D2.1 – Agent-based model & scenario analyses

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Table 1 Keywords

Dissemination Level		
PU	Public	X
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
CO	Confidential, only for members of the consortium (including the Commission Services)	

Table 2 Dissemination Level

History			
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Table 3 Version History

Executive summary

The aim of WP2 is to develop recommendations at urban scale to prevent or mitigate the spread of the COVID-19 epidemics. To take into account the many uncertainties related to the epidemiological characteristics of the disease, we explore a set of plausible scenarios and find robust policies that are efficient and effective in combating the outbreak of an epidemic. Within this context, D2.1 makes a headstart on agent-based modeling that provides insights into the dynamics of the spread and the impact of different policies in two cities. Based on this, we provide recommendations for cities and governmental bodies on robust policies that help to control the spread of the disease.

Approach. Epidemics essentially spread through contact networks. To consider the impact of local population structures and behaviour from the bottom up, this WP developed an agent-based model (ABM) that represents a full-scale artificial city. As such, we include factors such as population density and age group, family role. social role, and typical behavioral patterns. By simulating individual activity and person-to-person interactions we are able to trace the behaviour of infected people that are contagious, but not (yet) sick, and design effective policies to combat disease spread. At the same time, we integrate the impact of different policies (as identified in Task 1.1) while keeping track of healthcare system capacities (Task 2.2).

The WP uses open data to generate the synthetic population, their workplaces and subsequently inferred activity patterns. Additionally, epidemiological parameters defined from literature are used to define state transitions within the model. In order to check for the robustness of policy implementations, we performed exploratory analyses over key uncertain parameters. The parameters were selected from the input data to represent uncertainty both with respect to epidemiology and behaviour. The effect of the policies is stress tested against these uncertainties to identify robust measures and develop recommendations for implementation.

Results & recommendations. To compare different urban contexts, the ABM was applied to two example cities: The Hague in The Netherlands, and Helsinki in Finland. Although there is significant uncertainty in the results (driven by uncertain parameter in epidemiology and unpredictable human behaviour), our results show that for both cases, the 'soft' policies that rely on closure of only restaurants, bars, and recreational and educational institutions are comparable to the baseline (with no restrictions implemented), and are therefore not as effective in combating the disease as compared to a more strict policy of complete lock-downs. We also show that the timing of policy implementation has a great influence on the impact of the policies: because of the long incubation period and many asymptomatic cases, even a delay of only two weeks (15 days) leads to a significant increase in case-load, threatening to overload the health system. We demonstrate that in a policy of a strict lock-down, extra attention must be given to the combination of citizens' activity schedules, locations' working hours and area. To prevent mass infections at places with high numbers of visitors such as supermarkets or pharmacies, it is important to 'spread out' visits over the day.

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List of acronyms

Abbreviation / acronym	Description
ABM	**Agent Based Model**

Table 6 List of acronym

1 Introduction

Over the course of ten months in 2020, the SARS-CoV-2 virus (COVID-19), first identified in December 2019, has spread across the globe and - now, in October 2020 - has resulted in over 35 million confirmed infections and over 1 million deaths (WHO, 2020). The immediate impact of the highly infectious disease raised alarm, as the escalating number of individuals contracting the virus quickly overwhelmed local and national health systems world over (*Risk Assessment*, 2020). This greatly limited the capacity of the health system to meet the needs of patients, particularly amongst vulnerable segments of the population (e.g., the elderly and those with pre-existing health conditions).

To mitigate the spread of the virus, countries have adopted various strategies in accordance with available resource capacities and trusted knowledge of best practices. This knowledge is rooted in continually evolving scientific understanding of the disease spread. Since the onset of the pandemic, many studies with varying and often contradictory findings have generated an ongoing debate around the mechanisms of disease spread and the best practices to manage this spread (Day, 2020). In the face of this uncertain knowledge, public health authorities and decision-makers were required to take swift decisions, without the opportunity or time to clarify uncertainties - a situation that is characteristic of sudden onset disaster response (Comes et al., 2020).

With the limited knowledge at hand, no vaccine in sight and finite medical capacity to treat the sick, non-pharmaceutical interventions became one of the main strategies of the pandemic (Gössling et al., 2020). A crucial part of the non-pharmaceutical interventions is changing individual behavior to combat the spread of the disease (West et al., 2020). Many governments and public health authorities implemented measures to influence citizen behavior including encouraging individuals to wash hands regularly, maintain social distancing, and wear face masks in public. A stricter strategy adopted by many countries was to implement a 'lockdown'. The stringency of this measure varied from country to country, and ranged from closure of public spaces, educational institutions, and businesses in the service industry (e.g., restaurants and bars) to strict stay-at-home regulations that permitted citizens to leave their homes for limited and essential reasons only. While effective at controlling disease spread in the short-term, this measure is associated with undesirable trade-offs, with countries projected to have devastating impacts on national and local economies (IMF, 2020).

Overall, the pandemic has resulted in substantial reduction in the movement and interactions of individuals everywhere (Jakobsson et al., 2020). While this is largely due to the policies implemented by governments, such behavioral change may also be attributed to awareness campaigns surrounding the virus , as well as the effects of individual fear of the virus and other such psychological effects (Ahorsu et al., 2020; Epstein et al., 2008; Lee & You, 2020). When non-pharmaceutical interventions become critical to the disease, individual behavior can significantly vary the outcomes of interventions (Flaxman et al., 2020).

Individual behavior is deeply tied to cultural and socio-demographic contexts of a location. COVID-19 has therefore seen different levels of severity in interventions in different countries. However, even within a country, the interventions taken at the national level differ from the interventions taken at the level of a city. Municipality governments often work closely with local communities, businesses etc. to tailor the measures to the context. Such participatory approaches and tailored interventions are harder to realise at the national level. The need to cater for the context and the differences in the urban contexts has inspired multiple initiatives like city networks where governments and officials of different cities assisted each other during the pandemic (Sala, 2020; WHO, 2020).

Cities are also of interest because of their high population density. This enables viruses such as COVID-19 to easily spread through physical contacts between individuals, whereby infection risk depends on factors such as duration of interaction and physical proximity between infected and non-infected individuals (WHO, 2020). In dense urban environments, the increased rates of activities and interactions can facilitate rampant spreading of the disease. Thus, higher population densities found in urban environments render cities vulnerable to becoming potential "hotspots" of disease spread (Stier, Berman & Bettencourt, 2020). Understanding the mechanisms of disease spread in cities, and developing targeted, robust interventions to control that spread, can yield potentially high impacts in terms of mitigating loss of lives.

This study aims to understand the effect of human behavior and interactions on the outcomes of different policies taking into account the uncertainty around the epidemiological characteristics of the disease and the cultural and contextual characteristics of a city. The aim of this study is to identify robust policies that are able to contain the spread of the disease under different possible futures.

1.1 Objectives

The objective of this project is to answer the research question: **How can authorities control the spread of COVID-19 in cities?**

This study aims to compare the spread of COVID-19 in two European cities - The Hague in The Netherlands and Helsinki in Finland. Subsequently it aims to identify robust policies that can be applied to control the spread. While in the proposal, we were intending to include a city in China, the consortium agreed to focus on European cities to reflect the dramatic changes dynamics of the outbreak since the proposal was submitted in February 2020, and the impacts in European cities and for EU citizens.

