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Exploring the emergence of learned behaviour from intelligent agents in a constrained 3D spatial environment

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Abstract. The original Sugarscape agent-based model has been adopted by the modelling community as a simple yet very insightful model. It uses event-condition-action rules to simulate a society which ages over time and consumes sugar to survive. The model is well known and has been adopted in fields such as Economics, Computer Science and Biology therefore its utility will be explored in this research. The research will present an implementation of the original Sugarscape model (refined for 3D space) using Reinforcement Learning (a form of Machine Learning which enables autonomous agents to learn by rewards and penalties). A Reinforcement Learning algorithm such as Q-learning is implemented in this research as there is a lack of work being done to integrate Q-learning in conventional ABMs. Furthermore, Q-learning provides agents with the means to evolve overtime and adapt to changes without explicitly defining the actions to take under individual circumstances. On the other hand, agents that use event-condition-action rules do not adapt to change, they instead react to changes by applying actions that have been hard coded prior to model execution. The problem addressed is, can agents make more realistic decisions by learning from their environment using reinforcement learning? This research will explore reactive and adaptive behaviours to see if actions performed by agents within the given environmental circumstances would be as expected if they were humans. Furthermore, agents can anticipate future trends, for example; learning the fastest route out of a burning building while anticipating a fire alarm. This model will be implemented in Unity which is a video game development engine. Unity has not been widely adopted by the agent-based modelling community, yet does provide useful facilities for the creation of models.

Keywords: Agent-Based Model · Reinforcement Learning · Decision Making.

1 Background: Agents and Learning Algorithms

Learning algorithms such as Q-learning [12] have been around for many years. Signs of the emergence of these algorithms can be traced back to early video games. Early ABMs applied condition-action-rules, then came BDI [9] and then hybrid BDI frameworks such as [5], PECS (Physical conditions, Emotional state, Cognitive capabilities and Social status) [11] and so on. It is clear that frameworks for ABMs are constantly evolving. During this period, Machine Learning algorithms are also being developed. Reinforcement Learning algorithms (a subset of Machine Learning algorithms) are not domain specific, meaning they can be adopted by any system that requires autonomous control of software that makes decisions overtime (mainly good decisions). There is a gap in the research being done to supply ABM frameworks with the ability to allow agents to adapt to changes during model execution (which is usually what happens in the real world, we constantly adapt to changes in our lives that we may never have expected i.e. adapting to the death of a loved one). Moreover we evolve overtime, we learn new skills and apply these skills that we never knew before. Reinforcement Learning provides agents with these traits. This research aims to apply a Reinforcement Learning algorithm to agents within a defined environment (Sugarscape [2]) then, analyse these agents to see if they can adapt to changes overtime and evolve.

1.1 Q-learning

Reinforcement Learning algorithms are used to provide agents in models with policies to execute within a given circumstance. These algorithms can be applied to any model that has a goal which needs to be fulfilled. For example; modelling driver behaviour where agents (cars) need to navigate from point A to point B without causing congestion. Large rewards will be given to cars that follow a route and penalties will be incurred if cars collide. As we run the model over many iterations, the agents start by making mistakes but each iteration they learn something not to do and something that is acceptable.

Q-learning has been utilised in various domains and is an option for agent based modelling researchers. [14] used Q-learning to calibrate an agent based supply network model by using agents to find optimal values for parameters in their operating policies. Moreover, the competitiveness of the electricity market is modelled using agents that utilise Q-learning to learn from past actions and deploy strategies against other competitors to ensure a fair distribution of electricity among suppliers [7]. [10] implemented the Q-Learning algorithm in order to model the bidding strategy of suppliers (agents) in electricity auctions. The authors examined the change in policy under various conditions of demand.

The Q-learning algorithm referred to throughout this research is from [13]. Q is initialised to a value provided by the programmer, and at each time step t an agent selects the action a_t. It then observes a reward r_t, and enters a new state s_{t+1} (this depends on a previous step s_t and the selected action a), finally Q is updated.

$$Q^{new}(s_t, a_t) \leftarrow (1-a) \cdot Q(s_t, a_t) + a \cdot (r_t + \gamma \cdot \max_a Q(s_{t+1}, a)) \tag{1}$$

Where, a is the learning rate ($0 < a \leq 1$), $Q(s_t, a_t)$ is the old value, r_t is the reward at time step t, γ is the discount factor ($0 \leq \gamma \leq 1$) it values rewards received earlier, higher than those received later. Finally $amax\, Q(s_{t+1}, a)$ is an estimated optimal future value [13]. The learning rate a is defined as; how much do you accept the new value compared to the value learned previously. The difference between the new value and previously learned value is multiplied by the learning rate a, let us call this S. Finally, S is added to the previous Q-value which moves the agent in the direction of the latest update.

2 Methodology

2.1 Sugarscape

Sugarscape is an agent based model that simulates artificial societies. The idea was originally developed in [3] and several implementations of the model have been produced since [1, 4, 8]

The original sugarscape contains a heterogeneous population of autonomous agents that compete for renewable resources which are unequally distributed over a 2-dimensional environment [3]. Agents are autonomous, meaning there is no central guidance that makes them behave in specific ways. They are also heterogeneous, meaning each agent has unique traits and understanding of the environment (i.e. initial location and wealth). The environment contains randomly distributed sugar, some cells may contain no sugar and are classed as empty cells.

2.2 Unity

Unity supports many software engineering packages such as OpenAI's ml-agents [6]. These packages provide a wide range of learning algorithms that can be deployed in video games but can also be used in agent based models. Unity also allows for the development of 3D environments with a physics engine. The model will be presented using this platform.

3 Results

The application of the sugarscape model will be made up of several C# (programming language) scripts. These are;

- SugarCollector - agent framework.
- SugarArea - a script that randomly distributes sugar in the environment.
- SugarLogic - a script that describes how often sugar is distributed and where it is distributed.
- TFModelBrain - the Q-learning algorithm applied to each agent.

The TFModelBrain script is trained over 500 - 1000 iterations as this is the limit of computing power provided but can be increased if a more powerful computer is used. Once the training process is finished, the model can be executed and the behaviour of each agent is traced.

In Unity, to trace behaviour of individual agents, one can deploy ”gizmos”. This facility contains various widgets that can be applied to agents and the environment. The widgets used to trace behaviour in the model are;

- BoxCollider - sensor that detects how close an agent is to a physical object.
- Camera - used to allow agents to see.
- RayPerceptionSensor - a custom sensor that allows agents to compete with one another by shooting lasers at each other to disable one another for a given time period.
- AnimationTrack - used to track the movement of each agent during the simulation.

The behaviours that are of interest in this domain are;

- Do sugar collectors evolve overtime to hide behind obstacles from the snatcher (hostile agent)?
- How will the sugar collectors behave when the snatcher chases them?

To trace the behaviour on an individual level, first person cameras can be used to see what agents are doing (refer to Figure 1).

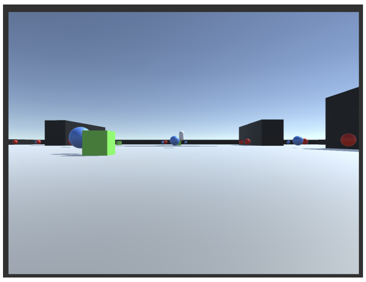

Fig. 1. First person view from agents perspective

4 Discussion

The motivation for this work stems from the lack of research carried out to address emergent human behaviours in agent based models. If the ABM community is to simulate human behaviour in models then it is necessary to test those methods that have already been developed by researchers to see if they really can be applied to much larger domains such as the simulation of people in cities, planning problems that require complex decision-making and so on. Sugarscape is a simple model, and it contains environmental features that can be used to test behaviours of agents. This research should hopefully provide agent-based modellers with new avenues to explore regarding intelligence representation and how deep learning can be a viable option when simulating human behaviours.

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2 Simulating the Physical, Cognitive, and Social: a Multi-Level Approach

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Simulating the Physical, Cognitive, and Social: a Multi-Level Approach

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Abstract. It is increasingly desirable to put together multiple models, capturing various aspects, when developing complex agent-based simulations. This paper presents a multi-level framework combining social, cognitive and physical aspects of an agent split across different components. The models individually encapsulate different levels of concern, but collectively form a consistent view of the reasoning agent in the simulation. We present this framework in the context of a large-scale evacuation scenario involving more than 35,000 vehicles. Results show that inclusion of the social level substantially affect evacuation outcomes.

Keywords: Social Network Diffusion · Mass Evacuations · BDI agents

1 Introduction

Combining models for a simulation application is increasingly useful as it allows scrutiny from different perspectives, while saving time and effort in building models from scratch (e.g., [23], [6]). In this work, building on [24] we propose a tiered agent reasoning framework consisting of a social, cognitive and a physical level. We are motivated by the observation that these aspects are often required together but exist in separate specialised systems. The physical level is commonly represented in agent-based platforms [1] that generally contain a 'thin' cognitive layer where single-agent reasoning is limited to reactive rules. On the other hand, mature cognitive reasoning systems exist today [3] but these are not typically concerned with physical environments. Moreover, these deal mostly in single-agent reasoning and lack learnings from social network diffusion research [13].

While creating monolithic systems that incorporate all concerns might be possible at times, combining systems to present a consolidated and consistent view of a reasoning agent split across several systems is often required. In [23] we address the case where the reasoning agent is conceptually represented across two separate but related agent-based models (ABMs). The approach was to build an external controller to orchestrate the progression of the models, inspecting/overwriting state variables, and rolling back steps as needed, in order to maintain a meta-level world-view that was consistent across both component simulations. Our BDI-ABM infrastructure [24] is useful where a new model is being built and it is desirable to combine specialised components–physical and cognitive–to realise ABMs that support complex reasoning agents [3].

A multi-level view of agents is indeed useful in simulations, and social networking, particularly diffusion in social networks, is an important aspect that has previously not been considered in this context. In this work we take the BDI-ABM components described previously [24] and add a new social layer. Specifically, we present a generic approach for incorporating network-based diffusion processes [15, 18, 11], which capture the spread of various influences (e.g., information, opinion, innovation), into simulations with complex reasoning agents. We apply our framework to a large-scale flood evacuation scenario and show that social influence can very significantly impact evacuation outcomes compared to optimised evacuation plans that assume people do as they are told.

2 System Architecture

We support simulation of reasoning agents that are conceptually split across the physical dimension represented in an ABM, the cognitive in a Belief-Desire-Intention (BDI) system, and the social in a newly added social network model (SNM). Here an ABM is a bottom-up system of interacting autonomous agents in an environment for representing complex systems. A BDI program [9, 20] is essentially a collection of plan rules of the form $G : \psi \leftarrow P$, which implies that plan P is reasonable to achieve goal G when (context) condition ψ is believed by the agent to be true, and is particularly useful for modelling human behaviour in social simulations [16, 2, 3]. A SNM manages the social network structure connecting the agents along with the network-dependant diffusion process.

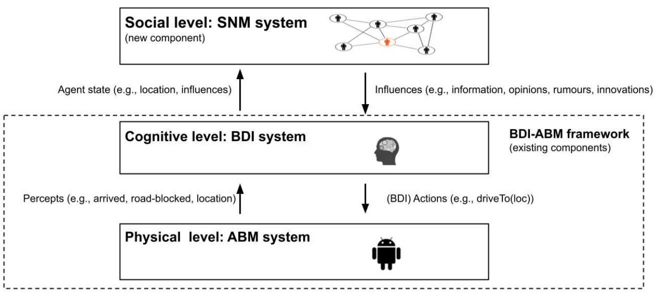

Fig. 1. Conceptual overview of the multi-level agent framework.

The architecture (Figure 1) is implementation-agnostic, affording choice in underlying models based on need. The modular architecture of the new SNM component allows easy swapping of network and diffusion models (via a configuration file), facilitating re-usability across applications. Numerous well known network (e.g., random, small-world) and diffusion (e.g., Independent Cascade, Linear Threshold Model (LTM) [10], Competitive LTM, separated-threshold version [4]) model implementations already exist in the system.

