresses flows as functions of densities in two formulations:

- An interface model, computing the flow exchanged at the level of an interface separating two cells (Figure 3.3).
- An intersection model, computing the flow exchanged at the level of an intersections of multiple pedestrian pathways (Figure 3.3).

A pedestrian network is then modeled as a CTM, i.e., a network of pedestrian links, where each link consists of several cells. The intersection and the interface model allow computing the flows at adjacent cells, given their densities at every simulation time. The

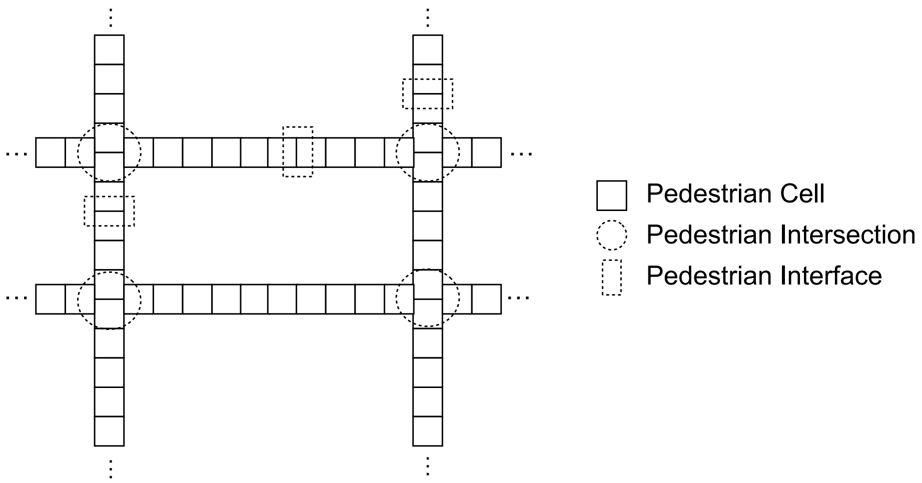

Figure 3.3: Pedestrian Cells, Intersections, and Interfaces

simulation allows for the network dynamics to emerge from those interactions taking place at the level of the cells. Figure 3.3 demonstrates an illustration of a small pedestrian network.

Through the generalization of the FD into a model, a pedestrian network can be fully simulated if provided with the following data.

1. Entrance rates over time, representing the amount of incoming pedestrian flow. In the case of Venice this is provided by aggregate data of the number of pedestrian incoming from select water bus stations, the mainland bus and train stations, and their distribution overtime given by expert operators.
2. Exit rates over time, representing the amount of outgoing pedestrian flow. In the case of Venice this is provided by aggregate data of the number of pedestrian outgoing via select water bus stations, the mainland bus and train stations, and their distribution overtime given by expert operators.
3. Fraction matrix at the level of intersections used through computation using the knowledge of experts of the major paths in the city, assisted by partial data of travellers. A map of the most used links is used to determine these fraction matrix.

Simulation Use

The pedestrian model provided the possibilities of all the strategies expressed at the investigation of the goals of the Venice simulation. It allowed, for example, to test the closure of a pedestrian corridor, moving access and entrance points (water-bus stations) to the network. The use of the simulation in line with the objective was twofold,

1. Dynamic travel times between points of interests were used in a travel app in Venice. (see Paper II, Section 4.3.2)
2. Intervention of multiple actors dealing with crowdedness of the pedestrian network in specific scenarios (see Paper II, Section 4.3.1).

3.2 Study Case II: Metropolitan Emergency Departments

Background and the Simulation Objectives

In the metropolitan area of Stockholm, the major hospitals that are responsible for most emergency care provision are often exchanging flows of patients and information. The provision of the emergency care in Stockholm goes under constant changes in physical infrastructure and operational and managerial measures to tackle problems related to the quality of emergency care in the region. As the region becomes even more connected, it behooves emergency care planners to look at the emergency care provision as a system problem. Effects of changes at the level of an emergency department (ED) or population behavioral changes can propagate beyond one ED boundaries. The goal of the simulation is to provide a tool to study EDs at a system level. An urban system where EDs are the provider of care through the healthcare staff, and where the patients, as the seekers of care, choose or get assigned specific EDs. The simulation objectives are to determine if a simulation is a plausible tool to investigate such a complex system and to test under the simulation new measures to reducing waiting times (WTs) at the level of the systems and its multiple overlapping subsystems.

Simulation Building

The literature of the operations and design of emergency care show three dominant cores of literature.

- Studies that were concerned with the effects of the unpredictability of patient flows and their consequences on quality of care, patient satisfaction, and staff overload (Derlet and Richards, 2000; Sun et al., 2000; Gerard et al., 2004; Hoot and Aronsky, 2008; Guttmann et al., 2011).

- Studies that investigated ways of reduction waiting time, decrease pressure on emergency care through analytical methods such as simulation, optimization, and general operations research such as queueing theory (Bagust et al., 1999; Wang, 2009; Stainsby et al., 2009; Monks and Meskarian, 2017).

- Studies that looked into account the characteristics of the demand and its origin, often using empirical studies to understand the volume of the demand and the reasons leading for consultation of emergency departments (Suruda et al., 2005;

McCarthy et al., 2008; Knowlton et al., 2009; Chen et al., 2015; Brown et al., 2015).

The simulation objective is to have a system approach to investigate the effects that are shared beyond a single hospital boundary that combines elements of these three bodies of literature. The method used is an incremental (sequential) building of an agent-based simulation. The agent-based simulation takes into account the demand origin, the demand distribution over multiple EDs, the transportation to an ED, the waiting, the interaction with the staff, and the end of the visit. Figure 3.4 shows the conceptual model of the simulations in both paper III and paper IV.

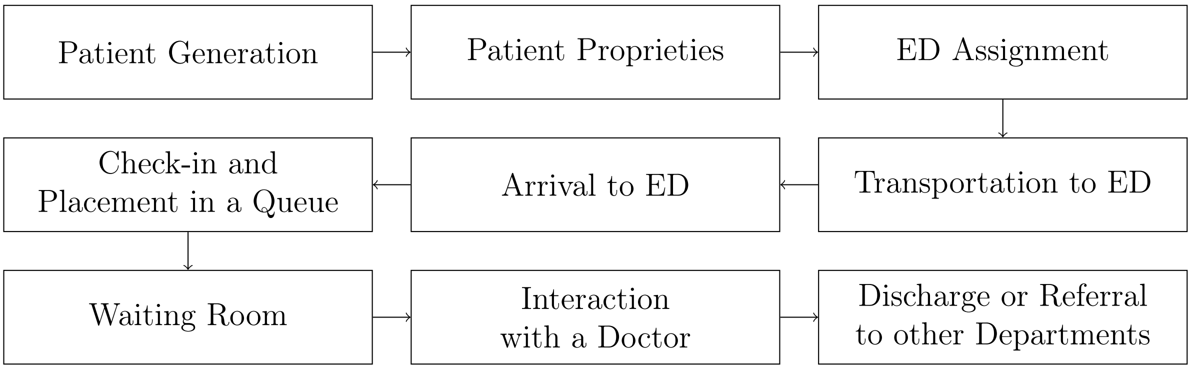

Figure 3.4: Emergency Care Provision Conceptual Model (Moustaid and Meijer, 2019b)

The model Paper III was the first step in trying to build a simulation model using such a system approach. The model simplified all the aspects of demand and supply to see if the model could result, after calibration, in patterns that are consistent with the real data. While the ABS showed promising results in the form of emergence of complexity, it was over simple to be useful for testing complex policy measures.