Even within the same city, there is evidence that the virus has had an uneven impact on different socio-demographic groups (Goldin & Arouet, 2020) . The number of spatial contacts is not equally distributed within a city, for reasons such as land use, commuting patterns and individual behavioral factors (Zhang, Verbraeck, Meng, Chen & Qiu, 2016). For example, city centers typically have higher numbers of businesses, which attracts more people to visit and interact throughout the day, thereby creating more opportunities for rapid disease spread. At the same time, the interplay of various attributes (e.g., occupation, social activities and average travel time to work) on an individual level lead to specific behavioral patterns that result in manifold effects that give rise to varying patterns of disease spread across a city (Ge, Meng, Cao, Qiu & Huang, 2014). To answer the research question this study simulates individual behavior in an artificial city during a pandemic using an agent based model (ABM).

1.2 Methods

The modeling formalism used in this study is agent-based modeling to capture the emergence of patterns from behaviour and social interactions of the agents that is characteristic for the dynamics of the disease. To understand the implications of different measures for cities, an agent-based model (ABM) of a full-scale artificial city was built. This model simulates individual activity and person-to-person interactions, thereby enabling us to observe and analyse the collective impacts of individual behavioral patterns on the spread of the disease in a city. To compare different urban contexts, the ABM was applied to two example cities: The Hague in The Netherlands, and Helsinki in Finland.

The spatial granularity of the model is at a building level, whereby the different functions of each individual building are represented. This enables us to observe the aggregate effects of individual activities at those locations across neighborhoods in the city. The spatial scope is the boundaries of the city. The temporal scope of the model simulation spans a time period of 120 days, which we found sufficient to capture the effects of the initial outbreak of the disease as well as the impacts of policy implementation in response to such an outbreak.

The key subsystems that impact mechanisms of the disease spread in an urban area were incorporated into the model. According to Zhang et al. (2016), there are two potential drivers of the disease spread in cities - the number of activities happening every hour within the city and the number of people involved in these activities. Consequently, when people are getting sick the first action is usually taken by the local healthcare system operating within an urban area thereby expanding the findings from T2.2. Country-wide demand is generated by individual cities, therefore to investigate how sudden increase in demand can be more efficiently tackled there is a need for a simulation model on the city scale..

The resulting model can be used to investigate policies such as school or workplace lockdowns; restriction on social gatherings; or awareness campaigns to analyse their effectiveness and efficiency given the time of implementation (versus the spread of the disease).

In addition to observing the collective impact of individual actions and the effectiveness of policies, we designed experiments to test the implications of different uncertainties surrounding the mechanisms of disease spread as well as behavioural uncertainties. First, the set of uncertainties pertains to the epidemiological parameters which characterize the transmission of the disease. These parameters, such as infectiousness of the virus and percentage of asymptomatic transmission are hotly contested in literature (Ferguson et al., 2020; D. He et al., 2020; X. He et al., 2020; Nishiura et al., 2020). Any small difference in these parameters may result in vastly different outcomes. Second, we capture the behavioural uncertainty in terms of the agent's decisions on the specific points of interest that they decide to visit as well as changes of behavioural patterns as a reflection of the policies implemented.

In the face of such uncertainty, tools are needed that enable decision-makers to explore the implications of their choices under deep uncertainty that can not be immediately reduced (Comes et al., 2015). To cope with this uncertainty, the approach of decision making under deep uncertainty is used. Such an approach allows the model to be experimented with across wide ranges of highly uncertain parameters, resulting in an ensemble of plausible futures in the form of scenarios. These scenarios can then be analysed to identify robust policies that can perform effectively in a wide range of possible future scenarios (Marchau et al., 2019). Therefore, we aimed at performing exploratory analyses by running a high volume of experiments in the model using the high-performance computational facilities at Delft University of Technology. The exploratory analysis was carried out by sampling combinations of all the debated parameters in the model, such as infection probability and asymptomatic transmission, in conjunction with initial number of infected individuals and possible policies. In so doing, we conducted a systematic exploration of the consequences of the various uncertainties, thereby shedding light on the possible COVID-19 responses that show a robust performance under a wide range of conditions.

Based on our research question, the model metrics were defined as the number of infections, hospitalizations, ICU admissions and deaths across geo-demographic parameters**.** For example, in both The Hague and Helsinki, schools and workplaces were shut down, and bans on social gatherings were implemented during the first wave of the pandemic. By implementing variations of such policies in the model and evaluating the outcomes in response to policy experimentation within the model, we are able to paint a better picture of the robust design (e.g., duration, extent and implementation time, worst case scenarios) of such policies, thereby informing the response to the second wave.

1.3 Data

The ABM is constructed with open data on population statistics and land use, made available by city governments. This is supplemented with data on buildings available on OpenStreetMaps and from secondary research such as Dataplatofrm Den Haag, Den Haag in Cijfers, Helsinki Open data service and others, in accordance with the data management plan and ethics agreements to preserve privacy and data protection standards.

Given the granularity of the model, extensive data is required to model each individual agent with attributes that correspond to that of the citizens in the cities of interest. However, such data, if it exists, is often expensive and challenging to gather and verify. An additional challenge is that individual-level data is challenging to obtain, or cannot be used due to privacy and security concerns (e.g., related to patient data). Such microdata is often anonymized or provided at a higher level of aggregation by governments. With that said, given the objective of observing the dynamics of disease transmission and the impacts of different policies and uncertainties, we considered it sufficient to generate a model of a city that maintains the overarching characteristics of the city of interest on a neighborhood level, using synthetically generated microdata.

Thus, we generated an artificial city with land use functions and a synthetic population that approximates the cities of interest. In the case of both cities, the summary statistics made available by the government were often on a neighborhood level (e.g., family structure, age structure, and income structure by neighborhood). This data was used to empirically inform the design of the artificial city, and to generate agents in the model with attributes such that the agent population of each neighborhood is consistent with data on neighborhood-level population statistics. Open data on buildings and land use were also generated that matched available open data by governments (e.g., cadaster databases) and OpenStreetMaps. More details on the use of data collection and analysis are provided in Sections 2.2 and 2.3 below.

1.4 Overview of the contents

The report is divided into eight sections following the introduction. First, the simulation model is discussed (Section 2). This includes the conceptual model (Section 2.1), data collection (Section 2.2), model implementation (Section 2.3), verification and validation (Section 2.4) and the design of experiments (Section 2.5) for the exploratory analysis. The design of experiments includes the uncertainties (epidemiological and behavioural) and the policy combinations for which the model was tested.

Following this section, the results are presented (Section 3), discussed and compared between the two cities (Section 3.3). The results are presented under each policy and under different scenarios within the policy. In this section the capacity of the healthcare system (Tasks 2.2) is compared with the requirement in each scenario.

After discussing the assumptions and limitations of the model (Section 4) recommendations are presented (Section 5). The policy recommendations are based on the results and discussions and implications for global mobility via the EpiRisk modeller The report ends with future enhancements to the model, future research questions that can be explored using this tool and exploratory research arising from this project (Section 6). The report is concluded in Section 7 followed by a bibliography (Section 8) and annexes.

2 Simulation model

The simulation model is designed to inform policymakers on how cities potentially can control the spread of COVID-19. In order to do so, we developed an Agent Based Model (ABM) that represents an artificial city. This model was then adapted to both The Hague and Helsinki.

2.1 Conceptual model

The conceptual model of this artificial city has five main components: *citizens* (people in the city) are central to the model, see Figure 1. These agents conduct *activities* (behavior of the people) and visit different *locations* within the city, which is influenced by different *policies*. The *epidemiological state* transition determines the state of infected people. All these elements are characterized as submodels. In the following, we discuss the design choices and implementation for each submodel.