Technically, the conceptual agent is identified in each subsystem by a common identifier. The BDI-ABM machinery [24] allows BDI reasoning to instantiate actions that are then carried out in the ABM system, while observations from the ABM simulation generate percepts which are passed back to the BDI system to inform further reasoning. We allow an influence received by an agent via a diffusion process in the SNM to affect a specific belief in its BDI counterpart. This can then either directly trigger a goal, which instantiates a whole new set of plans and actions, or it can influence the achievement of existing goals, by affecting which plans are chosen, and what actions are eventually taken by the ABM counterpart. The opposite flow of a percept from the ABM triggering some BDI deliberation that results in communication via the SNM is also possible, though we do not demonstrate this in the scenario here.

The decision on how to split reasoning depends on functionality provided by each system. For our scenario, it makes sense to use BDI for evacuation decision making of an agent based on its circumstance, but leave path planning to the ABM that maintains the road network model. We discuss such design choices in [24, 25]. Interactions between agents can occur in each layer: directly (via messages) or indirectly (via the environment) in the ABM; inter-agent communication in the BDI system; or through the diffusion processes in the SNM. Which mechanism to use again depends on what aspects of the complex system are important to model. In our example, interactions occur at the physical level (congestion on roads) and social level (spread of influence).

We maintain synchronisation between the three subsystems with respect to simulation time and data. The ABM and SNM are time-stepped models that may internally run at different atomic time steps, and the BDI system is event-based and does not explicitly model time (end of the BDI reasoning cycle is used to progress time [24]). At initialisation and subsequently at each temporal synchronisation point, the physical, cognitive, and social data are shared across the systems to maintain a consistent view of the conceptual agent. For instance, physical aspects (managed by the ABM) are abstracted out as percepts (e.g., arrived at a location, road blocked) for the BDI system. The SNM system may also require physical information, for example, geographical locations of agents are sent to the SNM side (at initialisation) to generate proximity based social networks (e.g., neighbourhoods).

3 A Flood Evacuation Case Study

Optimal evacuation schedules (e.g., [8, 19]) often assume that people will follow their assigned plans diligently. However, empirical studies show that residents rely on social networks amongst other things for evacuation decision making in addition to official warnings [17, 7, 21]. To understand this better, we examine how social influence affects outcomes of an optimised evacuation simulation.

We used optimised evacuation plans from Data61[4] for 38,343 agents in the Hawkesbury region, NSW, Australia as the *baseline*, and compared these with

[4] https://data61.csiro.au/

simulations that incorporate social influence, across a range of configurations. In the social scenario, an agent reasons and modifies its scheduled evacuation start time based on level of influence from others, which causes it to either evacuate early (low influence), on-time (moderate level of influence) or late (high influence). We experimented with two networks (a random network and a proximity-based network), and three input factors (seed[5] (5%-20%), activation threshold (0.3-0.5), and degree[6](2-10)). We ran 340 simulations (5 iterations * 17 configurations (combinations of seed, threshold, and degree values, selected using the Latin Hypercube Sampling method [22]) * 2 networks * 2 effects (diffusion and evacuation)). Before considering evacuation effects, we first analysed how the chosen factors affect diffusion dynamics, to fully understand their influence on the diffusion process. The social, cognitive, and physical aspects of our evacuating agents were encoded in the LTM [10] for diffusion of social influence [14], JACK platform [5] for cognitive reasoning, and Multi-Agent Transport Simulation (MATSim) [12] for simulating road traffic, respectively. We find that:

- *Social influence has a substantial impact on evacuation outcomes.* In the worst case ≈41% of the population is exposed to higher traffic congestion, resulting in delays of up to three hours. Whereas in another run where high levels of information diffusion were evident, the time to evacuate the whole population improved by as much as 2hrs from a baseline of 10hrs.
- *Precise effects on evacuation behaviour vary a great deal based on specific characteristics of the social network as well as the diffusion process.* Network structure can have substantial impact, for instance, a neighbourhood network may lead to 8821 more evacuated agents compared to a random network. Threshold level is the most influential factor, followed by seed and network degree, when it comes to the sensitivity of the spread of influence on the diffusion process parameters. For example, in two contrasting configurations for threshold but with similar values for other inputs, the number of evacuated agents changed from 8131 (21%) to 38,343 (100%).

4 Conclusion

We propose a multi-level agent reasoning framework for social simulations that extends the cognitive-physical integration provided by the BDI-ABM layers [24] with a new social networking layer encapsulated in a social network model. This allows different kinds of social networks along with well understood information/influence diffusion mechanisms to be included in simulations with complex agents. In the context of a flood evacuation scenario, we show that the social level with its network-dependant diffusion processes is an important aspect that can have a substantial impact on simulation outcomes. The SNM-BDI-ABM framework presented here provides a good basis for further research combining social networking, cognitive reasoning, and agent-based simulation.

[5] Set of agents that have initially adopted the influence to start the diffusion process.
[6] The degree refers to the number of links an agent has in its social network.

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3 Multi-level Agent-Based Simulation for Supporting Transit-Oriented Development in Beijing

Liu Yang, Koen van Dam, Bani Anvari and Lufeng Zhang

Multi-level Agent-Based Simulation for Supporting Transit-Oriented Development in Beijing

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Abstract. Planning new transport infrastructure that is integrated in the wider urban environment is key to promote use of public transport and other greener modes, while also ensuring high quality of public space around transport nodes and links. This work presents a multi-level approach to provide decision-support using a simulation model of a city neighbourhood combined with a more detailed model of a small scale area around a new development site. By linking these two models scenarios can be explored which take into account urban planning and the effect of long-term changes in a city on a detailed design for one particular location. A model in Repast Simphony covers the land-use and transport infrastructure in a district, while a NetLogo model simulates pedestrian movement. This is applied to a case study in Beijing, China, with preliminary results showing the potential of this approach to introduce this style of modelling to architects and urban planners.

Keywords: transport system, pedestrian modelling, agent-based model, TOD

1 Introduction

Although car-oriented development has stimulated urban expansion, it has generated a large number of negative spaces affiliated with transport infrastructures and resulted in fragmentation of the urban fabric. Similarly, rail infrastructure can lead to poor quality urban space if it does not take into account the wider area. Integrated Land Use and Transportation planning, infrastructural urbanism, and Transit-Oriented Development (TOD) have gained worldwide attention. Initially promoted by urban planners as a basic principle of New Urbanism, the TOD strategy aims at encouraging individuals to use public transit in preference to private vehicles and complementing public transport with non-motorised travel for shorter distances [7]. Recently, urban researchers and practitioners have realised the need to consider a wide range of spatial scales, multiple transport modes and people-oriented public spaces design in developing successful TOD [4]. Moreover, urban and transportation planning, urban design, and architecture design are co-dependent processes, meaning that the decision of high-level planning could have direct impact on lower-level urban and building designs (and vice versa). Therefore, employing a holistic approach that arises from a negotiated, multi-scale, and proactive style of design is of great importance.

Simulation tools can support this decision-making process by assessing various planning and policy alternatives against a range of performance indicators. Urban models, in particular agent-based models, are powerful in testing different configurations of an urban system to support decision-making [5]. Agent-based modelling can reflect the behaviour of the people in the environment linked to land use and availability of transport infrastructure [6]. Simulating navigation of humans among other users in different environments is key to assure safety and comfort in a cost-effective and efficient manner before real-world implementation. For instance, studies on simulating emergency passenger train designs and conditions play a crucial role in identifying challenges in evacuation scenarios, offering possible solutions, and ultimately saving lives of passengers [13]. With the introduction of innovative urban design such as shared spaces, beside replicating collision-free navigation among other users, the importance of understanding socio-psychological interactions between road users for predicting road users trajectories, estimating flow and density relationships has been highlighted, achieving solutions for the optimal design of a new area before implementation [14]. In [10] such pedestrian models are compared with data from controlled experiments. Instead of building massive and highly detailed agent-based models of urban systems, Perez et al. [15] suggested "developing modular architectures that can host complementary modelling paradigms in different and fit-for-purpose modules".

Despite a growing body of literature on modelling the interactions between transport, urban spaces, and humans, there is limited research on multi-level simulation for TOD. This paper aims to integrate the high-level land-use and transportation modelling with micro-level pedestrian modelling in areas around public transport hubs. There are two ways of model integration (also known as model coupling), i.e., schema integration and process integration [1]. In this work, the latter approach will be used: the output of one model is an input for another. In earlier work we analysed the impact of transportation and public space designs on local air quality and micro-climate condition [2, 3], and others have demonstrated similar approaches (e.g., [9]). This paper introduces a pedestrian simulation model which receives input from an agent-based model of the wider city, applied to a case study in Beijing.

2 Methodology

The multi-level approach uses two models, as follows:

1. **Macro-level**: Simulate private car and public transport travellers' behaviour in transportation network – land use systems at an urban district scale, by adapting a Smart-City Model implemented in Repast Simphony.

2. **Micro-level**: Simulate the movement of pedestrians around a public transport node. Agent-based modelling is performed in NetLogo by adapting the pedestrian_floor-2exits-usepath model [11, 12].

The output of subway station areas' occupancy over time from the macro-level will be used to generate pedestrian agents within and around transit hubs in a micro-scale simulation, as it reflects the number of people entering and leaving this location as an effect of its position and function within the wider urban environment. The output of the micro-level model then provides insights in the throughput and dwelling time of the transport system.

2.1 Macro-level modelling

In the macro-level model, firstly, the status quo of the road network, subway system, and land use is represented at a self-defined sampling segment in QGIS. Linking to the GIS data, the Smart-City model then generates a heterogeneous synthetic population based on the socio-demographic data from the 6th population census of Beijing and the public transport statistics in 2018 Beijing transport annual report. Afterwards, the agents travel for a workday, following their activity patterns, selecting destinations, and determining the time spent on different types of land uses. These lead to the output of individuals' arrival and departure times in public transit stations.

2.2 Micro-level modelling

The micro-level model selected here is a simple model of pedestrian movement compared to the more detailed models reviewed above. One reason for choosing such a model is for education purposes, as it allows users with little modelling experience to understand the code and even adapt it to their needs. In the 2019 and 2020 ABM summer school held at HZAU in Wuhan, China, the authors explored different ways of teaching agent-based modelling to beginners, finding that using and extending an existing model is a powerful tool for instilling simulation techniques to students. Moreover, this model is a good demonstration of linking CAD representation, as often used by urban planners and architects, with an agent-based simulation.

3 Case study and results

Beijing Subway FANGSHAN Line is located in the south-west Beijing. At present, this Line is being extended to the north and Sihuanlu station is a new subway hub. Being surrounded by residential buildings, a hospital, a school, and commercial centres, station areas planning should consider the distribution of land uses and non-motorised transport network, in line with the design of public spaces. Along these lines, we chose an area within a radius of 2.5km from the subway hub for macro-level modelling (see Figure 1, left). Afterwards, we zoom in to an area within a radius of 500m from the subway station, as depicted in Figure 1 (right). Figure 2 shows a snapshot of the micro-scale pedestrian modelling in the station area in NetLogo.

Having simulated the baseline scenario, different urban design alternatives are tested and assessed to compare different accessibility and walkability of the road networks, kinds of designs of the public spaces, and multiple land use redistributions.

4 Concluding remarks

The case study results show how model integration can give valuable insights in the impact of design choices on TOD, in a way that is accessible to not only computer scientists, but especially to architects and urban planners who typically do not have experience with such agent-based models. Preliminary model results demonstrate that relevant output can be generated for a range of scenarios, including changes in the design and the function of the TOD within the district. These scenarios will be presented and discussed in more detail at the ABMUS2021 workshop and in the full paper, with a particular emphasis on the link between the multiple simulation levels. Next steps in our research are to combine this with the air quality and thermal comfort results of other micro-simulation models [2] to study the impact and exposure of pedestrians, which might again influence their behaviour at the macro-scale and could support further revision of sustainable master plans and the design of transit networks.

Fig. 1. Case study: the micro-level site (left) and the macro-level site (right). The yellow dot indicates the station, the red dash is the subway line, & red tracts are commercial land uses.