Paper IV, added more complexity to all the sub-models by basing them on realistic data profiles and the use of theory. Mainly, paper IV adds a dynamic relationship between crowdedness and quality of care. Under the new implementation, a model is used to simulate the way doctors rush non-urgent patients when confronted with a high level of crowds.

Table 3.1 shows further differences between the two models.

Simulation Use

The use of the simulation relied on the capability of the agent-based models to produce a lot of data that can be analyzed. The simulation was run multiple times with different randomization to explore the state space of the system, and the used descriptive as well as statistical analysis to assess the results.

- The model was used with realistic scenarios to verify and validate that it reproduces realistic behaviors.

Table 3.1: Difference between the agent-based models in Paper III and Paper IV.

	Model I (Paper III)	Model II (Paper IV)
Patient Proprieties	Location, Symptoms, Priority	
Patient Generation	Using simplified data models	Using realistic demand models
ED Assignment	Based on an ED matrix with 5 origin zones	Based on an ED matrix with 24 origin zones
Transportation	Travel time proportional to distance	
Check-in and Queuing	Constant check in-times, low and high priority queues	
Doctor Interaction	Constant Times (Calibrated)	Dynamic depending on crowdedness

- The simulation was tested against the provision of information on waiting times in different scenarios. Information of waiting times provides patients with the ED that can provide them the fastest way to access care. The simulation showed the second-order effects of providing information to subgroups of patients based on their geographical location, or through testing different adherence rates.

3.3 Study Case III: Urban Mental Health Planning

Background and Simulation Objectives

Mental health has been seen traditionally as a burden on healthcare systems. Mental health in urban areas is shown to be affected by many aspects such as employment, housing, social environment, and built environment (Warr et al., 1988; Evans et al., 2003; Evans, 2003; Nagai et al., 2007; Lederbogen et al., 2011; Gruebner et al., 2017).

As mental health in urban environments is a burden of multiple systems in cities, it is crucial to 1) define these systems and 2) to come with ways of coordinating across these systems to achieve the best outcomes for mental health. The goal of modeling and simulation, in this case, is to; 1) elicit the factors that affect mental health in cities and the relationship between these factors, 2) and find the bridges between systems that can enable best policies to improve urban mental health statuses.

Simulation Building

Paper VI (Moustaid et al., 2019a) shows the development of an SD model using a participatory model building approach to elicit a distributed knowledge around urban mental health. It also presents the results of qualitative validation and quantitative analysis of the model. The participatory model building aimed to construct a general model of factors affecting mental and did not focus on a particular city or a city system. The participatory model building hence relied on a diverse group of experts. A geographical and professional background diversification defines diversity.

Figure 3.5 shows the model building journey. First, a starting model was built and was used as a starting point for the model building. Second, participants were split into five different groups. The groups were diversified geographically and professionally. Third, the rules within the groups for the model building were explained. The rules intended to provide all participant time to present factors from their background. This would allow for the knowledge of all participants to be elicited. Participants added in turns factors and causal links between the factors. Finally, the five models were merged into one model and went through a validation process both with a group of experts and later in the form of individual interviews.

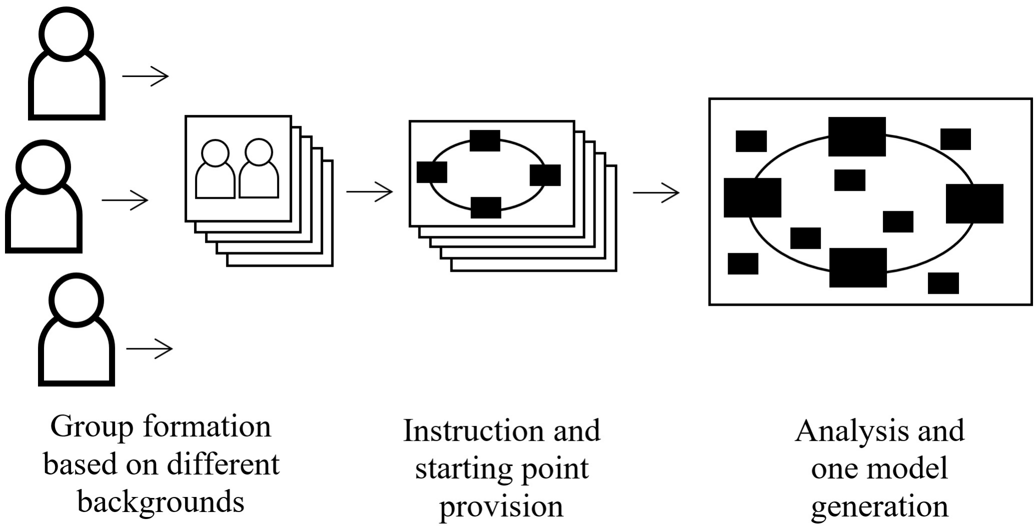

Figure 3.5: Model Building Process (Moustaid et al., 2019a)

Simulation Use

Paper VII (Moustaid et al., 2019b) describes the use of the model to investigate specific possibilities to find bridges between constituent systems of urban mental health by exploring the dominant feedback loops of the model. This was done by formalizing the model using fuzzy cognitive mapping (FCM) combined with system dynamics (SD). Fuzzy cognitive maps is a modeling technique that investigates and analyzes causalities in qualitative social systems such as social, political, or economic systems (Axelrod, 1976; Carvalho, 2013). The formalization of the model, described in greater detail in Paper VII, and the combination of SD and FCM allowed to investigate feedback loops that affect the system in significant ways showed a way to explore the model further given a specific scenario. This allows the model to find bridges that can help coordinated policy to have the most significant impact.

3.4 Similarities and Differences between the Case Studies

Some of the similarities between the case studies are already given by the research design of this thesis in that they all represent urban complex adaptive systems and that a mixed research methodology in building the simulations is used.

The additional methodological similarity is the development of these simulations from a complexity science perspective, which means that the simulation duplicated system behaviors through the focus on the elementary interactions between the components of these systems. The analysis of the simulations also took into account a complexity science perspective.

Structural Differences

The cases built simulation around real-world systems and all intended to reach a level of representation of urban systems. The cases differed in terms of the granularity of the systems they represented.

- The Venice pedestrian network represents a single system that is planned by multiple stakeholders.
- The metropolitan emergency care provision represents a system with multiple subsystems of the same nature and the same composition, dealing with the same variables and following similar processes.
- The urban mental health system represents a system with multiple subsystems of different natures, having different granularity and different compositions.

The structural diversification between the study cases is essential to provide a range of system compositions. This is practically important to answering the research questions I,II, IV, and IV, as they are concerned with the capability of simulation to reproduce systems behaviors, to understand the complexity embedded in the multi-system structure of cities as well the level of details that render simulation useful.