A simulation that captures the varying effects of disease transmission in a city must model contacts between citizens as *spatial* contacts are considered to play an important role in disease transmission (Zhang et al., 2016). Spatial contacts are a result of dynamic interactions between people in a city at work, at home, or while engaging in social activities. Thus, adequate representation of the urban population is critical, including the diversity of geo-demographic characteristics and daily activities across a city. To achieve this, each individual in the city is modeled as an agent. The agents' daily activities are dependent on their demographic traits (e.g., age or family role), and generally revolve around work or school, socializing, commuting, and leisure (e.g., personal care, eating and shopping).

To capture the epidemiological component of the study, a modified SEIR model was used, whereby individuals who are susceptible may be exposed, infected (asymptomatic or symptomatic), hospitalized, admitted to the ICU. Infected individuals can recover or die (Batista et al., 2020). Infected people pass through different stages of the infection starting from early to late. During this transition their transmission rate changes (He et al., 2020) Exposed individuals who become infected then pass through the different epidemiological states within the model and also infect others. This is explained in complete detail in Section 2.3.4.

Policies introduced within the model take effect by changing the activity schedules of people. Changing activity schedules is used to model the act of people changing their behavior towards the disease or other policy interventions. For example, people will begin to stay at home to reflect compliance with work-from-home policies.

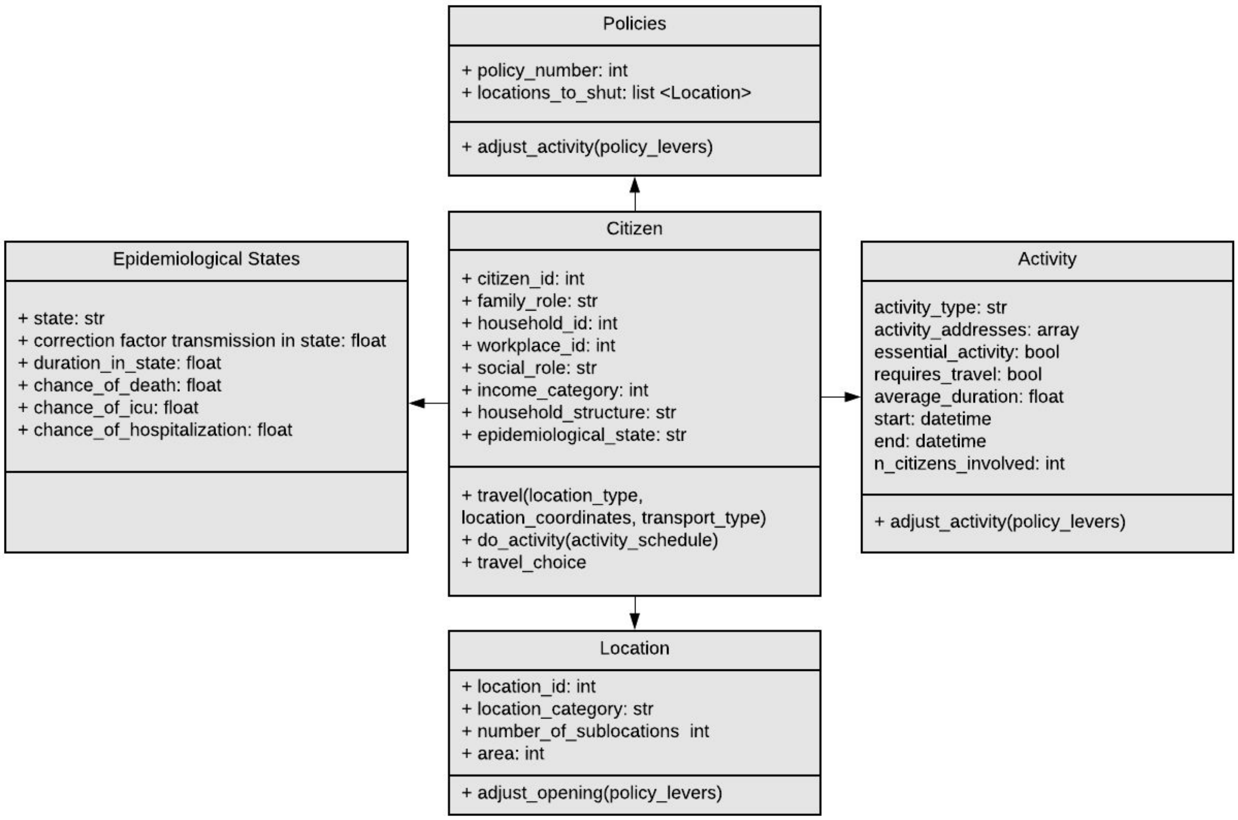

Figure 1. Conceptual diagram representing the main components of the agent-based model.

2.2 Data collection and analysis

Our modeling approach utilizes literature and publicly available data to inform and construct each of the submodels. For individuals, neighborhood-level population statistics for each city were obtained from the respective government databases (i.e., Den Haag Cijfers and Helsinki Region Infoshare). For locations in both cities, geospatial data pertaining to land use, building types and urban amenities were collected from OpenStreetMaps and supplemented by data on land use or buildings made available by city or national government. Key demographic statistics for both cities are provided in Figure 2.

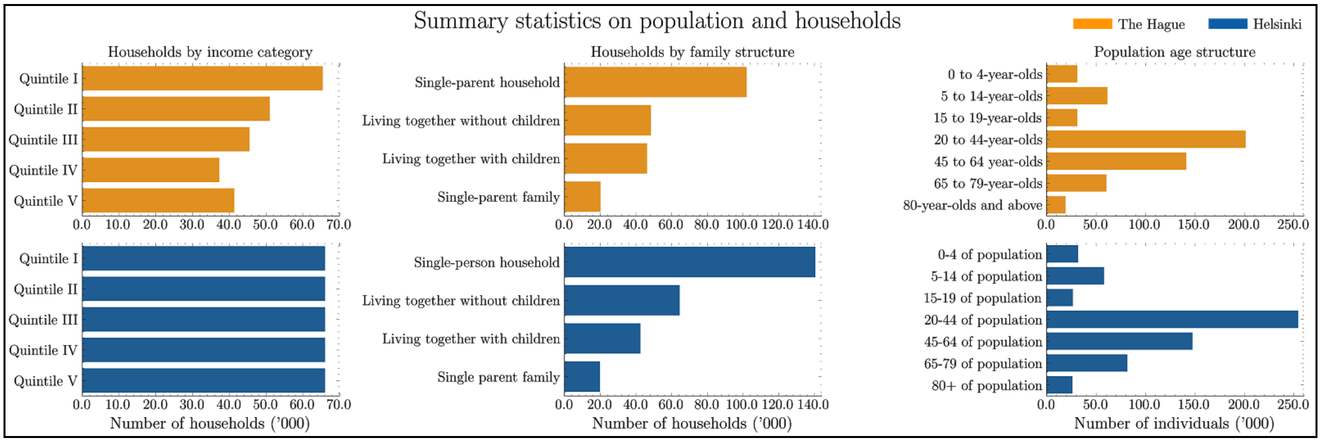

Figure 2. Summary statistics: income category, households, and age distribution for households in The Hague (orange) and Helsinki (blue).

Individuals' activities are defined based on their social roles and the day of the week. Time Use survey by the Netherlands was used to identify differences in patterns in day to day activities for different days of the week (Roeters & Vlasblom, 2019). The data from this source is at an aggregated level and exact values for activities were inferred based on weekly schedules. The actual duration spent per activity is specified using different stochastic distributions. It is believed that the schedule can be approximated for Helsinki as well.

The time use survey was also used to inform the split of activities between different age groups of people which was later mapped to the social role of the people. The choice of workplace, schools and home is adopted from the synthetic data. The choice an agent makes while implementing their activity schedule is described in greater detail in Section 2.3.3.