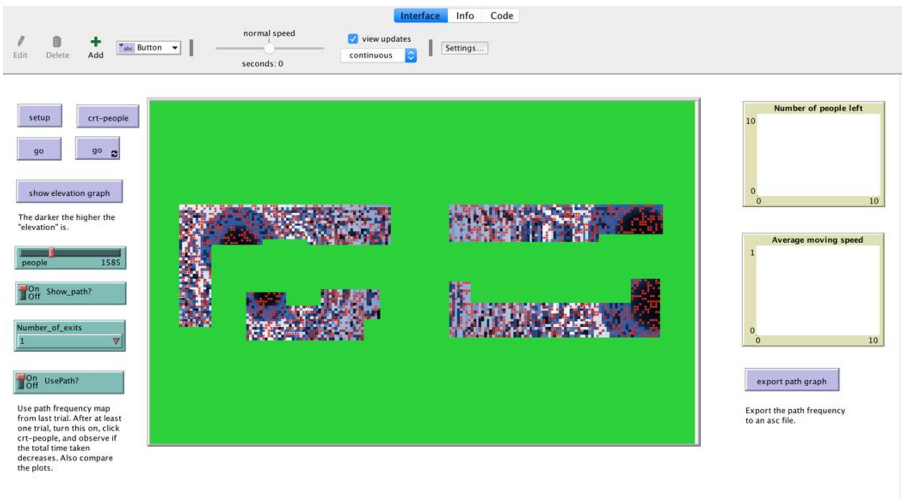

Fig. 2. A snapshot of the building-human system modelling in NetLogo, adapted from [11].

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4 Simulating SIGChain: Microgrid Agent transactions with a Lightweight Blockchain
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Simulating SIGChain: Microgrid Agent transactions with a Lightweight Blockchain

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Abstract. Solar production is becoming a growing source of new energy worldwide. More and more consumers and companies are interested in investing in photovoltaic (PV) panels and battery storage for different reasons: ecologic interest in green and renewable energy, economic interest in energy trading. This paper presents simulation results between neighbor customers (agent nodes in a Microgrid) trading their solar photovoltaic production overhead. The simulation is run with AnyLogic. Different scenarios with different types of nodes have been implemented such as: agents using storage (battery) versus agent without storage, agents with different trading motivations (green agents versus greedy agents. Also, each scenario is played at different seasons of the year taking into account the different sunshine levels. A "lightweight" blockchain has been implemented and added to the simulation tool to handle the transactions of surplus energy among customers in each Microgrid: 100 nodes split in 16 Microgrids according to the neighborhood are running so far. Different statistics have been collected and averaged per year such as the average energy savings per year and the average customer benefits per year. The simulation is currently tuned with real consumption and production data produced by the SIG (Services Industriels de Genève) in order to incorporate it to the existing SIG smart meters and discover the price interval at which trading customers can achieve benefits while maintaining the SIG infrastructure cost-effective.

Keywords: Agent-based Simulation, Microgrid, and Blockchain

1 INTRODUCTION

Solar production is becoming a growing source of new energy worldwide. More and more consumers and companies are interested in investing in photovoltaic (PV) panels and battery storage for different reasons: ecologic interest in green and renewable energy, economic interest in energy trading. This paper presents simulation results between neighbor customers (agent nodes in a Microgrid) trading their solar photovoltaic production overhead. The simulation is run with AnyLogic[1]. In order to support the inter-agent electricity trading a SIGChain[2] (lightweight blockchain) has been implemented. The remaining of the paper is organized as follows: next chapter describes recent related works, chapter 3 details the different agent types. Chapter 4 explains the simulation context and the different scenarios. Chapter 5 provides the SIGChain implementation. The conclusion is provided in the last section.

2 RECENT RELATED WORKS

This section summarizes the use of blockchain technology in recent energy market. In 2014, [2] first uses blockchain technology in energy markets. The authors propose a virtual currency (Nrgcoin) for trading renewable energy in smart grids. However, the system is not fully distributed since the market model keeps depending on the central network operator. A recent paper

[1] AnyLogic is an agent-based simulation tool at: https://www.anylogic.com/.

[2] SIG is the main company providing the public services at Geneva (Switzerland) such as: gas, electricity, and water. at: https://ww2.sig-ge.ch/en/home-en.

[1] proposes the concept of a blockchain-based microgrid energy market without central energy management. The Brooklyn microgrid is used as a case study and the authors show that three of the seven identified requirements are fully satisfied. In [3] and [4] the authors focus on maintaining the privacy aspects when performing energy trading in a local environment with anonymous participants. An issue with classical blockchain mining paradigms [5] is their greedy aspect in terms of power consumption, which is particularly undesired in a microgrid environment. Therefore, research works to implement lightweight mining paradigm in a local grid are desired. We use the point of view of implementing such a paradigm for our project with the SIG Company. Our work is inspired by the lightweight blockchain model proposed by [6][7].

3 AGENT DESCRIPTION

Entities used in AnyLogic simulation tool are called agents. There are of two types: Producer Agents (PAs) and the Power Plant Agent (PPA).

3.1 Power Plant Agent (PPA)

There is just one PPA. It has two parameters that are collected for statistics purpose: a) the number of received transactions that have been carried out, b) the total bought energy amount expressed in kilowatts per hour. This amount is re-initialized every day in the simulation.

3.2 Producer Agents

PAs play both roles of purchasers and buyers. They produce electricity for their own use according to their consumption. The overhead is either stored in a local battery or directly sent to the network. When sent to the network, the corresponding amount (expressed in kilowatts per hour) is saved by the PA. At the time the user needs to buy electricity from the power station, this amount is deducted by the PPA and provided for free to the user PA. Only the network usage fee will be charged to the user according to the SIG photovoltaic network usage policy.

4 SIMULATION

4.1 Initial Conditions

At the beginning of the simulation, the PAs are randomly dispatched. Then, they are gathered in 16 identical sectors called districts. PAs of the same district are considered as neighbors. Only neighbors of the same district (neighborhood) can execute power transactions between each other. In the current simulation, different agents and parameters can be configured which are:

- finalProducers: The table, which contains all the producers. It defines desired agent number as well as their initial parameters.
- powerPlant: The SIG power network.

4.2 State Machine Explanation

- When the simulation starts, all the agents are in “statechart” state. This state will define each agent neighborhood from the beginning.
- Then the agent moves to the “production” state. This state will attribute each agent its electricity balance.

- Third, the state machine will move the agent in the “NoBattery” (agent does not have a battery) or “HaveBattery” (agent owns a battery) state.
- These two states have a reflexive (self) transition, which is used when the agent electricity balance is positive. An agent without battery will send its overproduction to the network. Otherwise, the agent saves its surplus directly in its battery. When the battery is full, the surplus is sent to the network. As long as an agent is in a negative balance it needs to buy electricity and it stays in the “Buying” state.

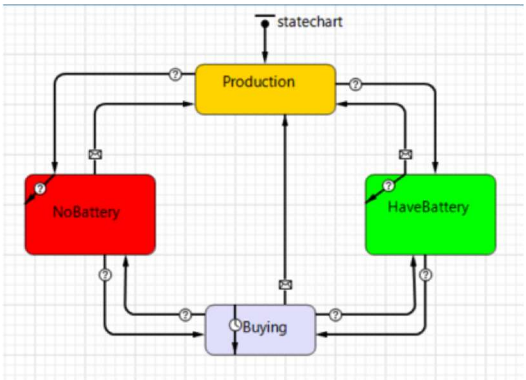

Figure 1: PA state machine during the simulation

When the simulation is started, the interface in Figure 2 is displayed. All running agents are on the left side with different colors corresponding to different neighborhood (community of self-consumers) that agents belong to. On the right, appear the several useful statistics.

- The two pie charts correspond current SIG tariff distribution and battery distribution.
- Below the pie charts, 1) the two savings blue chart: one is the average savings made by agents when by buying electricity to their neighbors. The other, is the average savings made when re-buying produced electricity previously sold to the SIG. This corresponds to the same purchase price exempt from the network usage tax. For example, with a purchase price of 24 cents: 24 - 10 (network usage tax) = 14 cents of savings.
- In the right, the graph containing bars is the production and consumption in one of the self-consumer communities (district in the figure).
- The bottom graph is the purchase of electricity from the SIG, which is simply the electricity that the community did not produce and asked the SIG for. The chart on the right is the profits made by selling electricity to its neighbors.

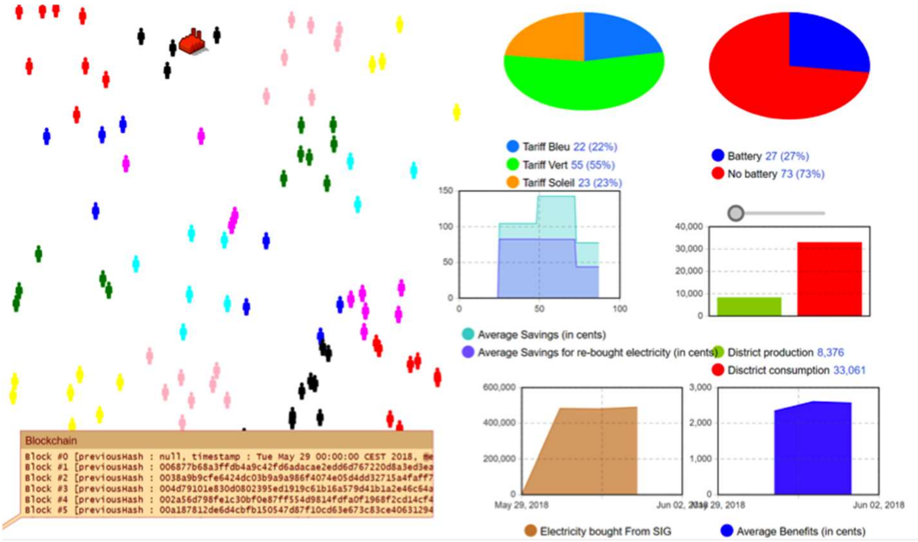

Figure 2: Simulating 16 Microgrids with AnyLogic

4.3 Different scenarios

For the moment, there are two different scenarios in the simulation.

- Scenario 1: First of all, the user who absolutely wants to buy his electricity at the cheapest price possible. This type of buyer will analyze its neighbors to see if there is not a way to have electricity cheaper than its current SIG agreement.
- Scenario 2: In the second scenario, a user absolutely wants to buy green electricity regardless of the price. He is willing to pay more to get neighbors' photovoltaic electricity. He also distinguishes the type of electricity in his neighborhood; for example, he refuses to buy electricity from a neighbor at the blue tariff.

5 LIGHTWEIGHT BLOCKCHAIN

The blockchain (called SIGChain) that is used in the simulation appears as a standard blockchain where blocks containing electrical power transactions are linked between each other. Each neighborhood constitutes a consortium where the mining node is randomly designated every hour in order to mine the next block. The blockchain has been implemented in java.

5.1 Block description

Blocks are the crucial part of the blockchain. They contain all the transactions and ensure that the blockchain is secured and has not been forged (blockchain integrity). The "Block" class implements the blocks with the following parameters (Figure 3):

- Index or: Block number in the blockchain
- PreviousHas: Previous block hash
- Timestamp: Mining date (when the block has been mined)
- merkleRoot: Root value of the transaction Merkle tree
- transactionsID: Table with transaction identifiers of the current block
- Data: Optional field used to store information. Notably used to announce the first

block.

- idMiner: Identifier of the block miner
- Hash: Block hash
- Nonce: This value is incremented until the bloc hash fits to the blockchain difficulty

```
Block #0 [previousHash : null, timestamp : Tue May 29 00:00:00 CEST 2018, merkleRoot : null, transactionsList : (null), data : First Block, miner : 0, hash : 006877b68a3ffdb4a9c42fd6adacae2edd6d767220d8a3ed3ea181c1b34b4fa9]
Block#1[previousHash: 006877b68a3ffdb4a9c42fd6adacae2edd6d767220d8a3ed3ea181c1b34b4fa9, timestamp : Tue May 29 00:00:00 CEST 2018, merkleRoot : null, transactionsList : (null),data:null,miner:62,hash: 0038a9b9cfe6424dc03b9a9a986f4074e05d4dd32715a4faff79385be7a60d0e]
Block#2[previousHash: 0038a9b9cfe6424dc03b9a9a986f4074e05d4dd32715a4faff79385be7a60d0e, timestamp : Tue May 29 01:00:00 CEST 2018, merkleRoot : null, transactionsList : (null),data: null, miner : 19, hash : 004d79101e830d0802395ed1919c61b16a579d41b1a2e46c64af6c86bb31703f]
…
…
…
Block #12 [previousHash : 0045966e20d2e9d075e6d66babb9d6d93da5d6a775e883f35e334af3f6691a4a, timestamp : Tue May 29 11:00:00 CEST 2018, merkleRoot : 72e15901cdb3cc1641848b043af8d021a7c1cdbc8c7aa581ade21253f82210c2, transactionsList : ([3aec7299a12f10e11b6fadd04595528fdd33a0393627459a1771b28ac832ce2d, 055bd91288284fefa26756d2dfe7f4835964b528659a8baf372b9376739bd234, 8f30bedc65b72f854c581568ac3fd05e6778d8707970f8a9c237b6550aa7b834, f5389c11f002912da52fa82316f37aee740726d76499f8be55ce50cb15599a81]), data : null, miner : 93, hash : 0065b5da3bcc73293f7ed13d73c0c70255240e6f6e2126bb30d831106df545c7]
```

Figure 3: A SIGchain example

5.2 Building the blocks

The block class owns two constructors:

- constructor 1: is used for the first block only. It assigns the values corresponding to index, timestamp, previousHash, and data.
- constructor 2: is used for the other blocks. It assigns more values: index, timestamp, previousHash, and idMiner. Besides, it computes the Merkle.