Table 3.2 shows the synthesis of each simulation developed through the thesis detailing the simulation logic, variables, the input data, the control parameters, the output variables.

Methodological Differences

Figure 3.6 presents a comprehensive summary of the methods and the experiments within each of the cases.

Table 3.2: Summary of the simulations in the case studies

	Venice Case Study	ED Case Study	MH Case Study
Simulation <F>	Flows in Pedestrian Networks	Netowrk of EDs	System Dynamics Model for MH
Variables <X>	Density, Flows, Velocity	Patients, doctors, and ED proprieties	Unknown prior to the model building
Data <D>	Geographical and Mobility data	Geographical, Population Data, and statistics of EDs	Simulated data
Outputs <Y>	Crowdedeness and travel times	Waiting Times and treatment times	Population Status
Controls <C>	Unknown prior to simulation use	Provision of Information	Testing simultaneous controls of specific factors

The simulation development for all cases follows the use of both quantitative and qualitative methods. The building and the use of the simulation models, guided by the simulation development framework, are mixed methods. The three case studies are classified through the topology of the mixed approaches by Leech and Onwuegbuzie (2009). Leech and Onwuegbuzie (2009) relies on three levels of classification.

1. The mixing dimension represents the level of the mix between the quantitative and the qualitative parts of the study. *Fully* mixed refers to studies that combine quantitative and qualitative research methods at some stages of the studies, while *partially* quantitative methods refer mainly to studies that use quantitative and qualitative approaches in separate ways, then combines the results at the analysis stage.

2. The time dimension refers to the time order of the quantitative and quantitative parts of the study. A *concurrent* method is when the methods take place simultaneously at a study stage, while *sequential* refers to when the methods take place in different steps.

3. The emphasis dimension refers to the method that takes most emphasis in the study, i.e., whether the methods are *Equal* or if one of the methods is *Dominant*.

The three case studies can be classified using this classification.

- The Venice case study relies on a Fully Mixed Concurrent Equal Status design. The quantitative facet of the approach is the pedestrian FD while the qualitative approach was the elicitation of expert knowledge throughout the study to scope, run, and validate the simulation. The equal status is a result of both the quantitative and qualitative approach being important for the building and the final assessment of the simulation.

- The ED provision case study relies on a Partially Mixed Sequential Dominant Status Design. The qualitative part of the ED provision case study is defining the scope of the model with practitioners from one of the hospitals in the Stockholm Region. The rest consisted of iterations of model building that relied on quantitative models uniquely.
- The urban MH case study relied on a Sequential Mixed Concurrent Equal Status design as the qualitative part of the approach, i.e., the participatory model building, took place before the model was formalized and run using a quantitative method.

This diversification allows answering the research questions with different configurations. Especially research questions II and III, which study the impacts of the implication of experts in model building as well as how quantitative and qualitative methods can assist each for reaching the usefulness of simulation models.

Summary and Limitations

The methodology has its shortcomings as it is often the case for research relying on case studies. A multicase study is often stronger, the higher the number of cases studied and the higher the diversity of these cases. However, the structural methodological differences between the three cases in this work in the model building allow for this thesis to explore a wide range of systems, phenomena, modeling techniques, and different degrees of the implication of experts. This design sought to bring answers to the research questions posed by the thesis in a wide range of settings. The process of simulation building is often a long one, and the scope of a doctoral thesis is often limited in time and resources.

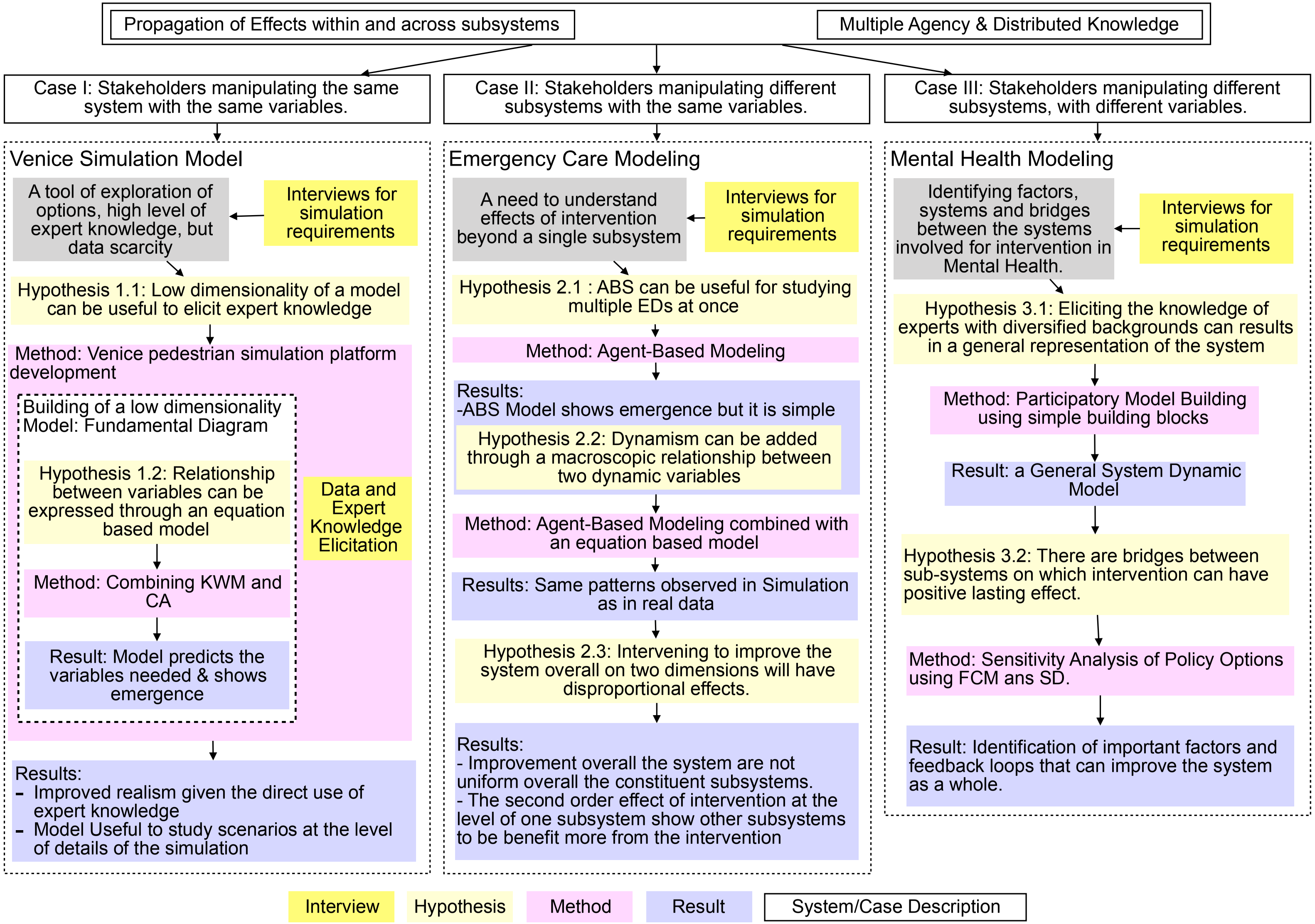

Figure 3.6: Summary of Experiments and Methods used in the Thesis

Chapter 4

Contributions

Mathematics ***can*** *be a useful tool for describing reality but reality is it messy self, not a higher abstract order existing in mathematical form*

(Byrne and Callaghan, 2013)

The analysis of the multicase approach followed for the thesis consists of a combination of Track I and Track II modes of assertions in the classification of Stake (2005). The track I model of analysis relies on an emphasis on the individuality and specificity of each use case. The track II model of analysis explores the difference and similarities between the use-cases.