The epidemiological submodel consists of a series of states which the infected individual passes. These states are based on a modified Susceptible-Exposed-Infected-Recovered/Dead(SEIR) model (Batista et al., 2020). How an individual passes through each state in the modified model is based on several parameters, which are sourced from latest scientific research on COVID-19 (see Section 2.4 for the details). These parameters ascribe to each agent the likelihood of transitioning into a different state, such as the chance of hospitalization (e.g., from infected to hospitalized state) after a parameterized duration (e.g., duration of illness).

2.3 Model implementation

To allow for dynamic interactions, we adapted the artificial city model by Zhang et al. (2016) to represent COVID-19 transmission in the cities of Helsinki and The Hague. The following subsections first summarize the procedures used to develop a synthetic population to represent the city population (Section 2.3.1). We then discuss the methods used to define and represent the physical locations in the model in Section 2.3.2, followed by the activity schedules that characterize the daily activities and individual behaviors of the agents in Section 2.3.3. Lastly, we describe the epidemiological state machine that models the COVID-19 infection process experienced by the agents.

2.3.1 Synthetic population

One approach to model the population of a city is to use individual-level data (e.g., microdata) to obtain the parameters and conditional probabilities that characterize the population of a city and its behaviour. It is insufficient to rely only on existing open data, as such data is typically available on an aggregated scale (e.g., neighborhood or district level), and does not extend to individual level. Moreover, microdata that does capture the desired individual attributes for whole city populations, if in existence, is often kept confidential or otherwise not openly available as it often contains private and confidential information about individuals (Ciriani et al., 2007). Hence, we adapted the approach implemented by Ge et. al. (2014) to generate a synthetic population based on available real statistical data and geographic information described in Section 2.3.2.

The process of generating a synthetic population is described as follows:

1. For each neighborhood, generate households based on neighborhood-level data on the number of households, household structures, household sizes, and income. Each household is specified with a household structure, size and income category.
2. Assign age to individuals based on neighborhood- (The Hague) and district-level (Helsinki) data on age of head of household by household structure. For households other than single-person households, family members in the same household are assigned ages based on the partner or parent age.
3. Assign social roles to individuals based on their age and unemployment data.
    a. One of the assigned social roles is 'essential worker'. Essential workers are categorized primarily as those who work at supermarkets or in healthcare. These roles are designated based on income following the initial allocation of social roles. We selected essential workers in supermarkets from the 40th income percentile of workers, and essential workers in healthcare from the 60th income percentile of workers.
4. Assign workplaces to individuals based on social role and available data on number and size of enterprises in each neighborhood.
5. Assign schools to individuals based on social role and available data on number and types of schools in each neighborhood.
    a. Children are allocated to closest schools first until the schools are full, then randomly.
    b. University/college students are allocated randomly.

This implies that each generated individual is attributed with an age, social role, income category, and household structure. By following the approach outlined above, the attributes are determined based on a set of decision rules whereby interdependence is assumed (e.g., social role is based on age). The range of values for each of these attributes are summarized in Table 1. The synthetic population does not take into account multigenerational households or outliers such as households with many (i.e., more than three) children. The individuals belong to specific households with unique household identifiers, and each household (and every individual contained within) is assigned to a home location within neighborhoods in the city.

Attribute	**Range**
Age	[0, 100]
Social role	{Kindergarten, primary school student, secondary school student, college student, university student, worker, weekend worker, essential worker, unemployed job-seeker, pensioner}
Family role	{Single, partner, parent, child}
Income category	The Hague: {Low, average, high} income category Helsinki: {1st, 2nd, 3rd, 4th, and 5th} income quintiles
Household structure	{Single-person household, married with children, married without children, single-parent with children}

Table 7. *Range of possible values for attributes characterising agents and households in the synthetic population*

The generated individuals make up a synthetic population that approximates the real population in the city. To validate the synthetic population generation procedure, we compared summary statistics of the population between the real and generated datasets for each city. These comparisons are shown in Table 8 and Figure 3.

	The Hague, Netherlands		**Helsinki, Finland**	
	Real	Generated	Real	Generated
Number of individuals	546015	535335	632645	602128
Number of households	271455	271381	335061	278203

Table 8. Comparison of population and household sizes between the real and synthetic (generated) populations.

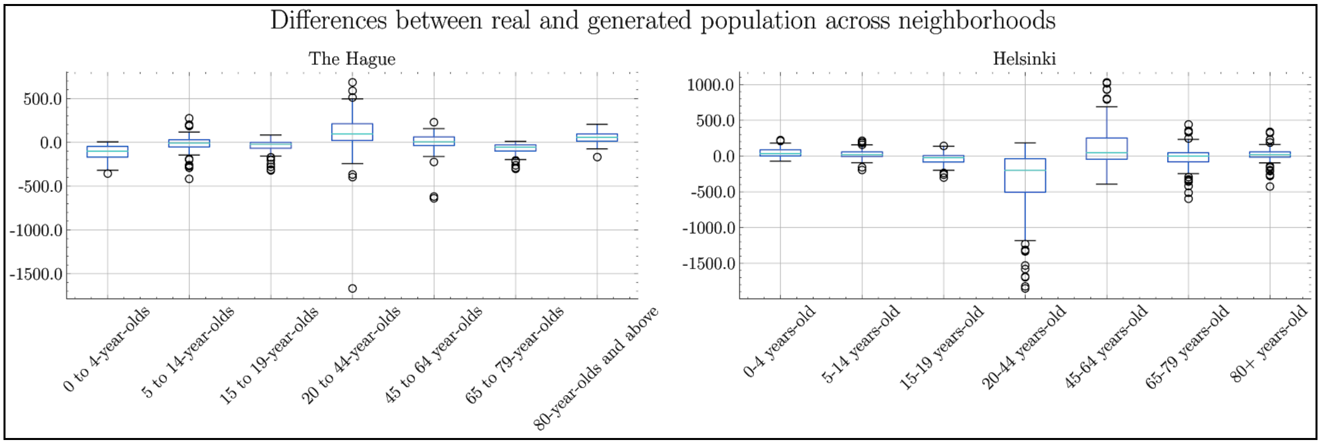

Figure 3. Differences between real and generated population numbers by age groups in neighborhoods.

Table 8 shows that there are numerical differences between the statistics of the real and generated populations. Figure 3 shows that the difference is greatest for the 20-44 year old group for both The Hague and Helsinki. This is due to our lack of access to data on the actual distributions and parameters of the real populations, as well as the lack of insight on the conditional probabilities that inform how various attributes relate to one another (e.g., how age depends on household structure or income). Inferring such probabilities would require microdata and can also violate privacy. With that said, this approach was considered sufficiently representative for our purposes as the mean distributions per neighbourhood were in line with the real data (see Figure 3) and given the objective of the study to capture the relationships and dynamics of the system within the model.

2.3.2 Locations

The built environment of the artificial city is geographically referenced with geospatial data obtained from OpenStreetMaps (OSM). The OSM data includes geolocated buildings which contain points-of-interest associated with one or more use functions identified with the OSM “amenity” tag. The points-of-interest are then categorized into 20 location types, which are mentioned in Table 9.

As modeled by Zhang, et. al. (2014), each location can be composed of multiple sublocations, each of which are designated a floor area based on location type. For example, an accommodation building may contain multiple households, each of which are allocated $100m^2$ of floor area. The numbers of each location type in the modeled cities are summarized in Table 9.