5.3 Root Tree

The root tree calculation function works as follows:
(1) Verification that there are transactions to work on. In this case, their respective identifiers are saved in a temporary list for future calculation.
(2) Verification that the number of transactions is even. Otherwise, the last transaction is duplicated.
(3) Transactions are paired in a loop to compute their common (intermediary) hash. This operation creates the upper nodes of the tree. They will not be kept in the root tree process.
(4) If there is more than one intermediary node created, the function returns to step 2 with these nodes. Otherwise, the function goes to step 5.
(5) There is one last node, the function keeps it as of the tree root.

When the block has been successfully created, its hash has not yet been determined. The agent creating the block must then call the "mineBlock" function. This function computes the hash by incrementing the nonce so that the created hash respects the nonce difficulty linked to the nonce. This difficulty is the number of zeros that the hash must contain at its beginning. For example, if the difficulty is 4 zeros, the hash must start with 0000. All blocks must then be stored in the blockchain.

5.2 SIGChain Operation

The blockchain is created from the start of the simulation. It has two properties:

- Difficulty: The difficulty of the blockchain corresponding to the number of zeros at the beginning of the hash.
- Blocks: The blocks that make up the blockchain.

Operation:
The Blockchain class constructor deals with assigning the value of the difficulty as a parameter and initializing the block list. The first created block of the list is mined and added.
For this purpose, the Blockchain class calls the "newBlock" method that creates a new block. It is available with two different settings options. After a block has been created, the agent that created it must add it to the blockchain. For this purpose, the "addBlock" method of the Block-chain class is called. The method uses the "mineBlock" method of the class Block to correctly mine the block. Once it has been mined, the block is added to the chain.

Validity verification methods are available:
The "IsBlockchainValid" method checks the first blockchain block and the 24 next created blocks created. This method calls the "isValidNewBlock" method that checks the links between the blocks and the new block hash value.

To summarize, a randomly selected agent adds a block in the blockchain by following the logic below:
(1) Check the blockchain validity with "isBlockchainValid" method.
(2) Add this block to the blockchain with "addBlock" method.

6 CONCLUSION AND FUTUREWORK

In these scenarios, only the first is economically viable. In the second scenario the user is losing a significant amount of money because he finds himself paying more than SIG prices. The next step of this work is to include the real data and up to date production and consumption data from the SIG Company and integrate our SIGChain to the SIG smart meters.

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5 Multiscale Data Integration and Modeling for Understanding Vulnerability During Disasters

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Multiscale Data Integration and Modeling for Understanding Vulnerability During Disasters

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Abstract. We describe the data integration and modeling framework in an ongoing project, which is creating an agent-based simulation of Hurricane Harvey. The goal of the project is to create a dynamic vulnerability index by augmenting the CDC Social Vulnerability Index, which would provide a better estimate of vulnerability and risk during disasters by taking human behaviors and mobility into account.

Keywords: Disaster modeling · Hurricane Harvey · Vulnerability.

Introduction

Vulnerability is broadly defined as the extent to which persons or things are likely to be affected by a hazard. The vulnerability of a human population group (in relation to other groups) is known as social vulnerability and is thought to be influenced by many factors, including demographics, neighborhood characteristics, the networks in which people are embedded, underlying health conditions, and more. In 2011, the US Centers for Disease Control and Prevention (CDC) introduced the Social Vulnerability Index (SVI) [4] to provide a measure of social vulnerability derived from census variables. The CDC SVI is increasingly being used in preparing for disasters and in planning relief and rescue efforts.

Health risk during a disaster is a spatiotemporally-dependent phenomenon in general that can be impacted by vulnerability [3]. People's risk varies as they move through areas of varying levels of hazards over the course of a day or week and social vulnerability may influence both the expected exposure to hazards as well as the outcome after exposure to a hazard. For example, exposure to extreme heat generally occurs in the middle of the day when temperatures are highest and when people may not be at home. Similarly, exposure to hazards like flash flooding are exacerbated when spending time in low-lying areas during periods of intense rainfall.

Estimating the spatiotemporal variability of risk, incorporating both social vulnerability and hazard exposure has always been limited by the lack of high resolution environmental and human mobility data. Lately, investigators have started turning to machine learning [10] and simulation-based methods [5, 9]. We consider the latter to be especially promising because they use multiple sources of data, integrated together to provide a model of human mobility patterns and consequent exposures to hazards. This offers the opportunity not just to estimate exposures, but also to evaluate the influence of vulnerability and ultimately potential interventions for mitigating risk.

In our current work, we are creating a detailed agent-based simulation model of Hurricane Harvey, in order to augment the CDC SVI and create a dynamic vulnerability index that takes into account human behaviors during disasters as well. In the following we briefly discuss some of the multi-scale data integration and modeling challenges in this ongoing work.

Hurricane Harvey

Hurricane Harvey was a Category 4 hurricane that was one of the most catastrophic and costliest hurricanes on record. It made landfall in August 2017, causing approximately $125 billion in damages and affecting 13 million people from Louisiana, Mississippi, Tennessee and Kentucky. With the hurricane making landfall three times in six days, the Houston area was flooded and thousands were forced to evacuate the area. In four days, areas around Texas received more than 40 inches of rain which caused flooding that peaked at 5 feet. With the damage inflicted by Hurricane Harvey, houses were left without power or were ruined beyond repair, forcing 30,000 residents of Texas to move into shelters [7].

Beyond the harm to infrastructure and housing, there were reports of damage to the mental and physical well-being of people affected by the storm. Sixteen percent of Texas Gulf Coast residents reported a worsening health condition or a new health condition. With an introduction to bacteria, dust and mold growth from damaged homes, there was an increase in respiratory problems. As well, following the hurricane there was an uptick in skin, eye, and ear infections after sewage-tainted water flooded the streets and waterways. Besides the damage to wastewater treatment plants, damage to industrial equipment exposed residents of the Houston-area to chemicals from pesticides, detergents and other common products contributing to conditions like nausea and eye irritation [2].

Multiscale Data Integration

Relevant data have been collected by many organizations and agencies, in multiple forms. Table 1 lists several of the data sets we have identified and are integrating into our agent-based simulation. These include data about environmental conditions (rainfall, flooding), damage to homes and infrastructure, data about the affected population, and about hazards such as Toxic Release Inventory (TRI) facilities.

To do data integration, we use two frames: a *person frame* and a *location frame*. Some data are naturally associated with people, such as demographics, activity patterns, health status, and behavior during the disaster. These are largely integrated from survey-type data, to construct a synthetic population [6].

Spatial data sets are at multiple resolutions and in multiple reference systems. The standard US Census hierarchy of regions is state – county – tract – blockgroup – census block [11]. In this reference system, smaller regions nest perfectly within the next larger level, e.g., blocks align perfectly with blockgroups, which align perfectly with census tracts, and so on. However, other reference geographies, such as neighborhoods, zip code regions, and grids can be of varying sizes and can overlap arbitrarily with the census regions.

Table 1. Data sets.

Data	**Description**	**Resolution**
Harvey Registry	Survey on impact from Harvey	Neighborhoods
Damage Assessment	Damage levels from inundation height	Latitude/Longitude
Hourly Rainfall	Hourly precipitation totals	Gridded region
Social Vulnerability Index	Quantification of vulnerabilities of regions	Tracts
Transportation Infrastructure	Condition of roads and bridges	Pathways of roads
TRI Facilities	Locations of toxic release inventory facilities	Latitude/Longitude
Inundation Raster	Presence of flooding	Latitude/Longitude
City of Houston Harvey Damage Assessment	Harvey affected property counts	Block group
Power Outages in CenterPoint Energy Service Area	Percentage of customers without power	Zip code
Individual Assistance Open Disaster Statistics	Data on registrations and Individuals and Households Program	County
American Community Survey	Demographic data	Block group
Spatial Hazard Events and Losses Database for US	Losses from Harvey	County
Harris County Flood Gauge Readings	Hourly rainfall and channel elevation readings from flood gauges	Latitude/Longitude

To integrate these, we take intersections of shapes of regions and are developing methods to assign variables from regions to resulting subregions. For example, hourly rainfall is available in a gridded reference frame through NLDAS [12]. To integrate this with the City of Houston Harvey damage assessment, which is given for each blockgroup, we take an intersection between blockgroup shapes and the NLDAS grid and assign damage estimates to each subregion of a blockgroup based on the rainfall in that subregion. A similar method has to be employed for integrating all the data sets with unaligned geographies.

This results in a data set with relatively small regions. To find the conditions at a given (latitude, longitude) location, we need to query this data set. To avoid having to do a large number of shape membership queries, we are developing an indexing scheme from grids to the smaller geographies that lie within them. A query point is first mapped to the grid cell that contains it, and from there to the regions that intersect with that grid cell. The goal of the data integration is to create a single data set that can be queried efficiently for all the variables at a given (latitude, longitude) location for modeling exposure to hazards, as described next.

Multiscale Modeling

Our agent-based simulations are not valid at the individual level, because synthetic individuals do not have a one-to-one mapping with the real inhabitants of the region. Synthetic populations are statistically accurate at the blockgroup level [1]. CDC SVI is constructed at the census tract level. During a hurricane or other disaster, people may engage in various behaviors, such as evacuation, sheltering-in-place, shopping for supplies, picking up family members, and more [8]. These result in complex spatiotemporal trajectories, crossing multiple tracts and blockgroups, with varying exposure to hazards.

Thus the overall agent-based simulation involves integrating data at multiple scales, as described in the previous section, modeling individual movements through these regions, and integrating exposures back to the census tract level. The effects of exposure eventually show up in syndromic surveillance data sets, when people report symptoms such as infections, rashes, nausea, eye irritation, etc. [2]. We plan to use these data sets to validate our model.

Conclusion

An improved understanding of the spatiotemporal variability of population vulnerability will lead to better preparedness and planning for future disasters. Risk is contingent upon local circumstances, such as the specific nature of the disaster, the topography, the built environment, and population demographics, and spatiotemporal patterns of vulnerability will vary across regions and types of disaster. Our goal is to demonstrate that with the right tools for data collection, analysis, and simulation in place, we can rapidly generate models and possibly forecasts of vulnerability in advance of the next major hurricane to help mitigate its effects.

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6 Toward phygital agent-based interactive simulations to support urban planning

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Toward phygital agent-based interactive simulations to support urban planning

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Abstract. To support urban planners in assessing and comparing various alternative scenarios, this paper provides a novel methodological framework for phygital agent-based simulation, *i.e.* simulations with which the user can interact through the usage of a physical 3D model and visualize in augmented reality (digital).

Keywords: urban planning · agent-based model · phygital interaction · 3D animation

Urban planning practices have changed deeply over the last 50 years requiring now to consider the whole complexity of the urban area before planning a new development [5]. Indeed, planning the construction of a new building is not limited to ensuring the possible access to the building for people, vehicles, electricity, water... The city needs to be considered as a complex system and many other factors (material or immaterial, qualitative or quantitative...) and feedback loops need to be taken into account and understood. In addition, evolution of the individual behaviors (*e.g.* in terms of mobility mode) and institution regulation (*e.g.* the Local Urban Plan (PLU)) are key factors that can influence the impact of an urban planning. Finally making all these aspects more easily exploitable by different stakeholders is crucial.