4.1 Contributions by Paper

Table 4.1 shows the contribution of each of the papers to each of the research questions. The case study III contributes to all the research questions. The case study I contributes to all except question III. The case study II contributes mainly to questions I,IV, and V. Table 4.2 shows the levels of contributions of each of the cases to the research questions. 'H' (respectively 'M' or 'L') mean 'High' importance (respectively 'Middling' or 'Low' importance).

For simplification, in further mentions, the case study I (respectively II and III), are also referred to as the Venice case study (respectively, the ED case study and the MH case study).

Table 4.1: Papers contribution to each of the research questions

Research Question	General	I	II	III	IV	V
Case Study	All	All	I and III	I and III	II and III	All
Papers	All	All	II,VI	II, VI, VII	III to VII	All

Table 4.2: Research question answered from case findings

Utility of Case	Case I	Case II	Case III
Research Question I	H	H	M
Research Question II	H	L	H
Research Question III	H	L	H
Research Question IV	M	H	H
Research Question V	M	M	M
General Research Question	H	H	H

4.2 Contributions to the Research questions

***Research Question I-* What elements of complexity in urban systems are simulations capable of capturing?**

The case studies relied on bottom-up approaches in modeling. The systems were represented by simulations and models that drive the system behavior from system parts. The Venice Simulation parts were the pedestrian cells, intersections, and the entrances to and exits from the pedestrian network. The metropolitan ED modeling relied on an agent-based representation, where the agents are patients, doctors, and EDs. The MH model and simulation represented the system at the level of factors that interact within the system boundaries. All of the simulation-model relied on equation-based and data-based models to provide these systems with dynamism or inputs.

- **Emergence.** All of the simulations showed the emergence of complex behaviors at the system level. Although emergence means the appearance of system behaviors through from the interactions of the components, the Venice and the ED case show mainly two ways in which emergence is studied.

  The Venice case shows the emergence of crowdedness and its propagation in ways that correspond both to theory (The model based on an analogy to KWM) and reality. The consistency of the FD model with KWM theory is explained in great detail in the paper I. As for the application of the model in Venice pedestrian network, Figure 4.1 shows a realistic case of emergence, where planners from different agencies investigated a scenario where one of the main access points to the city is out of service. On Figure 4.1, routes on the left represent new access routes that can be established by the planners. The plots on the right represent density over the main pedestrian links in Venice network, the darker the color, the higher the crowd level. From left to right, top to buttom, the four subplots represents the system evolution over-time. The results show the crowdedness and the way it spills in areas of cities. The stakeholders evaluated the result as a realistic behavior. This case shows the emergence of system behavior from the elementary interactions. It is one instance of running the simulation and not as a common system behavior.

  The ED provision modeling also shows the emergence of complexity from the interactions of patients with EDs at the level of waiting times. The difference between this

Figure 4.1: The Evolution of the Pedestrian Network Given the Mainland Bridge to the City is Out of Order (Moustaid and Meijer, 2017)

case and the case of Venice is the stochastic nature of the models. System-level behavior is hence studied through analysis of data coming from different simulation runs, which, when analyzed, produce patterns at the system level that suggest the existence of dominant patterns. In the case of EDs, those patterns are seen in WTs. Figure 4.2 shows the simulated waiting times at different hospitals in Stockholm in comparison to real median waiting times in different scenarios. Each scenario is representing the average demand for a year (2013,2014,2015). The results are obtained through the analysis of multiple simulation runs.

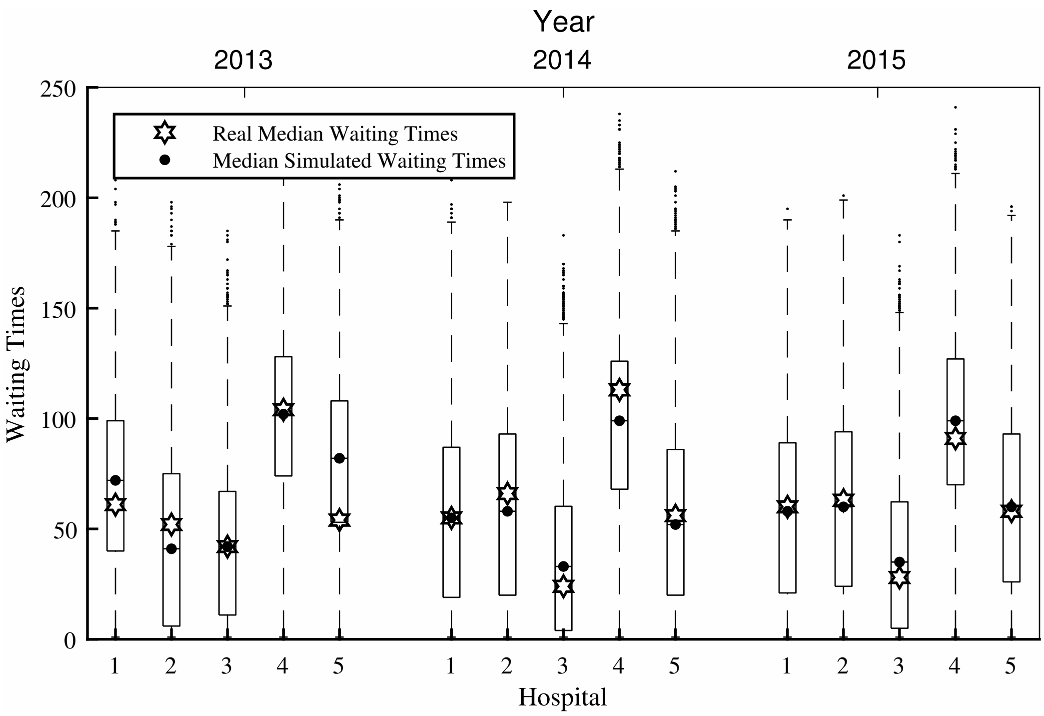

Figure 4.2: Simulated Waiting Times against Real Waiting Times for the years 2013-2015 (Moustaid and Meijer, 2019b).

- **Non-Linearity.** The three study cases relied on non-linear models. The Venice use case relied on an FD that expresses flows non-linearly as a function of densities. This results in the emergence of non-linear behavior at the network level, as well. The changes in crowd levels do not result in linear changes in travel times.

  The case of Stockholm ED departments also exhibits a case where simulation results in non-linear behavior. The experimentation with the effect of information on WTs showed how the system level WTs do not change linearly as a function of the rate of patients using that information to choose an ED. This is shown from the manipulation of the simulation in paper VII, also shown in Table 4.3. The table shows that an increase in the proportion of patients choosing the hospital that is expected to provide the least WT does not result in a decrease of WTs on a system level. α represents the adherence rate, i.e., the percentage of patients using real-time information to choose an ED. α_{ISMO} represents the adherence in the scenario where only patients from Stockholm Municipality have access to that information. α_{IAM} represents the adherence in the scenario where information is given to all patients regardless of their origin municipality. Increasing adherence to information does not necessarily result in decrease of WTs overall the system.