Location Category	**Location Type**	**Average Sublocation FloorArea (m^2)**	**Hague (locations)**	**Helsinki (locations)**
Home	Accommodation	100	84,348	20,512

Occupation	Workplace	30	53,457	42,169
Education	University	100	7	28
	College	100	13	22
	Secondary school	75	68	74
	Primary school	75	159	173
	Kindergarten	50	114	356
Essential services	Hospital	75	13	24
	Fire station	100	6	25
	Police	30	15	3
	Healthcare	100	277	233
	Pharmacy	75	63	67
	Supermarket	200	133	89
Shopping	Mall	100	9	37
	Retail	100	2,014	2239
	Food and beverages	100	511	355
Places for social activity	Bars and restaurants	200	1,652	2255
	Recreation	250	244	293
	Park	300,000	21	506

Table 9. Numbers and average floor areas of location types in The Hague and Helsinki.

Agents in the model are linked to locations, whereby they leave from their designated home locations at the start of each day to travel to and spend time in locations selected based on the activities that they are participating in. Crowd mixing and spatial contacts, which is the predominant source of infections (described further in Section 2.3.4 Epidemiological States) occur when agents are located in the same sublocations. The model further incorporates the Zhang, et. al. (2014) approach of location selection: each location type is categorized into broader categories relating to the activities that agents take part in daily (see Section 2.3.3 Activities). When deciding on locations to visit, agents randomly select from a list of locations in the category related to the activity that they are scheduled to do within a specified radius of distance from the agent's current location. Alternatively, they may select the closest location type to their current location for certain activity types (e.g., shopping, see Section 2.3.3 Activities). In the case of supermarkets, agents will select to visit only the supermarkets that are closest to their home locations. The distance calculated between the current and selected locations are also used to determine the travel time of the trip. The travel time is determined based on the distance between the agent's current and target locations, and a travel speed based on selected travel mode.

Studies have shown that the risk of infection in large outdoors spaces is relatively low / negligible (reference). To take this into account, we increased the size of the Parks locations to approximate a very low value for the contagiousness parameter, thereby lowering the chance of infection between agents at parks (see Section 2.3.4 Epidemiological model).

2.3.3 Activities

As in the model by Zhang, et. al. (2014), the variant behaviors of agents are modeled by means of an activity schedule that is defined and assigned based on the agent's social role and the day of the week in the baseline model. Mitigation policies such as lockdowns will influence the schedule. For example, individuals spend specific sets of hours during weekdays participating in activities per their social role (e.g., students go to school, workers go to offices and pensioners engage in voluntary work). Outside of these main activities every citizen may perform two activities - personal care, shopping and social activities. A sample activity schedule for the social role students can be seen in **Figure 10.**

Activity	**Duration (distribution in hours)**	**Agent Choice**
personal care	uniform(8,9)	
travel	location based	
voluntary work	uniform(1,1.5)	
travel	location based	
personal care	uniform(0.08,0.25)	

travel	location based	
shopping	triangular(0.25,0.54,0.75)	Choose to go to retail, malls, pharmacies, supermarkets or stay home
travel	location based	
dinner	triangular(0.5,1,2)	
travel	location based	
social activity	triangular(1,2,3)	Choose to go to bars, restaurants, parks, recreation spots or stay home
travel	location based	
personal care	until midnight	

Table 10. The activity schedule of a healthy pensioner on a Friday without any policies.

Each day, the order of activities undertaken by a social role is static. However, they could choose to go shopping or do social activity. The duration they spend in a specific location is drawn from stochastic distributions of time pre-assigned in the activity schedule (see example for a student in Table 10).

The model incorporates 11 sets of day patterns for each social role that reflect the typical daily activities of citizens in the Netherlands and Finland. The day patterns from Monday to Thursday are identical, while the day patterns from Friday to Sunday are different on each day to reflect increased social activities on Friday and Saturday, with more resting and staying-at-home on Sunday.

As shown in Figure 4, during the time that an agent spends shopping, there are five possible location types that they can go to - retail stores, food and beverage stores, malls, supermarkets and pharmacies. The exact location of the shopping activity is selected using the nearest location identified with the distance calculator, ensuring that the person goes to the shopping place closest to their home. When engaging in the activity "personal care", an agent will choose to stay at home. Supermarkets and pharmacies are considered essential services and stay open even when policies are implemented to close businesses.

For social activities, agents select between going to parks, bars and restaurants, and recreational points of interest (e.g., museums and libraries) or to stay home. The exact location of which place to go to is picked using a RandomLocator within a 2.5km radius (i.e., if a person decides to go to a bar on a Friday, they will pick a random bar within a distance of 2.5km).

The locations for all the other activities are fixed for each citizen. Locations assigned to the individuals in the synthetic data determine their workplace, schools and accommodation locations. Every day in the simulation ru an agent will pick the same work, school and home locators when their schedules demand it.

To travel from place to place, each agent may decide to either walk or take a bike to their respective destinations. If the travel distance exceeds 5km, they may choose to drive. For short distances up to 1 km, agents walk to their destinations, while for distances in between 1 and 5km, agents choose to cycle. In the model, we assume that individuals do *not* get infected while traveling, and the selected travel mode defines the amount of time for an agent to reach their destination.

The likelihood of a person going to one of the locations is modelled by allocating that social role a probability to pick that location on a certain day. The probabilities are picked on each day by the agent. This is done to avoid crowding of these places with an excess flow of citizens on a single day, as is the case in real life. The amount of time spent by an agent engaging in an activity is done as per their activity schedule.

Figure 4. The distribution across shopping and social activity locations for workers during different policies. The colour codes signify the percentage of people doing a certain activity.

When policies are implemented, the day patterns are modified to reflect different activities throughout the day. With the lockdown policy, schools, workplaces, and shopping and social activity locations are shut down, with only essential services and parks remaining open to the public. The majority of agents begin to stay at home for most of the day, while essential workers continue to go to work daily. Agents also spend more time at parks, which remain open during the lockdown.

When a person transitions from one epidemiological state to another, they change their activity schedules. In the contagious middle stage, when they are likely to be extremely sick, they stay at home more. When an agent is infected and passes into the states Hospitalized or in ICU, the agent is assigned a new day pattern whereby they remain in the hospital closest to their home location at all times.

2.3.4 Epidemiological model

The epidemiological model is characterized by two distinct phenomena - the transmission of the disease and the stages of infection once a person is infected.

State Transitions

A person passes through multiple epidemiological phases once they are infected. The overview of the state transitions can be seen in Figure 5. An important characteristic of COVID-19 is its potential asymptomatic transmission (Mandić-Rajčević et al., 2020; Zhou et al., 2020). There are multiple studies that suggest that 30-50% of the infected population could be asymptomatic (Ferguson et al., 2020; Nishiura et al., 2020). This has been incorporated by splitting the state transition into symptomatic and asymptomatic contagious states.

The infectiousness or transmissibility of a person is different in each phase of the disease. COVID-19, unlike another airborne disease like SARS, is transmittable before the incubation period (X. He et al., 2020). These different levels of transmissibility during the disease is modelled using different states. A person is most contagious during the middle stage and least contagious in the late stage.