Agent-based modeling and simulation has become a tool of choice to simulate such complex socio-environmental systems [6]: it is suitable to take into account very diverse dynamics from various fields and their feedback loops. Thanks to its expressivity, an agent-based model can become a very powerful virtual laboratory to experiment and understand the effects of alternative urban plans. A key challenge is now to make such tools available and usable by any user to help understanding and thus improve the acceptability of urban plans, but also by planners to provide insights and support their decision. This requires innovative approaches in terms of visualization of simulation and interaction with them.

Much recent effort has focused on extending the limited input/output interaction capabilities of desktop computers through the use of interactive tabletops, augmented reality [2] or tangible interaction [1]. In our context, we explore an original interaction mode that we called "phygital interaction": it depicts the use of a physical 3D model, representing the physical location to which a data set is related. The use of 3D physical referent 1) provides support for tangible interaction, which ensures a better memorization through proprioception, and 2) allows for a more situated data analysis, which provides a physical anchor for data facilitating large data sets exploration and understanding [4]. Rendering of the data is then performed using a Head-Worn Display (HWD), such as the Hololens, which provides a large immersive display area to augment the 3D physical model.

Along with the physical 3D model, there is a need for a digital 3D model which will hold all the simulation information. This model would be superimposed on the physical 3D model to enhance the user's understanding of the impact of urban planning on ecology or traffic through the visualization of pollution clouds or pedestrians movement. Furthermore, urban planners use 3D representations to design new infrastructures. These models often consist in a static description of the different parts of the buildings, using classical file formats like CityGML or IFC. Such a single visualisation, even with high level of details needs to be integrated into a huge area to have a more precise vision of the project. In our approach, we propose to visualize not only the 3D model of the project but the environment that is directly impacted. The next step is then the animation of all the movable elements like pedestrians, cars, buses.

The objective of this work is to provide a methodological framework for **phygital agent-based simulation**, *i.e.* simulations with which the user can interact through the usage of a **phy**sical 3D model and visualize in augmented reality (di**gital**). Through different scenarios, we aim to test the impact of the urban project on road traffic and more. In the following, we introduce the three main components of the framework (Simulation, Interaction and 3D animation) and the way they interact.

Simulation component. The *Simulation* component is in charge of computing evolutions of the system and providing information about the current simulation state to the Interaction and 3D animation components. Four simulation use cases have been identified to provide an optimal phygital simulation experience: (i) step-by-step simulation allowing to visualise and interact at runtime with the simulation, (ii) visualisation of recorded simulations, in this case interactions will be limited to query the 3D model to display information (no modification is possible), (iii) comparison between 2 (or N) alternative simulations, and (iv) interaction with the simulation at its initial state, to modify deeply the environment (*e.g.* create a new building). Visualisation and interactions with simulations in real-time (cases (i) and (iii)) require fast (and thus reactive) simulations. In these cases, the model or some of its dynamics will be simplified to preserve this execution time constraint. The designed model should thus be modular enough to adapt these constraints. The GAMA platform [6], an agent-based modeling and simulation platform providing powerful tools to develop spatial models, has been selected to implement the models and run the simulations. GAMA provides a multi-simulation feature, allowing to run several synchronized simulations. It has already been used in several projects coupling simulation and tangible interface, in particular to study urban planning and the impact of new mobility [3].

Phygital interaction component. Two major interaction forms has been identified: exploring the simulation results and tuning the intrinsic simulation parameters. To explore the simulation dataset, users' inputs on the physical 3D model trigger the visualization of the data charts associated with the physical referent (building, street, red light). The chart is displayed above the model using the HWD and can be configured using different physical features (point, edge, surfaces) of the physical referent, *e.g.* a touch on the edges of a building allow to configure the axes of the 3D chart. The adjustment of the intrinsic simulation parameters corresponds to a modification of the physical environment's topology, or a digital modification of a parameter of the simulation engine. For example, a physical floor can be added to the desired building, using a 3D printed pluggable floor, to analyze the impact of higher population density on traffic. Another example is when the speed of a red light requires adjustments to streamline the traffic. To do so, the user may select the red light using a touch on the physical 3D model, then slide on its pole to change the light switching speed.

3D animation component. The main role of this component is to run precomputed simulations in 3D realistic environments. Visualization is the last step of validation for urban planners. Each element of the scene (building, road, tree, street furniture) is rebuilt from open source data (OpenStreetMap, IGN) providing information about coordinates, height, name, function... We here focus on the buildings which is the most complicated part. To generate realistic buildings, we need accurate data. The first step is preprocessing to recompute the coordinates to make right angles and parallel sides. Then the set of GPS coordinates defines a polygon (footprint) that is extruded regarding the number of floors. The second step is for missing data, we use default values, hierarchically organized by areas, to provide two main characteristics: texture and roof. Then the roof is added and the textures are applied for each wall. Similar algorithms are used for each type of object (road, vegetation...). Finally, we can add 3D models proposed by urban planners.

Overview of the interactions between the three components. The *3D animation* component is in charge of reading the input OSM data and to augment them with additional metadata (*e.g.* obligations and constraints from the PLU). This augmented file is then used for visualisation, to initialize the *Simulation* environment or, once transformed into an augmented STL file for the *Interaction* component. The *Simulation* initialisation is completed by demographic, synthetic data. During its run, the *Simulation* will transmit to the two other components updates of the simulation states (*e.g.* location, state...), to allow

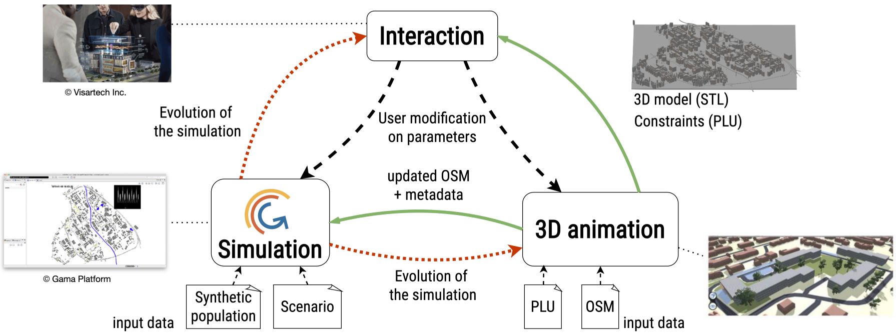

Fig. 1. Workflow of our phygital simulation approach. (*Interaction* will use Hololens by Microsoft, image credit: https://www.visartech.com/blog/)

them to visualise the simulation. When an interaction occurs, either the environment is modified (*e.g.* add a new building), in which case the *3D animation* will regenerate a new 3D model for the 2 other components, or the parameters of the simulation or agents' states are updated and only transmitted to the *Simulation*.

Coupling agent-based simulations with a tangible interface has demonstrated its benefits in terms of communication, but the improvement of the interactions is mandatory to let it become part of the urban planner toolbox. The project goal is thus to apply this approach to support Toulouse Metropole in its planning of a new ward.

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7 Simulating the transition of mobility toward smart and sustainable cities

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Simulating the transition of mobility toward smart and sustainable cities

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Abstract. This paper introduces a simulation framework to model and study mobility changes. Novelty comes from the possibility to combine different agent-based models into the GAMA platform, and to interact with the simulation through pre-designed scenarios and a serious game. The objective is to explore the impact of different urban policies on future mobility.

Keywords: Agent-based model · Mobility · Smart Cities

1 Introduction

Transport infrastructures play a large role in defining a smart, sustainable and resilient city. Innovative urban policies might either facilitate mobility and increase citizen well-being, or create negative side effects [7]. Urban planning therefore requires the city to assess the impact of these disruptive innovations based on "what if?" prospective studies [9]. However, cities are complex socio-technical systems: dynamics of transportation are nonlinear, and even wise choices might lead to negative side effects (*e.g.* the improvements in road layout might decrease the number of accidents, but increase car use and therefore pollution). Unfortunately, even if urban planning models and methodologies are available for traditional modalities (car, bus, etc.), no tool, nor methodology, exists today to assess the potential impact of these disruptive innovations, and how they can be progressively integrated into planning infrastructures.

The SwITCh project aims at providing a simulation tool for a participative reflection on the evolution of urban mobility in the next 30 years (horizon 2050). The ambition of the project is not to produce a simulator that can predict what will happen from now until 2050, nor to solve all the problems, but rather to help stakeholders (urban planner, citizen, etc) to enrich their reflection and build a shared project to improve transport infrastructures. The tool is based on an agent-based model (ABM) of citizens' mobility that simulates different evolution scenarios and tests different strategies to face them. The tool will be experimented and calibrated in the real context of two French cities, Bordeaux and Dijon. In this paper, we introduce the project architecture in order to illustrate three scientific challenges: (I) modeling individual mobility choices, (II) multi-level modeling of the city, and (III) design and exploration of different scenarios of mobility evolution.

2 Project Architecture

SwITCh uses ABM as a unifying framework to couple different models and take into account multiple temporal and spatial scales, in order to build a holistic model. The ABM contains different models to simulate individual mobility behaviour (daily activities, transportation choice, etc), transport infrastructures (streets, train tracks, etc) including different types of vehicles (private cars, taxis, bicycles, etc.), and city dynamics (pollution, etc). Those different models are dynamically combined through a dedicated middleware. SwITCh includes: a city model based on real geographic data obtained from publicly available Openstreetmap data; and a realistic representation of the city inhabitants based on a synthetic population, generated from public data records by the Mobisim generator[4]. The ABM is implemented with the GAMA platform [8]. Interactivity with the simulation is performed through either the exploration of different scenarios translated into the model by defining values of contextual parameters, or a serious game that allows users to change the configuration at runtime. The framework will include a scenario generator allowing users to easily implement new scenarios based on elementary bricks.

3 Modelling individuals choices of mobility

SwITCh aims to create a tool to explore and discover scenarios for smart and sustainable cities. So far we have developed a first model of citizens' decisions regarding their mode of transport for their daily home-work commute. This choice is influenced by a variety of factors, both internal (profile of the user, level of fitness, etc) and external (denivellation of the journey, weather, availability of public transport, etc). Based on these factors, we have designed a first multi-criteria decision model. Concretely, each agent (representing one resident of our town) has different priorities (or values) for 6 different evaluation criteria: comfort, price, ecology, simplicity, safety and time. Each transport modality also receives a mark on each of these criteria (for instance cycling has the best mark *w.r.t.* ecology, but a lower mark for comfort depending on the level of fitness of the user). Finally, the agent combines the marks weighed by their priority to choose their preferred transport mode (according to their own attributes and priorities). Different agents with different attributes or with different priorities will make different choices, even in the same situation.

[4] http://thema.univ-fcomte.fr/mobisim/

This choice is further moderated by a logarithmic routine coefficient. Therefore, when an agent is very used to a given transport mode, it will not reconsider it every time, even though the context might have changed (for instance keen cyclists will not be stopped by rain, and keen drivers will bear with increased petrol price and daily traffic jams) [2]. Our first results with this simulator [5] show that better cycling infrastructures result in an increased number of cyclists; and that a simple petrol price rise is not enough to discourage car users. Future work will further focus on the role of routine in the inertia often noted in mobility habits.

4 Multi-scale coupling of agent-based models

In the frame of the SwITCh project, various models will be implemented within the GAMA platform to model individual behaviors (activities, choices of transportation, etc.), transportation infrastructures (public transports, cars, etc.), and city dynamics (pollution, etc.). Each model has its own set of parameters, dynamics, and hypotheses. The approach chosen in the project is to build models dedicated to exploring different scenarios by combining different models. This model combination can be performed either at runtime, because of the user's actions, or before the simulation, through descriptive scenarios.

Multi-level model coupling is a technique used to combine the advantage of complementary representations of the same system (implemented in different models). There are different ways of coupling models: integrated (model as a new model from the combination of two, or more, models), weak (the model as a set of interconnected independent models), and strong (model as a set of parallel models sharing data during the simulation), these techniques have some advantages and drawbacks (in terms of modularity and easiness of maintenance) and not all models can be coupled [6, 3, 1]. The coupling could be static or dynamic, *i.e.* the composition plan could (or not) change during the simulation [4].

The novelty of the SwITCh project is to develop a model composition framework providing a dynamic model coupling service to help the development of coupled models, to increase the expressiveness of such models, and to help to choose the good coupling way. The goal is to: (1) enable the exchange of models at runtime (for example in the serious game) depending on user needs, (2) switch between models, for example, to zoom in/zoom out, and to improve scalability by finding a balance between simulation accuracy and computation time, and (3) reuse existing models in the composition.