Table 4.3: Average waiting time under different scenarios (Moustaid and Meijer, 2019a)

Scenario	Average waiting time				
α	0	0.25	0.5	0.75	1
IAM ($\alpha_{IAM} = \alpha$)	60	58.2	55.9	54.5	55.2
ISMO ($\alpha_{ISMO} = \alpha$)	60	60.2	58.5	60.2	58.9

- **Non-Equilibrium, State Space, and Attractors.** The simulations do not assume the existence of equilibrium states as all the simulations are dynamic over-time. The systems at each time step of the simulation are at a state described by the simulation variables and outputs. The complexity of the dynamics requires analytical methods such as visualization of average values of variables of interest (Crowdedness in some areas of Venice, WT in EDs, Population status in MH). The ED case where input data feeds into stochastic models makes the simulation goes through a large number of states. However, the analysis of the model only focused on the 'average' behavior, which is represented by average WTs overtime. The state described by the average waiting times is not an attractor in the sense that the system always evolves around a state where the WTs are around those averages. It is just an easy way to evaluate the behavior of the system by considering the average evaluation of all states it was in.

  The MH case shows a different model behavior. In most scenarios, the simulation showed to converge to a stable attractor after transitioning through multiple states.

- **Boundaries, Bridges, and Feedback Loops.** The boundaries and bridges between subsystems were explored in two different ways.

  In the ED case, one visible bridge between all the EDs has been investigated through simulation: Information on waiting times. The investigation of such a bridge is related to the fact that shared information between all EDs can lead to higher visibility of which subsystems (EDs) can lead patients to doctor contact in the shortest time possible. Information can break a negative feedback loop, which is that more crowds result in longer waiting times, which results in turn in higher crowds. Information can break this by diverting patients in real-time to the hospital with the least crowd. The simulation investigation of the effects of information showed the non-intuitive effects of information in the simulation scope.

In the MH case, such clarity of bridges does not exist. The goal of the modeling and, consequently, the simulation was to find those bridges. The simulation model then, after establishing boundaries between the constituent systems, found bridges that can bring impactful coordinated policy measures. This is done by finding the feedback loops that are dominant in the system constructed using experts distributed knowledge over the system.

Through looking at emergence, non-linearity, attractors, and bridges, the simulations are shown for their usefulness to understand both structures and dynamics. For structure, the simulation showed the ability to understand relationships and effects between subsystems and actors of these systems. For dynamics, often relying on theoretical models or simple rules of interaction at the elementary components showed the emergence of dynamics, which after calibration of models, resulted in dynamics that are comparable to one seen in the real-world systems.

***Research Question II-* How can quantitative and qualitative methods assist each other in achieving usefulness of models?**

The thesis used expert knowledge to enrich the simulation models and make them useful to the users. In doing that, the thesis found ways for quantitative methods that elicit expert knowledge and quantitative methods that seek formality to assist each other in the process of building useful simulation models.

The Venice use case is a case where the elicited knowledge of experts helped fed the simulation model with the right level of data, completing it in providing realistic dynamics in the network. The data provided by the experts was used directly as a simulation input. In such a way, the fundamental diagram model has been able to exhibit realistic dynamics.

This case showed an answer to an often encountered problem in modeling. Simulation and models that predict real variables such as travel times require data to be at some level of precision (granularity or details), and accuracy (not faulty). Using a theory-based model that was not data-hungry allowed for the expert knowledge to cover up for lack of data.

The model being complex allowed planners, on the other hand, to have useful, engaging tools to test different strategies to manage flows in the city pedestrian network. The qualitative validation experiments (Paper II) run with stakeholders from different agencies in the city of Venice allowed for testing different strategies to respond to scenarios that require their collaboration to find measures to manage the system under the circumstances of the scenario.

The use case of MH is a different case of the combination of quantitative and qualitative methods. Unlike the Venice simulation Platform, the MH Model relied on a qualitative method for building the model and a quantitative method of analyzing and enriching it. The model, built qualitatively, was enriched quantitatively in two ways.

1. In Paper VI, the model is presented in Figure 4.3 as a graph of causal relationships. The structure of the model presented a directed graph or a network where the nodes are the factors, and the links are the causal relationship between those links. It allowed analyzing the importance of these factors in the model from multiple perspectives. This analysis showed the factors that had the highest reach and the ones that are the most central (For instance: *Monetary Resources, Job Stability, Language Barriers*). This allowed understanding a complex model as a static entity.

2. In Paper VII, the model was formalized by giving all factors a quantitative sense. The quantification of the factors where they were all given a dynamic value v in the range $[-1, 1]$ allows for making a dynamic simulation from a static model. The dynamism is added by combining elements of FCM with SD. This formalization allows for the simulation to be run and gain more insights into the model. The analysis of feedback loops showed how the model could be useful to explore the state space of the model and to find useful bridges between systems to improve urban MH and make the system go to an attractor.

In summary, the case studies showed that using mixed methods in modeling complex urban systems can beneficial in many ways.

1. Quantitative models requiring input data can rely on expert knowledge if the model dimensionality allows it. A low-dimensional model being less data-hungry can be more useful in this case.
2. Qualitatively built models can rely on analytical methods of analysis, and through formalization can be explored further.

Research Question III- **What does the the inclusion of experts in building and running simulation models imply on the validity of models?**

The Venice case study allowed for a high involvement of the simulation users in the process of building, running, and using the simulation. The use of expert knowledge along the process allowed to scope the simulation and determine its level of detail. Furthermore, the low-dimensional nature of the simulation allowed for direct use of expert knowledge in running the simulation.

The use of expert knowledge allowed the simulation model to increase the realism of its outputs (Results in Paper-II). Particularly, the simulation model was validated to be useful in two senses. The first relates to the scope of the simulation: the simulation is a tool for the exploration of scenarios that relate to crowdedness in Venice. The second relates to the realism of the outputs and dynamics: The simulation outputs passed a qualitative and quantitative verifications.