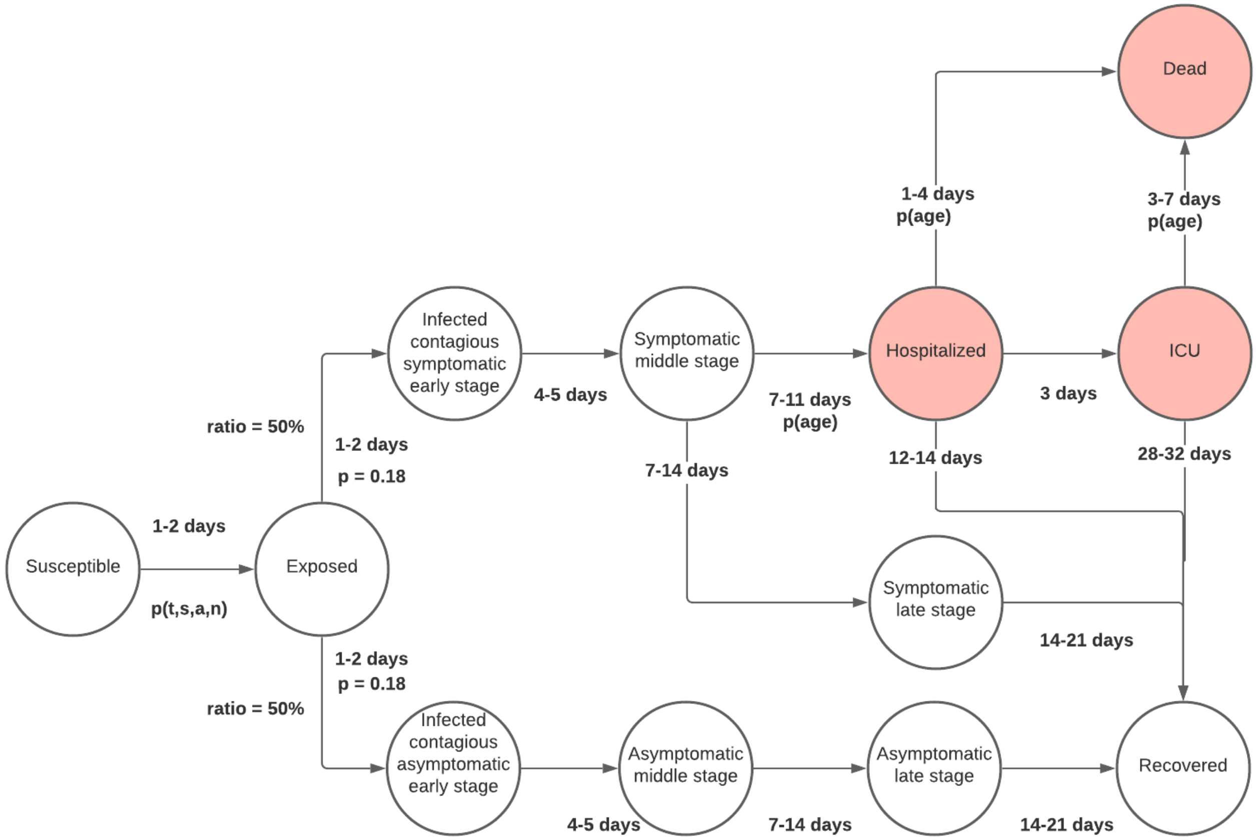

Figure 5. State diagram for COVID-19.

The chance with which a person goes to the hospital, ICU or succumbs to the disease is based on their age (Ferguson et al., 2020). Older people have a higher chance of having the need to hospitalize in comparison to the negligible chance for children. The data for this submodel is collected from literature which can be seen in Annexe A.

Disease transmission

Scientific literature differentiate at least 2 ways **how the virus can be transmitted** (Harapan et al., 2020). Firstly, from person to person (P2P) (Chan et al., 2020) which consists of droplet transmission (within 1 m) and aerosol transmission (> 1 m: 1 - 4 m) (Guo et al., 2020). Secondly, it can be transmitted from surface to person (Kampf et al., 2020). In this study we will consider only P2P disease transmission. COVID-19 is believed to be transmitted both through droplets and contact routes beyond 1.5-2m distance from a person (Setti et al., 2020).

In this model, infection happens through spatial contact. If a person shares a room with an infected person, they move to the exposed phase. Their chance of moving to the exposed phase is dependent on four parameters - time of exposure, area of the shared location, stage of the disease the infected person is in and number of infected people.

$$chance\ of\ exposure\ =\ \sum_{n=1}^{N}(contagious\ factor/shared\ area) * correction\ factor\ for\ transmissibility\ in\ the\ state\ *\ duration\ of\ exposure\ (hr)$$

Contagious factor is the minimum square area around an infected person where a one-hour exposure to a contagious person leads to an exposure (not necessarily an infection as that is also dependent on the infection probability). The probability of having exposure is determined by dividing the contagiousFactor by the surface of the (sub)location in which the contagious person and the other person are located, so the chance of picking up the disease in a space twice as large is reduced to 50%. The base contagious factor is 1.5*1.5 sqm. This is taken as the smallest square at a 1.5m distance around the infected person where a chance of exposure is possible. This is so because 1.5m is the smallest distance that is stated to have the highest chance of exposure (Sun & Zhai, 2020).

The chance of exposure is the highest when a room is shared with a person in the middle stage of the disease and the lowest when shared with a person in the last stage of the disease. Additionally, an asymptomatic person is less likely to transmit the disease compared to an asymptomatic person (D. He et al., 2020). This is included in the correction factor for transmissibility in that state. This chance is calculated every hour thus, increasing the likelihood of someone getting exposed every hour. Lastly, the chance adds up with every infected person an agent shares space with (represented in the equation as N).

Their chance of exposure results in the agent moving to the exposed state where their odds of being infected are determined by the infection rate. At this stage, they enter the early infectious stage symptomatically or asymptomatically based on a probability.

An important modeling choice made here is to look at the extent to which the area shared with an infected person increases chances of exposure. COVID-19's airborne nature remains to be an aspect of debate (Setti et al., 2020). A person could get infected if they share the same space as an infected person. Within this model there are two layers to shared space - shared sublocation and shared location. A shared sublocation is the same apartment or room within a building while a shared location is the building itself. For the current version of the model exposures only happen within the sublocations.

We assume, within this submodel that asymptomatically infected people do not require hospitalization and will definitely recover. Additionally, every citizen has an equal chance of being infected and transmission is according to the state of the disease. This does not take into consideration the individual characteristics of the person.

The number of people in the hospitalized and ICU states are used to determine if the city needs to have additional health care capacity in order to sustain the number of cases.

The model is then run for a period of 120 days. This is done to understand the effect of the early responses to the pandemic be i.e. the first wave. As such, this is also a means to better understand and intervene the so-called 'second wave', which we see - at the time that this deliverable is being written - see emerge.

2.4 Model verification and validation

Model verification is essential to build trust in the model (Browne et al., 2016). Verification tests are performed to ensure the model matches with the conceptual idea. Verification for agent based modeling is typically performed on three levels - single-agent verification, minimal model interaction verification and multi-agent verification (Dam et al., 2013).

A single agent verification is where a single agent is attributed correctly to their social role, activity schedule and age based epidemiological parameters. To verify this, it was observed if people were following their activity schedules correctly, walking, biking or taking the car when they were required to and going to the right places at the right time.

In order to perform minimal model interaction verification, the model was tested with a few infected agents at the beginning. No cross infections were allowed, thus, reducing the interaction effect between agents. The agents were then monitored to see if they were transitioning states appropriately.

Multi agent verification was performed by running the entire model under different scenarios and observing emergent behavior. Extreme values were entered in the input data to see if the model behavior changes as expected. All the agents within the model were forced to stay home and 100 people were infected initially. This should ideally allow the disease to die out faster than usual, which was the case.

Another important aspect of verification is sensitivity analysis of relationships between model parameters and the states of other variables within the system (Parker et al., 2003). Verification of this model revealed its sensitivity to the interactions between agents while they perform their day to day activities as expected. This was identified when multi agent verification was being performed to check the impact of the policies on activity schedules. This can be seen in Figure 6.