5 Modelling scenarios

SwiTCh aims at building a decision support tool that allows a group of users to test different choices related to infrastructures under different scenarios, and to assess them with respect to relevant indicators. This set of indicators (and the model to assess them) was built from the combination of a literature analysis and a set of interviews with various stakeholders. Each indicator can be computed from a set of the ABM variables by rules (equation, algorithm, expert rule...) allowing to evaluate them. It is thus possible for a territory to evaluate its level of performance via these indicators, for each scenario. Scenarios are sets of events, assembled together like bricks, describing a potential evolution of the city/environment (*e.g.* authorization of the autonomous car, world pandemic, increase in petrol price). The bricks can be assembled according to dedicated rules to create scenarios. Each scenario will be decomposed as a set of "snapshots" representative of the main situation that can be simulated by the ABM. This will make it possible to simulate (ABM) and evaluate (indicators) different evolutionary trajectories. Two important challenges are to make the model capable of simulating these future situations (model flexibility) and to make the results understandable by all participants in the context of a participatory simulation. This is essential to make it an effective tool for collaborative thinking.

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8 Sharing green spaces at the Umeå academic campus Cezara Pastrav, Maarten Jensen, Rene Mellema, Christian Kammler and Frank Dignum

Sharing Green Spaces at the Umeå Academic Campus

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1 Introduction

In Umeå, the university and academic hospital are located next to each other in an area that is relatively separated from the rest of town by a few large roads. The hospital is the largest in Sweden and is still expanding. Due to this expansion, the green spaces around the hospital are disappearing. Although there are plenty of green spaces connected to the university, these are hardly used by people at the hospital, even though they are neighboring the hospital as well. The challenge is to create (cost) effective interventions that push more people to naturally start making use of these available green areas.

Umeå's municipality is interested in using agent-based simulation to experiment with different interventions before putting anything in practice. Our goal is to create a model that allows them to try out different policies for the area and observe their effects. Thanks to the availability of detailed traffic data for the area, we can design a basic simulation in which the agents' patterns of movement around the city fairly accurately mirror some of the real life patterns measured by the municipality. These transport patterns are only a part of the whole pattern of life and need to be complemented with behavior at work, study, hospital visit, etc. Since the purpose of the simulation is to test various behavior modifying strategies, the agents also require motivations (such as intentions, goals and values) for their behavior such that these motivations will generate both the traffic behavior as well as intuitively realistic other behaviors. Almost no data is available for the non-transport behavior. Therefore, the design of the agents needs to include an underlying decision architecture that can then be customized to accommodate different assumptions about their motivations and cause them to respond differently to different proposed behavior modification strategies.

To properly account for these needs, the decision architecture of the agents will require explicit representations of cognitive and social concepts. First, goals. If we want to change the behavior of some agent, we must also know what that agent is trying to achieve. Were this not the case, it would be impossible to see the effect of an intervention on an agent, since the simulation cannot construct an alternative plan for the agent. Second, once goals and plans are in place, agents need a way to prioritize them. For this we use values [11], which determine what humans consider important. If after an intervention an agent needs to make a choice between different plans, then it can use its values to decide between these plans. Values have been implement in a number of simulations, for example in [2] and [4].

Since we want to influence behavior, it is also necessary to build an explicit representation for the routine behaviors that agents can have. For our purposes, two types of routine behavior are particularly important: habits and social practices. Habits are individual repeated behaviors, which can change given the right influence [6, 14]. Humans are also social creatures, so the simulation will also have to incorporate social practices [12]. Both habits and social practices have been used in simulations for behavior change before [1, 5, 7, 8]. We are interested in these particular kinds of behavior because they govern the routines of life and are resistant to change. Unlike planned behaviors, these behaviors are mainly automatic and are not likely to change based on new information or new available actions. In order to change these behaviors different interventions are needed. On the other hand, if they could be replaced with more desirable alternatives, the changes will impact everyday life and are more likely to last, both desirable outcomes of the project.

A close cooperation with the municipality is required in order to design scenarios for testing. This brings us to the other main challenge: the municipality wants to experiment with multiple (as yet undefined) types of interventions, which means we cannot deliver a single simulation. Our approach is to build a sandbox-type platform in which policy makers can design their own simulations around the interventions they are interested in, observe the results, and adjust their approach on the fly. This, in turn, emphasizes the need for agents capable of complex reasoning because they would need to be able to cope with an unknown variety and type of interventions.

2 Starting situation

The university employs about 4000 people, and is attended by more than 30.000 students. The hospital employs over 5000 people and serves more than 10.000 patients a year [10]. All this activity takes place within an area of about one square kilometer. The existence of several little used green spaces in the midst of this area is reason to investigate whether they can be shared between university and hospital users to promote overall well-being.

The Umeå municipality keeps very detailed traffic statistics [13] broken down by means of transportation (cars, bikes, buses, by foot), purpose of travel (work, leisure, errands etc.), time and start of travel, weekday, seasons, and demographics. In addition, this data is mapped over the geo- and urban area, which is important for a spatially accurate simulation, which, in turn, lets us account for how traffic participants get around and decide where to go and which paths to take. Note that seasonal data is important, because between November and April most ground is covered by snow and cannot be used in the same way as in summer.

Data concerning the habits, social practices and short term goals of the people in the area is not as readily available. Some of this information is easy to find for some of the categories (lunch times, students' free time), but it is more difficult for patients and their families, not in the least because they are a very heterogeneous group in terms of familiarity with the area, reason for being at the hospital (and therefore state of mind and priorities), ability and means to get around etc. Any assumptions made about this kind of data will have to be carefully documented in order for the simulation results to be interpreted correctly.

3 Conceptual model

We want to support the Umeå municipality with this model. The purpose of the model is to serve as a sandbox model that contains a suitable level of complexity, but is easily adaptable. This means providing a platform on which the municipality can test different solutions and ideas they have. Based on the results, the municipality can then derive indicators on how to implement the desired behavior change.

The sandbox will be able to represent and run simulations for the following intervention types.

Knowledge modifiers Signs or posters in the hallways and outside of the buildings could be used to indicate available green spaces at the university. This can help especially with newcomers or with people passing by. Furthermore, this can also help to incorporate another group of people into the behavior change process, namely visitors of patients. Additionally, flyers can be provided at the information desk to inform people about the green spaces. The hotel on the opposite side of the hospital can also be utilized to promote available green spaces. Flyers or other sorts of advertisements could be placed there. As a result, visitors could stay near the hospital and help promoting new green spaces through usage and word of mouth instead of going to the city center.

In addition, more noticeable techniques could also be utilized. Info stands can be placed in front of the hospital or at other places to actively inform people about available green spaces and where to find them. With this, specific areas could be promoted more actively than others. The advantage of this type of interventions is that they cost little money and effort. However, due to their nature, they will probably have little impact on normal practices, only affecting first time and infrequent users of the area.

Physical environment modifiers A more invasive type of intervention consists of physical barriers and restrictions. These force people into certain areas and prevent them from going to other areas. Although, such installments can be the most successful because reaction to them is not optional anymore, several things have to be kept in mind. The first thing is that certain solutions are only acceptable during certain seasons. So, for example relocating parking space close to hospital and university to the fringes of the campus is more acceptable during the summer season than during winter time, unless patients and people with mobility issues can still easily get close to their destination building. Thus it is very important to keep in mind that physical changes should not hinder people in reaching their destinations in time and safely. For example, hospital staff who need to attend an emergency should not be hindered too strongly by lack of parking space. Therefore, the appropriate use of all physical spaces should be modeled carefully in order to get better insights in changes of these physical spaces. The advantage of these types of interventions is that they may also change social practices and habits. However, unexpected behavior may result from trying to keep to practices and habits by replanning and using unwanted alternative actions. E.g. parking in forbidden zones, shifting work hours, etc.

Policies and regulations The authorities of the hospital, university and municipality can enforce new policies that require certain behavior of the users of the campus area. E.g. working hours can be regulated to impact the amount of peak traffic, parking licenses can be given to certain types of employees etc. Policies and regulations have a similar effect as physical interventions if seen as constraints on behavior. However, they also have motivating and knowledge components that promote a certain type of values and thus reward people behaving according to the desired values. This might create a more general behavior change over the long term. However, regulations can also be violated and, if not uphold effectively, will have no visible effect at all.

The sandbox should have an interface that, in addition to allowing the design and insertion of the above discussed desired interventions into the simulations, effectively communicates key concepts to the users. For instance, that behavior change takes time and works differently for people following long term habits and practices and people that have no set ways yet. Thus we should be able to show not just how much success a certain intervention has, but also which types of agents successfully respond to the intervention. E.g. a temporary parking restriction might form new practices for infrequent and new users of the area, while having little impact on the regular users. Visualizing these differences is an important issue, as it influences the decision of whether to stick to a longer-term intervention or to try another intervention based on the results. Or maybe try a different combination specifically targeted at these groups.

The above requirements are the starting point of the model for our simulation. Given the types of interventions supported and the type of interface provided the municipality can use the developed simulation to test different ideas and solutions. Based on the results an informed decision can be made and tested in practice with lesser costs and with more chance of success. However, in case anything is missing or none of the provided solutions are satisfying for the municipality, feedback can be provided, and the simulation can be adapted accordingly.

3.1 Entities

Given the requirements discussed in the previous section we need to distinguish different groups of individuals in the simulation. First, there is the staff that works at the hospital, such as the doctors and nurses. They come into the hospital every day, and are likely to have set behavioral patterns. The second and third groups are the university staff and students, which go to the university every day as well (or at least regularly) - thus also likely to have set behavioral patterns. This group of students makes more use of the green space between university and hospital and it would be interesting to investigate which differences in knowledge and behavioral patterns account for this. Is this mainly due to the freedom in time students have? Or do other features play a role?

Other groups of individuals are the patients and their families, both long term and short term. These groups are particularly interesting since they do not spend as much time around the hospital and might not know the area well, which means that they do not have any set patterns in the area. They also have a large variety of reasons for visiting the hospital, which can determine their willingness or ability to make use of the surrounding green areas, and thus how receptive they are to possible interventions.

The last group in the simulation are traffic participants. All previously mentioned groups are traffic participants at times because they move around the city to get to work, classes or the hospital, but they are not the only ones to pass through the area. This additional, unrelated traffic, can act as barrier when it passes over roads between the hospital and green areas and thus make other agents less likely to cross from one to the other.

3.2 Time and Geographic Scales

We consider three different timescales in our simulation: days, weeks and seasons. During one day, the agents commute to and from work or school, go to appointments or run errands, have lunch, and find ways to occupy their free time. During one week, agents have different duties and free time on workdays and weekends, and thus different behaviors too.

Seasons have dramatically different weather in Umeå, with very cold, snowy, dark winters and warm, light summers. Spring and autumn are a mixed bag, with the notable feature that temperature fluctuates, which causes roads to become very icy, and walking outside becomes hazardous. Weather is definitely a deciding factor in deciding to go outside at all, never mind spending time in a park.

The geographical scale covers the university and hospital area in detail. Buildings, roads, cycling paths, walking paths, parking lots, bus stops, and parks are all represented to scale thanks to the available geo-data. Outside this area, the only features we represent are the main traffic arteries because we are only interested in the details of people's movements once they get to the university or the hospital. Inside the buildings we only need crude area descriptions, such as lecture rooms, hospital wards, examination rooms, etc. Mainly these distinction will be used to determine where people enter and leave the buildings and how mobile they are within the buildings.

A map of the hospital and university areas is shown in Figure 1. All details outside the areas of interest faded out, with the exception of roads and paths leading in and out of the area.

3.3 Cognitive and social aspects

The cognitive and social aspects that are relevant in our case are goals, knowledge, social practices, habits, norms and values.

Goals are states which the agents are trying to achieve through their behavior. Thus, in this simulation, they are the principle drivers of behavior. We can have goals with sub-goals, such as getting to an examination room is a sub-goal for a goal of hospital visit for a patient.