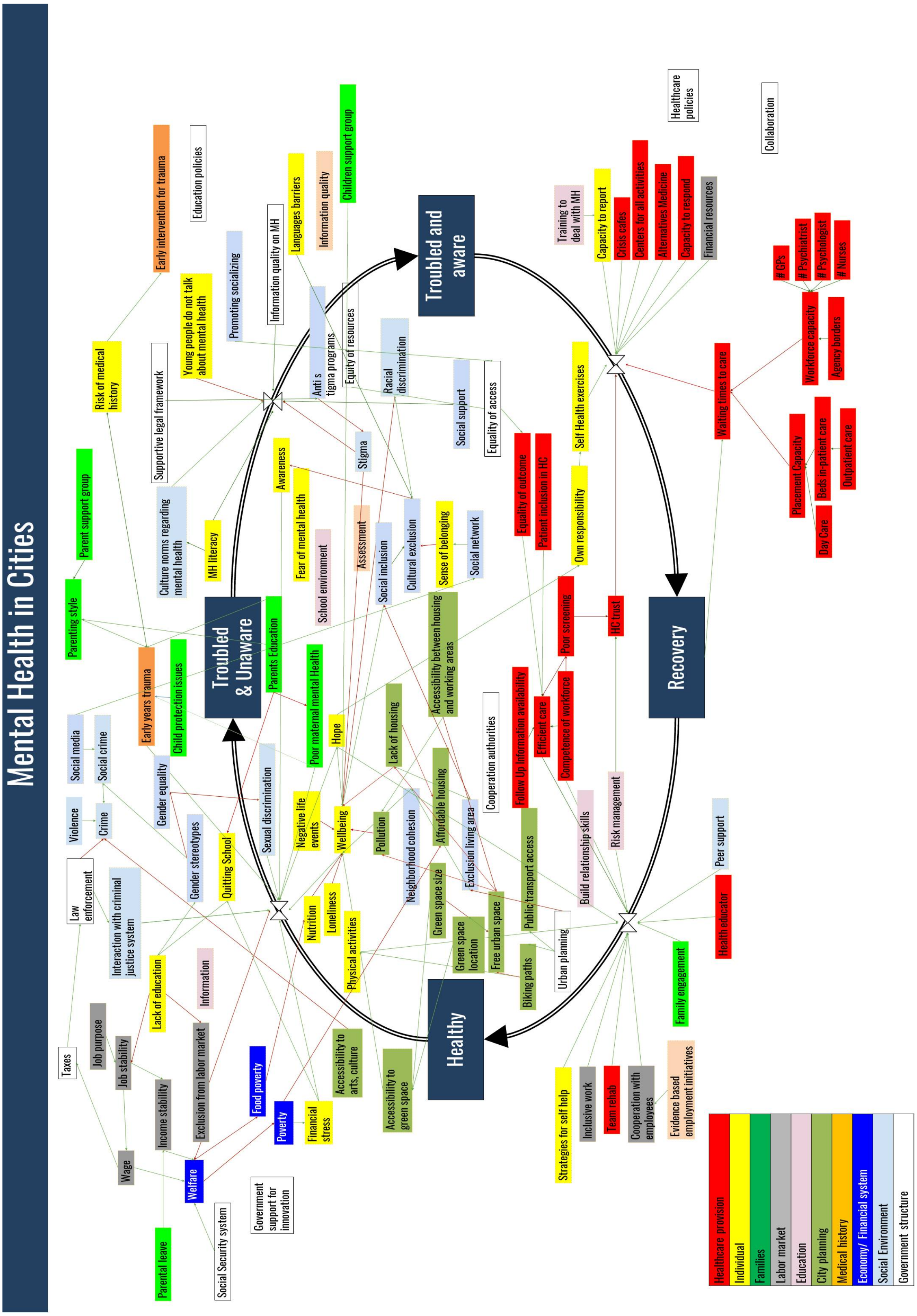

Figure 4.3: Urban Mental Health Model (Moustaid et al., 2019a)

The Mental Health use case (Paper V) shows a different approach to using expert knowledge. Experts are used to building a model based on a specific set of rules. The use of expert knowledge in this way allowed for the integration of multiple views and thoughts into one single model.

The model building exercise has resulted in a model that combined factors with a quantitative meaning such as *healthcare capacity*, *number of psychologists*, or *size of green spaces*, but it contained factors that are hard to measure such as *Wellbeing* or *Strategies for self-help*. This can be explained by the nature of the experts that were involved in the model building process, as most of them are often at the level of policy and management, and often deal with conceptual models rather than operational models. Furthermore, the inclusion of experts in the model building resulted in a pluralistic model. The model contained factors that belong to at least eight systems or domains of interventions in the city shown in Figure 4.3. The factors also represented different views of what mental health means and whether it is a question of survival or thriving.

The interviews that followed for the validation of the MH model all exhibited that the model can always be more detailed or more specific from the perspective of the interviewees. The model building sought generality, and consequently, the model represents a general picture of urban MH from the perspective of cities with the characteristics of the participants in the model building. Some interviewees pointed the lack of specificity of the model either to the problems they face within their sub-systems, or to the structure of their systems.

As merged learning from these studies, expert knowledge can increase the realism of simulation the simulation both at the level of representation, scope, and dynamism. It can also allow for the emergence of different views under a single model, which can be useful for policy-making in spaces with complex policy structures as cities.

***Research Question IV*- In which ways can simulation assist design of interventions in systems with multiple interconnected subsystems?**

City systems being very connected and often interacting in the same geographical space, serving the same populations, are often in the difficulty of finding the right policies that can have the best and lasting impacts.

In the ED case study, the focus was mainly on the propagating effects that information can have on patients' WTs as well as their quality of treatment. The learning from the use case through the simulation was the following:

1. Paper III and Paper IV show that sharing information on WTs does decrease WTs if patients choose to go to the hospital that can provide the shortest time to see a doctor. It also showed that adding dynamism through the introduction of variable treatment times increases the complexity of predicting the effects information can have on subsystems levels. Paper V shows that system changes are not necessarily proportional to the constituent subsystems.
2. Paper V explores the model further, as making all patients from all municipalities in Stockholm seems to be unlikely and costly, the most geographically central group

is hence looked at. Stockholm municipality, been the most central municipality in the Stockholm Region and the one where patients are already distributed between all five major hospitals, is the one that possibly has a significant impact if patients were diverted in real-time. The results show the second-order impact of diverting patients originating from Stockholm municipality on the rest of the system. While information is provided only to a group of patients, the best effects are seen in other subgroups.

Those two results show that when managing subsystems in urban systems, one can instead of trying to change the overall behavior system with overall system intervention, find which subsystems or sub-populations can bring impacts. Paper V mainly shows that the effects of intervening at a subsystem can result in other subsystems being more positively impacted.

Paper VII shows a much different approach to assist in planning city subsystems. As the subsystems in question are different in size, granularity, and nature, the approach focused on finding the most meaningful ways to cooperate across the boundaries of these systems. This is done by the analysis of the sensitivity of the system to the simultaneous positive control of multiple factors belonging to the same feedback loops. The reason behind such an approach is the fact that feedback loops are known to either stabilize systems at an attractor or to drag them into new attractors that can be different.

The analysis of the approach under different scenarios shows indeed that different feedback loops have different effects and the existence of loops that can be useful from a planning perspective. This method is useful to identify significant bridges that cut across multiple city subsystems.

Through these cases, simulation is shown to help intervene in urban systems with multiple subsystems in these two ways. First, finding bridges between these systems that can improve the system overall. Second, by finding in which ways these bridges can be effectively used.

Research Question V- **What can be learned about intervention measures in urban systems under the process of building models for such systems?**

The three case studies followed a process of building simulation models that started from real-world needs. Under the model-building processes, some learning occurred about the systems represented. These learning are categorized as follows,

- Learning about the nature of interventions that can benefit the system. In the Venice case, deciding the level of details of the model was also a decision on the type of interventions that can be tested in real-life. Hence through the model building, several intervention options to be investigated through the simulation are elicited and formalized. This elicitation is also an expression of the options that can potentially benefit the system. Those options later guided the simulation development.
- Learning about the scope of the system at which intervention is taking place. This is shown in the case of MH where the participatory model building combined knowledge of experts from different domains and revealed the extent of the system they

are part of. In the validation interviews, a common theme was that the model shows the extent of MH as a city and an intersystem issue.