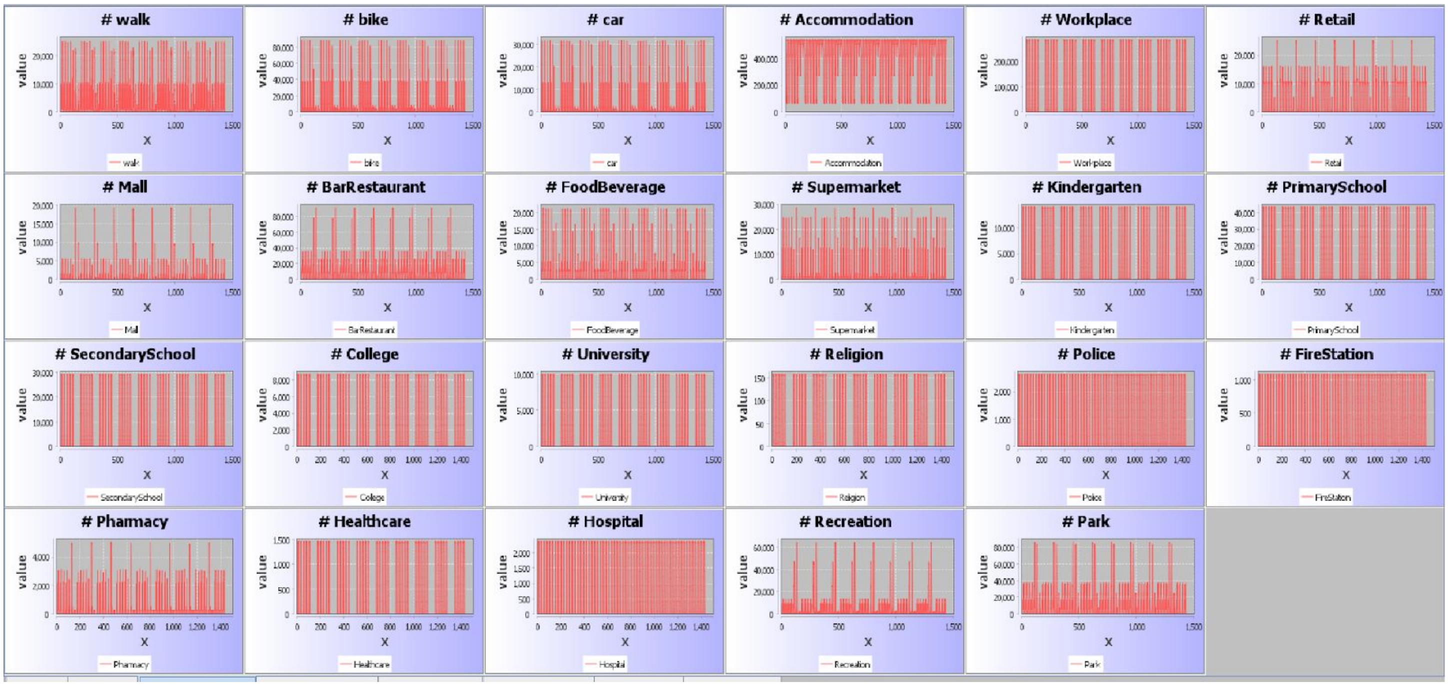

Figure 6. Activity schedules over 60 days with no lockdown.

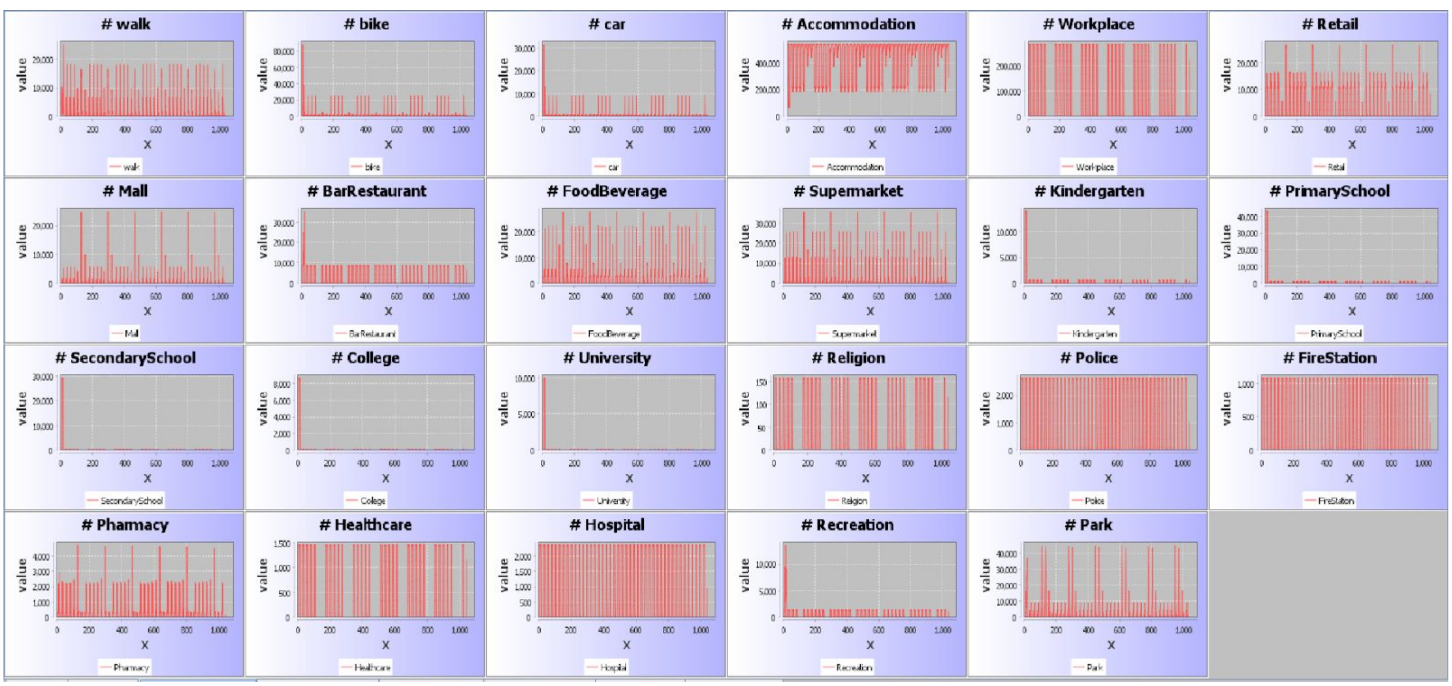

Figure 7. Activity schedules over 60 days under school and social gathering shut down policy.