Social practices and habits are partial plans that are used as defaults in the larger plans for achieving goals. These partial plans are interesting because they are resistant to change and thus special circumstances need to be created in order to overcome this resistance. Also, the longer they have been in place, the harder to

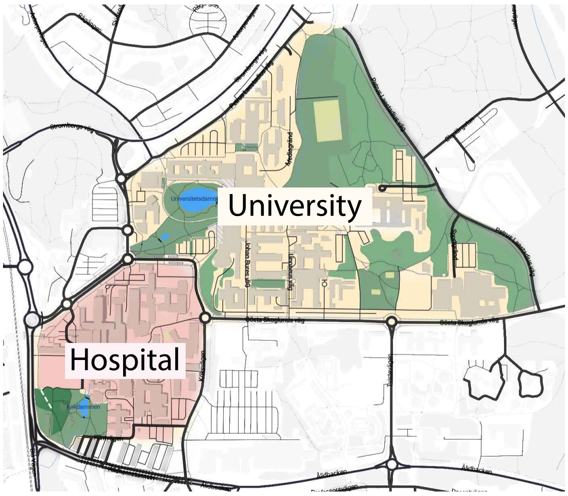

Fig. 1. A map of the university and hospital areas. The hospital area and the campus are fully detailed, with the rest of the map faded out, except for roads and pathways.

change they become. This means that habits and social practices, once established, are followed automatically and preferred over all alternative plans, even when other plans become more beneficial in some way.

We consider habits to be harder to change than social practices because habits are more personal, and thus less likely to respond to social pressure. This part of the model is based on [7].

Norms are used in the implementation to model regulations of the different institutions that make use of the campus. However, they also can encompass norms such as: a patient should be in time for her appointment with a doctor and students should be in time for a class. It is clear that people keep their appointments with a doctor more strict than students are in time for class. This illustrates that norms can be violated, although they always have some influence on behavior. The existing norms might also interfere with new policies that are created for the simulation and therefore are important to model. This aspect is modeled based on [9].

Knowledge defines how many alternative behavior options an agent is aware of and also determines the expected effects of certain behavior. The more knowledge an agent has, the more plans it can build in order to achieve its goals and the better it knows all the effects of these plans. For instance, an agent that wants to pleasantly spend an hour of free time and is aware of the existence and location of the green areas in the vicinity can plan to visit one of them, whereas an agent who lacks this knowledge, may choose to read a book or watch TV inside. It is important to note that knowledge by itself does not determine or change either plans or goals, it just increases options to choose from.

Finally, values are the overarching concept that ties every other cognitive and social aspect together and establishes preferences between alternatives when neither of the other aspects can be used to definitively choose. Values also determine which kind of changes an agent will be more likely to make since the goals, habits and social practices an agents has in the first place are all dependent on its values. See e.g. [4] for ways to model this aspect.

3.4 Expected results

Regarding the simulation outcomes, we expect results to depend on the invasiveness of the intervention. Therefore, the general expectations can be divided as follows.

For the least invasive, like putting up posters or providing information material at information desks or at the reception of the hotel, a slow starting rate should be expected. Most of the people will recognize the information and read it but also forget it soon afterwards if they are not really interested in it. However, it can be possible that the rate strongly increases after some time when enough people use the new green spaces and so make these areas more prominent to others. Habits, as referred to as solo social practices earlier, can then become general social practices.

The expectations of more invasive intervention techniques should be different, however. When placing info stands, it is more likely that the usage of new green spaces can happen faster because people are informed more directly, benefits can be promoted more heavily, and questions can be resolved. Thus, the knowledge about available green spaces can be strongly increased and people can be motivated more actively to change their habits.

The fastest change can be expected when implementing physical interventions by e.g. relocating parking places or opening or closing entrances to buildings since this forces people to react. They key aspect here is that reaction is not optional, like in the cases before, but rather necessary because previous options are not available anymore. However, it is not certain that the desired behavior change is going to happen. It can be possible that previously neglected options are becoming more attractive now and, thus, it is not certain that new options are considered but rather older options which have been available before but have been deemed less valuable than the chosen option which is now not available anymore. Nonetheless, a change of habits and social practices is enforced which also affects the knowledge aspect. If people want to reach their goal to go outside, they are forced to increase their knowledge about available places. Another thing which has to be kept in mind here is that it is not possible to install too many barriers because the daily business has to continue as usual and as smoothly as possible.

The impact of implementing new wellness policies strongly depends on their enforcement. The more strictly they are enforced, and the harder violations are punished, the more likely it is that new social practices get adopted and behavior change is going to happen.

4 Discussion

The data collected from the municipality gives us a base to describe the daily behavior of the users of the hospital and university space. It also gives a basis for distinguishing a number of important types of people that have different reasons to make use of the area. This information is important as it serves as the starting point for experimenting with interventions to change behavior.

We start with an assumption that people have an inherent resistance to behavior change. I.e. if they have a practice or habit, they would like to stick to it even though it might not be the optimal behavior (anymore). This implies that people do not change their practices on the basis of new information, and that information-based interventions are more likely to work on people that are new to the area and have not yet had time to develop habits or social practices.

Another important consequence of the resistance to change is that people tend to stick to their (sub)goals as long as possible. If their usual behavior is no longer possible or made difficult, they will try to create an alternative plan for the same goal. Only when their goal is no longer attainable, will they create alternative goals based on their values and opportunities. Thus, this will give a good prediction on how people react to changes in the environment.

The cognitive model required to model this behavior change is quite complex, but will give a detailed insight in changes of behavior. However, simulations that have agents with these rich models are not easily scalable. We estimate that we can run simulations with maybe a few hundred of these agents in real time. In order to scale up the simulation we have to simplify the agents in a useful way. Our proposal is to do this not by having one simulation that can have both scales at the same time, but rather use two different simulations. The first simulation uses the rich cognitive models and studies the individual behavioral changes based on the interventions. We analyze the behavioral changes in detail and classify them based on the characteristic of the models. E.g. individuals that are working as staff at the university and are concerned about the environment will usually respond to incentives to bike to work. This response will depend on the importance of their environmental value and how strong their habit is.

There will be a distribution of these values over the category of university staff that can then be used as a probabilistic measure on how this category of individuals will respond to an intervention. Thus we replace detailed deliberations based on complete models with probabilistic rules for categories. These much simpler rules can be used for the agents in a new simulation with a far larger scale to investigate the effects on a realistic scale model.

5 Future research

Future research will focus on developing the parts of the sandbox that interface with the policy makers (or even the general public) in order to create a digital alternative to the ComMod approach to participatory modelling [3]. Interface and user experience design is not trivial in the case of a software that aims to both be easy to use and easily communicate complex concepts and dynamics to people who are generally unfamiliar with the theory behind agent models, complex systems, or social and cognitive architectures. Parceling out information in useful amounts at useful moments or clearly guiding the user through possible courses of action will almost certainly require experimentation through multiple iterations. However, the advantages offered by such a sandbox in facilitating the collaboration between policy makers and model developers are worth the effort it would take to make it a reality.

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9 Integrated Agent-based and System Dynamics Modeling of the Spatial Diffusion of Home-based Decentralized Water Technologies and the Impacts on the Water System

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Integrated Agent-based and System Dynamics Modeling of the Spatial Diffusion of Home-based Decentralized Water Technologies and the Impacts on the Water System

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Keywords: decentralized water technologies · agent-based modeling · system dynamics modeling · integrated analysis · spatial planning.

1 Introduction

Cities are facing increasing water stress due to climate change and population growth. Although urban water use efficiency was improved, total water use continuously increases especially in the rapidly urbanized areas. Ensuring water availability and security has become an urgent concern to most cities in face of climate change. Centralized water systems dominate the urban water services in major cities and are important in ensuring sufficient water supply, sanitation, and drainage services to urban communities. However, such systems are considered inadequate to address future water challenges and the aspiration of ecologically sustainable development considering their high energy dependence and infrastructure aging problems. Upgrading the urban centralized water infrastructure is critical for a city to achieve the transition towards more sustainable and resilient water and sanitation services. However, considering the socio-technical lock-in effects and the strong path dependency of legacy water infrastructures, the upgrading and extension are costly and complicated.

Considering the challenges faced by centralized water systems, decentralized water technologies are recently emerging as potential alternatives to strengthen the reliability of urban water supply. By recovering and utilizing diverse local water sources to supplement urban water demands, these technologies can mitigate the pressure of water scarcity. Social preferences and choices of decentralized water technologies are critical to the level of mitigation. The demand-side investigation is important for water utilities and the government to make an investment and better plan the deployment. While past studies evaluated the critical socio-economic and technical factors that explain the household preference [1–3], there is a limited understanding of the spatial adoption and diffusion pattern of decentralized water technologies in a city and its impact on the water system. By answering this research question, our study can help the city develop an actionable plan to promote decentralized water technologies.

2 Methodology

We developed an integrated framework to explore the adoption and diffusion pattern of rainwater harvesting (RWH) and greywater recycling (GWR) systems in the city of Boston, and the impact on the water system that supplies water to the whole Metropolitan Boston (MB) region. In the framework, we first built a spatial agent-based model (ABM) to simulate the adoption of home-based decentralized water technologies by single-family households in the city. We used a system dynamics model (SDM) to evaluate the impact of decentralized water supply on reservoir water availability, hydropower generation, and carbon emission for water supply and wastewater treatments. The percentage of carbon reduction was used as the environmental benefit to update household adoption decisions of RWH and GWR in the spatial ABM. By exchanging "potable water supply" and "carbon reduction" between the ABM and the SDM (Fig.1), a hybrid model was thus established.

We validated our model integration by comparing the simulated places where early adoptions emerge with the validated installations (Fig.2), and the simulated reservoir elevations with historical records in the reference year (Fig.3). Several water drops (i.e., Feb. and Nov.) in Wachusett Reservoir were caused by precautionary measures that the SDM did not capture [4]. Nevertheless, the results are basically in line with the reported data in both simulations, and thus can validate the effectiveness of using our integrated model in predicting the spatial adoption and diffusion pattern of RWH and GWR, and evaluating the impacts of two decentralized water technologies on the centralized water system.

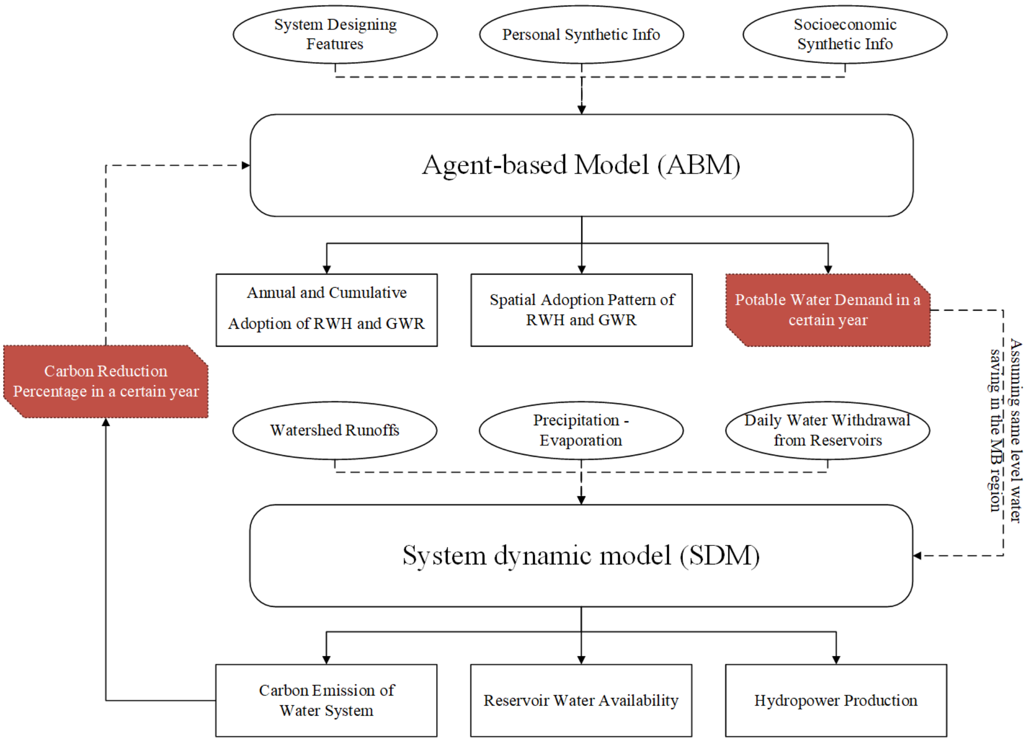

Fig. 1. Integration between the ABM and the SDM.