- Learning about the important dynamics that need to be taken into account for intervention measures. This is shown the most in the case of ED modeling. The model in paper III was too simple to draw useful information about the system behavior under the effect of an intervention measure. Comparing the results of the model in paper III, and the model in paper IV, isolated the effect of including a dynamic relationship between crowd levels and treatment times.

Merged learning from all the cases is that during the simulation or model building, the decisions made about the level of representation of the models is often one that is linked to the kind of interventions that needed to be tested. The factors, for example, in the mental health model, were all added as they are believed to be essential for planning for mental health. In the same way, densities in the pedestrian network are essential to compute travel times and crowdedness levels. Hence the model building becomes an exercise in deciding which elements, effects, and interactions in the system are of crucial relevance to the intervention measures that can be undertaken.

The Central Research Question. **What makes models and simulations a valid and useful instrument to design interventions in multi-stakeholder and multi-subsystem urban systems?**

Mediation Value of Models

Simulations and models are a bridge between the theory and the real-world. They mediate between two worlds that are often separated. The value of simulation models as mediators in that sense is not new. It is, however, corroborated in this thesis. The different applications of theory allowed the models, based on theory built by scholars over the years, to be useful through models, to the planners and relevant stakeholders in cities. This is the case specifically in the application of KWM to model pedestrian flows, which allowed planners to use the tools. This is also the case in the use of an ABM to simulate EDs using rational choice theory (patients' choice of EDs).

This thesis, through the use of expert knowledge in modeling, shows different ways of mediation of models. At the development of the MH model, using participatory modeling showed the model-building exercise to be a mediator between actors of different domains. Similarly, at the use of the Venice simulation, multiple actors were capable of discussing interventions relying on a simulation model.

Expert knowledge shows to be an important ingredient in the building of models for urban systems. The thesis shows two ways in which the knowledge of experts can be useful, both concerning theory and the real-world.

- Contextualisation of expert knowledge: This is the case in the Venice Simulation. The model focuses on pedestrian flows and relied on theory to simulate these dynamics. The system boundaries and composition are already known. It remained only to make the simulation models run. The expert knowledge was used in this case to feed the model. The expert knowledge is in this case contextualized. That it was elicited around few important variables.

- Full exploration of expert knowledge: This the case in the MH modeling. The system is not fully known before the modeling exercise with experts. The participatory model building hence allowed for exploration of the potential factors and components of the urban mental health system.

This leads to proposing a triadic relationship when it comes to building simulation models of complex realities in urban systems. The triadic relationship is theory, expert knowledge, and real-world systems. This triadic relationship can allow for models to be enriched through expert knowledge and appropriate theories, to be able to relate to real-world systems. Models, by being at the center of this relationship, can allow expanding knowledge about the real-world, theories, and be valuable for real-world interventions.

To conclude, it is hard in light of the evidence shown by the cases, to say that expert knowledge is as crucial as theory applications in model building. More studies should provide evidence for or against this proposition. However, in systems that are multi-system and multi-stakeholder, the inclusion of experts is paramount to understand the scope of the system, its composition, and its propagating effects. Theory can contextualize the inclusion of experts to increase the value of learning from these models.

Understanding Complex Effects

The simulations in this thesis showed that complexity science could indeed provide a tool to understand the complex nature of cities in simple ways. The bottom-up approach of modeling showed that simulation modeling can take into account that complexity in real-system is indeed bottom-up. The interactions at the component level explain behaviors at the system level.

The thesis shows that simulations using such ways of representation allow understanding of how interventions at the bottom, i.e., microscopic level (agents, cells, factors) affect systems and subsystems alike. This is shown in the case of the use of information at ED planning, finding bridges at MH planning, or exploring city options at the Venice simulations. This is particularly important today as the shift to bottom-up approaches in planning is happening. The system approaches are becoming more dominant in multiple fields (Carey et al., 2015).

Validity and usefulness

This thesis used both quantitative and qualitative validation methods. The quantitative methods compared simulation outputs (travel times or waiting times) to real-world outputs. Qualitative validation was used to (1) assess simulation results in scenarios that are novel (2) and to validate the level of representation of models from the perspective of planners.

Through the case studies, validation was shown to be indeed value-dependent. The quantitative validation often showed that after calibration, the simulations show an empirical link to real-world systems. It did not aim to claim truth of the models, but rather it showed the ability of models to predict some variables, using simple representations of the world.

Quantitative validation showed further the value-dependency of validation of models.

- The MH validation interviews showed that building a model that represents all values and perspectives is difficult. During the interviews, interviewees mentioned the specificity of the model to the decision-making structure for their cities. Another interviewee was rather concerned with the model being useful in planning for extreme neighborhoods. The model as a tool to find cross-system collaboration, however, was validated by multiple interviewees. Interviewees have indeed expressed that the model in its form can provide a catalyzer to finding ways of initiating policies around important aspects of mental health, such as prevention, or wellbeing.

- The qualitative validation in Venice focused rather on dynamism than representation. The validation experiment conducted with multiple agencies showed an emphasis on the ability of the simulation to provide plausible dynamic behaviors given scenarios of interest.

This is possibly explained by the fact that in the case of MH the system is unknown and hence the knowledge of 'what' is the system is more important on the specific of 'how exactly' the system behaves. In the case of Venice, the system is known from decades already, and the 'how' is a much more important question. It is also important to understand that the scope of Venice was limited to three variables that are predictable, which is not the case in MH, where the number of variables at the end of model building was 111.

The thesis shows that simulations are useful in that they can reproduce system behaviors and structures (boundaries). The simulation allows understanding non-intuitive behaviors and effects, as shown in the case of the effect of information on waiting times. The simulation also allows to evaluate bridges and find new bridges between systems to improve specific metrics overall the system.

4.3 Other Contributions

Besides each the contribution to each of the research questions, the thesis have the following contributions to the following fields.

- **Pedestrian Modeling.** The pedestrian model presented in the Paper is a novelty in pedestrian modeling. The model is a general one allowing for simulation of pedestrian networks besides the one presented in this thesis.

- **Emergency Care Modeling.** The models presented in Paper III and VI are amongst the first attempts to use system approaches in modeling metropolitan emergency departments from a multiple emergency department perspective. The model is a model of models, which makes it easy to extend. The model can be extended to test different strategies relating to different aspects of metropolitan environments, such as closure of an ED, changing capacities, or changing patient behaviors to only name a few.

- **Urban Mental Health Modeling.** The model presented in paper VI and VII is a novelty for the domain of mental health policy and it is inline with the application of system approaches in public health policy (Carey et al., 2015).