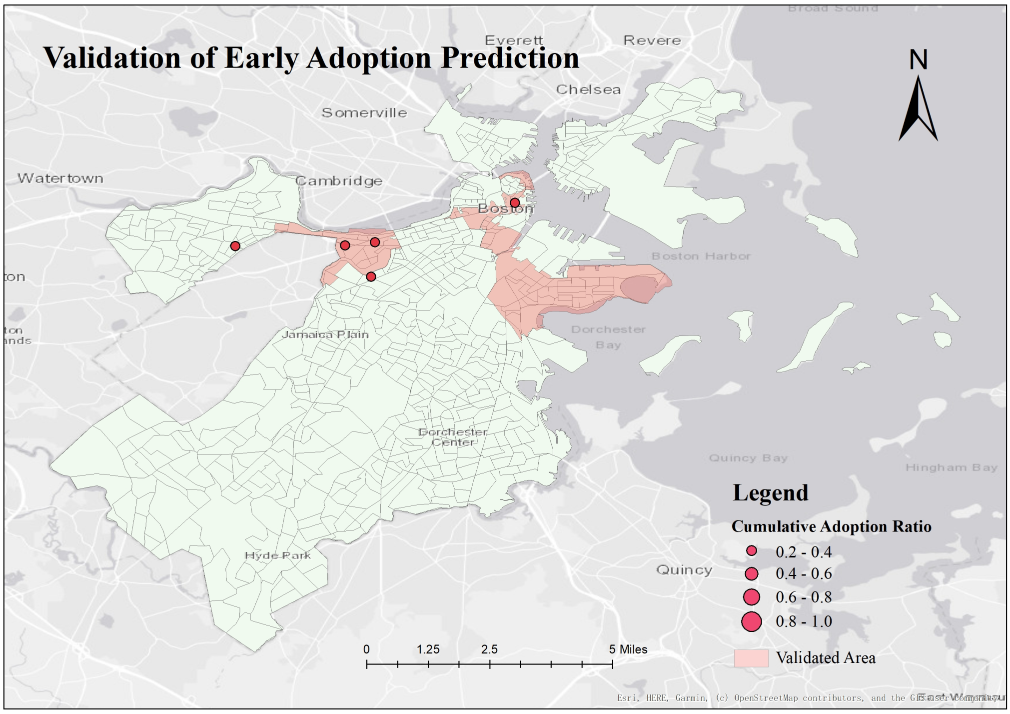

Fig. 2. Validation of early adoption predictions.

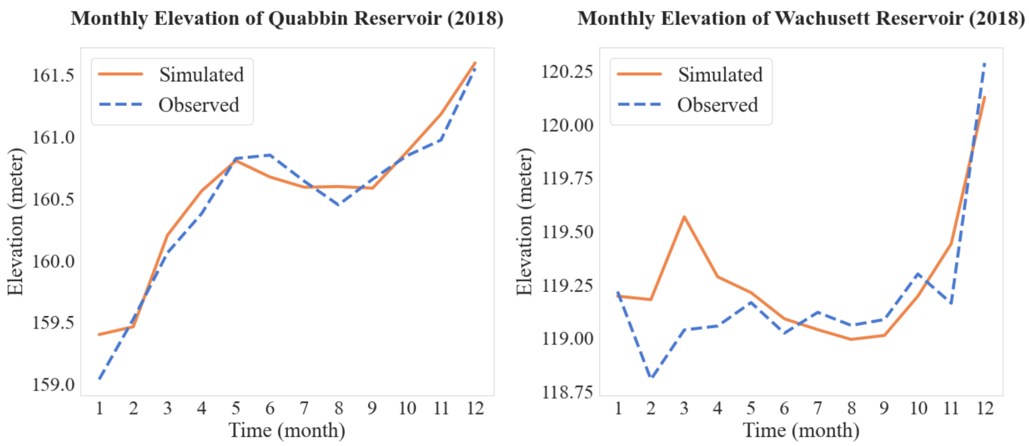

Fig. 3. Validation of monthly reservoir elevations in the reference year.

3 Results and Discussions

In the results, we first examined the sensitivity of RWH and GWR adoptions to market promotion, neighbor's influence, economic performance, and environmental benefits. Our ABM results revealed a much higher adoption and faster diffusion of RWH than GWR. The diffusion of both technologies starts from north downtown to southern suburban in the city. Spatial heterogeneity emerges in adopting two technologies with some communities having much higher adoptions of RWH versus some other communities that have more adoptions of GWR than the average. Our SDM results show that water availability increases in reservoirs with the adoption of RWH and GWR. However, hydropower generation from the water supply becomes less as water transfer between reservoirs decreases. More water is released from reservoirs to downstream rivers for safety purposes. Utilization of the increased water availability should be explored to produce more hydropower. Moreover, we did not find a significant reduction in carbon emission of water systems due to the high carbon intensity of GWR as compared to the centralized system. Reducing the impact of GWR energy consumption is critical to the benefits of large-scale implementations of decentralized water technologies.

4 Relevance for the ABMUS Workshop Themes (Multi-level Modelling)

Our paper is fully in line with the ABMUS overarching theme of multi-level modelling of urban system. The relevance is highlighted in the following aspects:

(1) ABM simulates both the spatial adoption pattern and the temporal diffusion pattern of decentralized water technologies in *a city-wide level*.

(2) SDM quantifies the impact of adoption on water system by assuming *the MB region* has the same level of water saving as single-family households in the city of Boston, which is acceptable because 53% of housing units in MB served by the centralized water system are single-family houses [5].

(3) By integrating the ABM and the SDM, the hybrid-modelling framework can provide systematic solutions for planning and evaluating the decentralized water technologies *at the nexus of human-infrastructure-environment* across *spatial and temporal scales*.

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10 Using the COMOKIT model to study the impact of the morpho-functional organization of cities on the spread of COVID-19

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Using the COMOKIT model to study the impact of the morpho-functional organization of cities on the spread of COVID-19.

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Keywords: Agent-based simulation · COVID-19 · GAMA platform · morpho-functional city organization.

1 Introduction

Are some urban environments more resistant than others to cope with a pandemic such as the one caused by COVID-19? This question is at the heart of many debates because this pandemic reminds us how vulnerable urban populations can be. It invites us to explore how policies could take advantage of the knowledge of local epidemic dynamics in given morpho-functional contexts to become more place-specific.

The problem is that although an impressive amount of data is now available regarding the impact of the pandemic in different geographical contexts, it is almost impossible to determine the relative importance of the spatial context in comparison to, for instance, social, cultural, epidemiological or political factors. A possible approach to disentangle those determinants is to use realistic simulation models in which the impact of different morpho-functional organizations on the effectiveness of public health policies would be evaluated.

Many models have been produced in recent months to respond to the emergency. While many of these models do not allow space to be taken into account, others, and in particular agent-based models [1], allow it and thus enable realistic morpho-functional organizations to be considered. This is the path followed by the COMOKIT[7] (COVID-19 Modelling Kit) framework [3]: COMOKIT combines sub-models of person-to-person and environmental transmission, a sub-

[7] https://comokit.org

model of individual epidemiological status evolution, an agenda-based one-hour time step sub-model of human mobility, and a policy intervention sub-model.

We propose in this paper to use COMOKIT to study the impact of the morpho-functional organization of a city on the containment policies that can be put in place.

2 COMOKIT in a nutshell

COMOKIT has initially been developed to respond to the Vietnamese government's need for tools capable of assisting in decision-making on intervention policy choices (containment, mandatory mask wearing, etc.) at the scale of a small town (about 10,000 inhabitants). However, it has been designed to be modular, extensible and able to be deployed in different case studies, with different available input data.

The core entities of the model are the *Individual* agents: they represent interconnected (relatives, friends, colleagues, etc.) individual inhabitants of the commune with their individual characteristics (age, gender, employment status) and their epidemiological status. They perform daily activities depending on their personal agenda. This agenda is a generated set of *Activity* that can be shared by several individuals (*e.g.* going to a restaurant with some friends), depending on the age and family status of the Individual agent. *Building* agents are the atomic spatial entities where the *Individual* agents can perform an *Activity*. Two special *Building* kinds have been defined as they have an important role in the simulation: *outside*, that represents everything outside the studied area, and *Hospital*, where sick individual agents with critical symptoms can be contained and healed.

A simulation step is set to represent 1 hour and starts by the agent to agent transmission: contagious *Individual* agents infect other susceptible agents in the same building based on a successful contact conditional probability. Then all *Individual* agents update their epidemic status, e.g. going from susceptible to infected. Next, they execute their daily activities depending on authority allowances. Finally, the Authority agent checks its current Policy and apply it, e.g. to test inhabitants.

3 COMOKIT Azur

To study the impact of the morpho-functional organization of cities on the spread of COVID-19, we focus on the case study of the urban area of Nice (France) which has been hit particularly hard by the pandemic and is considering the use of place-specific policies. We thus applied the COMOKIT model on 3 subareas with very different organization [2]:

- *Nice city center*: this is a compact pedestrian-friendly 19th century city, characterized by high urban density in the form of adjoining apartment buildings, finely meshed urban grid, many leisure facilities and small stores.In addition,

this subarea is used by a large population living in other districts of Nice who come here to do activities (work, shopping, leisure activities, etc.).
- *Nice suburban residential area*: this area lies outside of the city of Nice proper and is characterized by low population density in single-family homes with gardens, and an equally low level of services. Functional specialisation is the hallmark of this area, which also includes some concentrations of car-based commercial buildings. The overwhelming majority of residents work outside of this subarea. Few outsiders come to the subarea to carry out activities.
- *Nice modernist peripheral area*: this subarea is in an intermediate situation: this subarea is densively populated and mainly composed of collective housing, with a low level of service and a majority of inhabitants working outside of the area.

These different morpho-functional organizations beg the question of the favored patterns of encounter in the context of the COVID pandemic and of the possible impact of local containment policies.

We initialized the model using French high-quality data sources: the INSEE (French national institute of Statistics) and IGN (French National Institute of Geography) in addition to OSM data. Simulations were executed from January 24 to October 20, 2020, taking into account the epidemiological context of this period. On each area, we tested three scenarios: the absence of an intervention policy (basic scenario), a realistic policy inspired by government action in France and a hypothetical policy of closing urban areas. Each of the three scenarios follows the temporal development of the measures taken in France during the 1st containment between March 17 and May 11, 2020.

50 replications for each area and each policy were carried out to take into account the stochasticity of the model.

First results. Among other contrasting responses to the French lockdown scenario the simulations carried out allow to highlight a cleavage: on the first hand, suburb area has being relatively protected against the outbreak, while on the other hand, the two other areas have been hit by a curve up after the release of the intervention, even sharper for the intermediate area. This might be explained by the relative openness of the last two areas, where a half and almost one third of the population of agents come from outside of the studied area. It clearly supports the observation that lockdown in itself is not able to stop the outbreak if it is not followed by targeted interventions to fight again the re-introduction of new cases.

Another aspect to analyse is the differences regarding the epidemic rebound: it is sharp in the intermediate area, contained in the city center, and smooth in the last. This may be explained by the structure of activities and functional aspects of the urban area: in the city center there are a lot of small workplaces and retails that lead to a relative low and consistent number of daylong contacts and a large number of small contacts with interchanging agents; in the suburb there is very few contacts related to activities such as shopping and working but many prolonged contact with the same agents again and again, like relatives and friends; finally the intermediate area has a lot of large building that host workplaces or mall, leading to a large number of prolonged daylong contact between agent from within and outside the area. This contrasting responses should be considered when deploying a unified intervention policy and might be more effective if considered in conjunction with the specificity of the morpho-functional aspects of urban areas.

4 Conclusion

In this proposal we briefly introduce the COMOKIT framework that makes it possible to study the outcome of intervention policy over the course of a SARS-CoV-2 outbreak at the scale of a city. We apply the model on the city of Nice in the south of France and explore how different areas of the urban zone respond to interventions. In particular we demonstrate how important is the openness to outside areas to foresee lockdown style intervention efficiency and how provided activities and facilities in an area can impact the course of the outbreak after the release of the intervention.

While COMOKIT used in several context, we still plan to improve its ability to represent the new challenges to support mitigation strategies to fight against the pandemic. More precisely we want to make it possible to explore in depth spatial aspect of NonPharmaceutical Interventions (NPI), for example we want to add new feature in the framework to easily implement and test policies entailed by proposition related to the "NoCovid" strategy and the identification of Green zones with territorial based planing of the interventions.

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