Chapter 5

Conclusion

'Imagination rules the world'
Napoleon Bonaparte

5.1 Summary

The challenges faced today by urban systems arise from the very nature of urban systems as complex adaptive systems. Urban systems as spaces of interactions of political, economic, social, and physical entities are spaces that are ever-evolving. The consequent structure of urban systems as systems of systems poses particularly a challenge to planners to take into account the ways the effects of their interventions travel beyond their system boundaries. It also challenges them to find ways of coordinating beyond their own systems to reach their objectives. This challenges models and simulations aiming to be valid and useful mediators to help planners, managers, and operators, to take into account the complexity of such systems.

This thesis embraces nature of urban system as complex adaptive systems that are difficult due to their nature as systems with multiple components, whose interactions result in complex system behaviors. Relying on complexity science as scientific background and simulation as a method of exploring complexity, this thesis shows ways simulations can be relevant tools to assist intervention in urban systems in their current context. A context which is characterized by high connectivity between constituent systems of urban systems and which requires planners to take into account such a reality in planning. Through multiple cases, the thesis shows the relevance of simulation and modeling to be tools of exploring complexity. In that, the thesis investigated the ability of simulation to reproduce these system behaviours while taking into account their characteristics. The building of these simulations was also explored to involve experts in the process of building and running these models and to examine the implication of their involvement on the models. The thesis explored also multiple ways of learning from simulation models both at their construction and analysis, taking all into account the interconnection and the multi-actor nature of urban systems.

The method used to answer the research questions has its shortcomings and limitations. However, the diversification of the cases allowed to answer the research questions in different contexts. The methodological diversification in the model building also allowed to explore

- The different model building methods (quantitative methods); agent-based modeling, equation-based (dynamic) modeling and data-based (stochastic) modeling based on aggregate data.
- Different levels of involvement of experts (qualitative methods) throughout the model construction, running, and analysis.

The three urban systems that were investigated presented different granularity and different origins of complexity. Pedestrian modeling focused mainly on system level variables, emergency care modeling focused on subsystems with their own agency focusing on similar variables and similar objectives, the mental health modeling focused on systems with different variables with totally different objectives.

The findings of this thesis show the ability of simulation modeling to investigate the complexity that lies in urban systems at multiple levels. Bottom-up approaches in simulation modeling, relying on agent-based models or dynamic modeling, i.e., equations defining the relationship between simulation variables, can be useful at reproducing the complexity that lies in the systems investigated. As all the cases showed the emergence of non-linear behaviour and the ability to explore those system and their states far from equilibrium, as well as the ability to find meaningful bridges across systems. The bottom-up approaches relying on dynamic modeling are often classified as retroductive approaches (Sayer, 2010; Byrne and Callaghan, 2013). Retroduction being 'the mode of inference in which events are explained by postulating the mechanisms which are capable of producing them them'. The other contributions of the thesis is indeed in postulating and identifying these mechanisms at urban systems, and the learnings that can happen under that process.

The inclusion of experts in simulation studies is not new. Planners are often consulted to scope the simulations. This thesis, used planners to scope simulations as well, but it also went further with the implication of experts in two ways. The first being the use of expert knowledge as a direct input to simulation models. This was done methodically in matching the dimensions that experts have knowledge on, with a low dimensional model using that same knowledge. This allowed increasing the realism of the simulation outputs, making it useful as an operational tool. The second use of the expert knowledge was in building a model itself. While models are often built with experts, the approach explored in this thesis was one that embraced the full complexity of the urban systems as 'systems of systems', hence building a very complex model, using simple building blocks. The model analysis then relied on appropriate quantitative methods (FCM, SD, Graph Theory) that embraced the complexity. It showed ways of using such models to find bridges that can connect and build bridges between the constituent systems in ways that can improve the system overall objectives.

Through the implication of experts in model building, multiple ways of learning about the systems took place. The decisions taken at the model building increased the knowledge about the systems where interventions are going to take place. This thesis found that planners learning can take place under the process of model construction. Planners can learn about the scope of the system they are part of as shown in the case of mental health planning. The scope does not only mean learning about the actors or the systems that are part of the complex whole, but also, the level of interaction between these systems (propagating effects). Another learning that took place during the model building in Venice is to formalize the type of interventions that are possible given the means of the city and its resources. The incremental model building in the second case study showed that through the simulation building, one can learn which dynamics and effects in the system should be taken into account when formulating operational and policy measures. Overall, this suggests that the model building process can benefit planners in learning the scope and the important dynamics of the systems they intervene in.

5.2 Discussion

This work shows that simulations can actively assist intervention design in urban systems. Complexity science provides new ways of exploring complex systems, and simulation can truly be a tool that make complexity science a tool of exploration of these systems. This conclusion stems from the ability of simulations to reproduce aspects of these systems, both as dynamic systems and as systems that have a complex structure. The importance of reproducing both is due to the fact that agency really matters in planning social systems. For simulation to be useful, dynamics are only a part of the solution. Structure and system boundaries show the responsibility and the effects each subsystem and actor bring to the system level. This is rather an essential advantage of use simulations for interventions. To intervene in systems with the political and social complexity of urban system, agency and system boundaries matter.

In response to challenges faced by simulation modeling in terms of representation and validity, the thesis showed ways in which expert knowledge can be useful for building simulations. The Venice case showed that simulation with the right level of details of a model could provide the chance for expert knowledge to be an input, hence increasing its realism. The case of MH showed that in systems that are large and where cross-system coordination or collaboration is needed, expert knowledge could be used to build models that show the scope and the factors in play. The latter case also showed that a qualitatively developed model can have valid representation and that they can be explored further using quantitative methods.

Bridging urban subsystems is necessary as these systems grow more complex and more dependent. Finding meaningful bridges between urban subsystems is only a first step in interventions, it always remains to study those bridges and how they affect the system as a whole and its parts. Simulation can be useful in that as well, as shown in the case of ED modeling.

Interventions of one actor will always affect other actors in desirable or nondesirable ways. Modeling can be a tool of investigation of effects, but they can also help understand these systems in their multiplicity of actors. This is even further important as actors are becoming even more specialized with extensive knowledge of parts, but not on all the systems they deal with.

5.3 Conclusion and Outlook

In conclusion, this thesis shows the potential of simulation modeling to help planners in dealing with the complexity of urban systems. Planners can learn about the systems they are intervening in, as well as, explore their options, and see the effects of their interventions within their systems and across other urban systems. Taking into account the complex structure and dynamics of these systems can enable policy-makers, planners, and operators to affect systems in ways that take into account that these systems are adaptive and ever-changing. Including experts on these systems at simulation building, or through interactions with simulation models can benefit both the simulation model to have a level of realism, validity, and dynamism that is relevant to the planners. It also allows planners to learn about these systems and about the intervention possibilities they have.

The implication of the inclusion of experts throughout the models building journey can benefit other analytical models. As machine learning and artificial intelligence applications in urban systems grow, finding ways to make these technologies relevant and useful can benefit from the application of complexity science frameworks and theories, and from the knowledge of planners to understand the structure and the nature of the urban systems.

As urban systems keep growing in complexity and size, and as human knowledge becomes even more specialized, the need for interdisciplinary methods of solving social challenges will grow even more. Participatory methods and engagement of actors in the use of analytical ways of intervention design can be beneficial. This requires more research on methodological ways of integrating worldviews from the policy-making realm and the realm of technology, science, and mathematics.

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