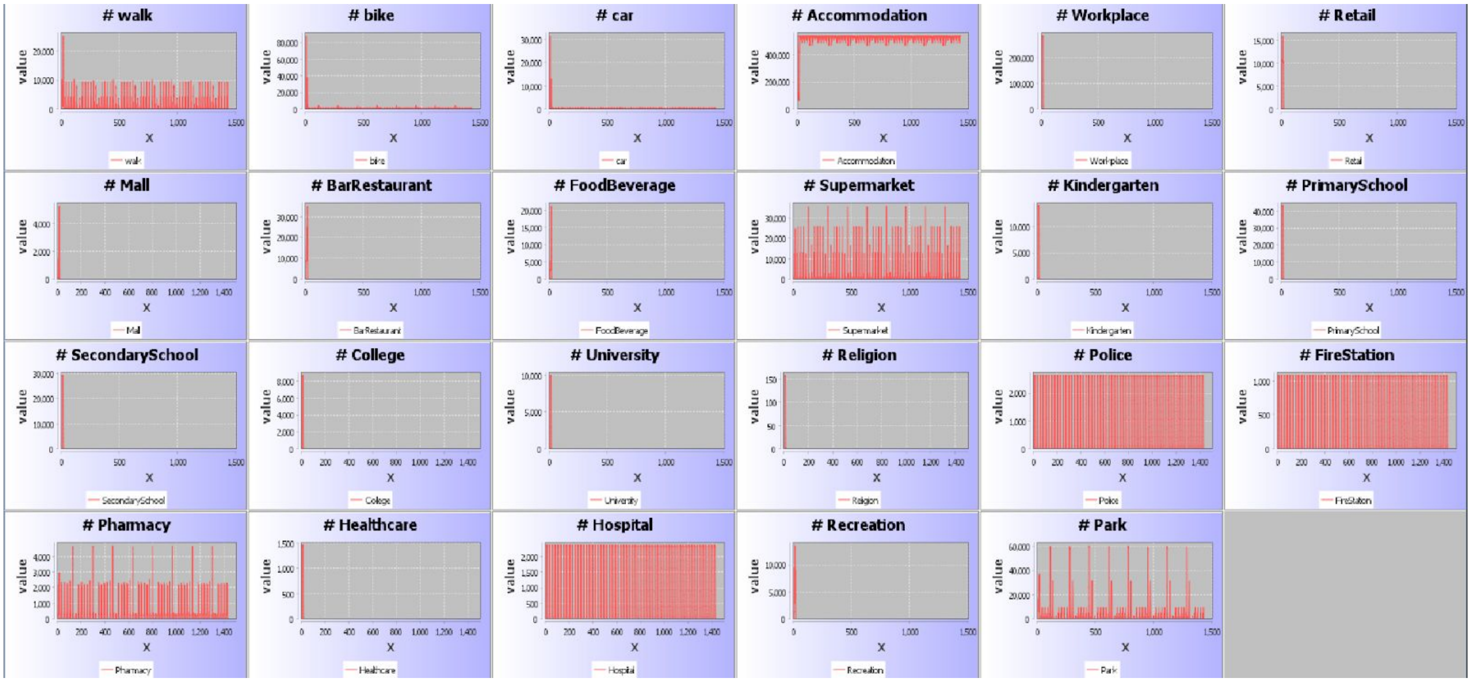

Figure 8. Activity schedules over 60 days under full lockdown.

Lastly, the model was designed to be fully reproducible. For the sublocations, being reproducible means that the agents always spend time in the same sublocation once it has been assigned. This holds, for accommodation, kindergarten, primary school, and most workplaces (see full list in Appendix B). While we acknowledge that for secondary schools, colleges, universities, religious gatherings, or critical services such as police, fire stations, or hospitals there are also less regular visitors (e.g., guests), for the time being we still work with fixed locations. This will be improved as we are working towards the more detailed model in Task 2.3.

2.5 Model experimentation

Once the model was verified, we implemented experiments in the model to explore our research question. The design of the experiments is on the XLRM framework (Figure 9), introduced by Lempert, et. al. (2003).

In this framework, X stands for the exogenous or external factors - in other words: the uncertainties that are outside the control of the decision-makers. These are built into the model as parameters that are inherently uncertain, such as the proportion of population who is asymptomatic but contagious. L stands for policy levers, which are measures that city governments may take to limit the spread of the virus. R stands for relationships inside the system under study which is represented in the model, while M stands for performance metrics or outcomes of interest, which in this study is defined to be the number of hospitalizations and deaths across geo-demographic parameters.

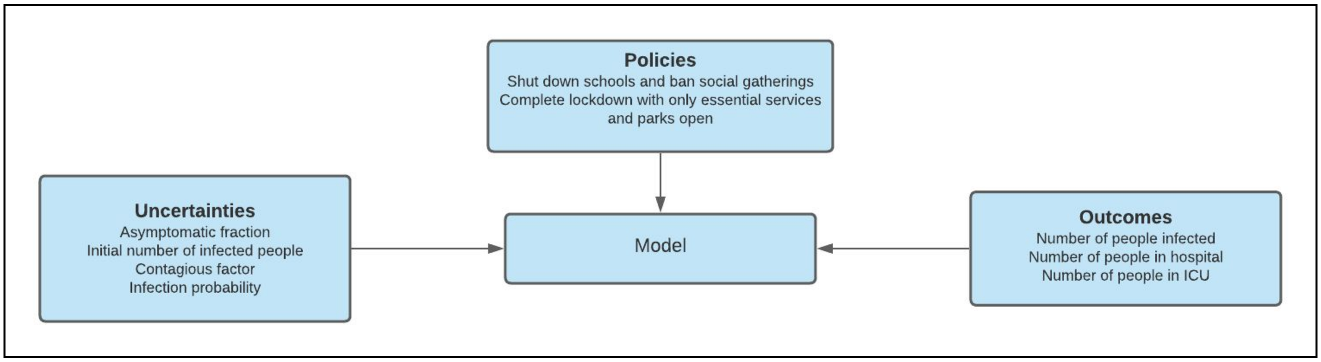

Figure 9. XLRM framework used for the experimental setup.

2.5.1 Policies

Implementing policies in the model is one way to observe how specific measures may affect disease transmission. When policies are implemented, agents in the model comply with said policy, thereby modifying individual behavior (see also Figure 4). In this model, people comply with the policies by modifying their activity schedules. Policy selection for experimentation was motivated based on real-life cases. The policies implemented from country to country were adapted as global scientific knowledge on COVID-19 evolved. Over time, it was observed that children are potentially less likely to contract and transmit the disease. As a response, many governments began to rescind school closure policies. Initial lockdowns in many countries entailed strict stay-at-home regulations as well as closure of most business establishments and public spaces.

This model incorporates three experimental measures:

1. A baseline policy with no regulations implemented or enforced.
2. Policy 1: Shut down locations of educational activities, recreation and social gatherings (Table 11).
3. Policy 2: Shut down of all public services and establishments, except for parks and essential services (Table 11).

In the model, Policies 1 and 2 may be implemented at various time steps after the first reported case. We studied the effects of governments implementing these policies on Days 1, 7 and 15 after the first reported case. This allowed us to evaluate the effects of delays in mitigation measures, and the extent to which such delays could impact the city. These policies are similar to those taken in both The Hague and Helsinki, whereby school closures were implemented, alongside closure of service industry and entertainment establishments. Further, both cities saw workplaces closed, and only essential workers (e.g., those in healthcare and in supermarkets) continued going to work. As with countless other governments, these cities encouraged social distancing behaviors. The effect of social distancing is proxied with the contagiousness parameter, which is further explained in *Section 2.4.2 Uncertainty in parameter values* below.

These measures are often taken in conjunction with numerous other measures, based on the urgency of decision-making, the decision-maker's best knowledge, authority and other constraints such as the ability to enforce and control measures in an efficient way (see also D1.1). As such, the individual effects of each standalone policy is unclear. Experimentation of policies as we carry out in this model will enable a closer evaluation of their effectiveness and impacts.

Policy	Open	Closed
0 (Baseline)	Workplace, Retail, Mall, Food and beverage, Supermarket, Police, Fire station, Hospital, Pharmacy, Park, Kindergarten, Primary school, Secondary school, College, University, Bars and restaurant, Recreation, Healthcare, Religion	
1	Workplace, Retail, Mall, Food and beverage, Supermarket, Police, Fire station, Hospital, Pharmacy, Park	Kindergarten, Primary school, Secondary school, College, University, Bars and restaurant, Recreation, Healthcare, Religion
2	Supermarket, Pharmacy, Police, Fire station, Hospital, Park	Workplace, Retail, Food and beverage, Mall, Kindergarten, Primary school, Secondary school, College, University, Bars and restaurant, Recreation, Healthcare, Religion

Table 11. Locations opened and shut under different policies.

2.5.2 Uncertainty in parameter values

The uncertain external factors are modeled as parameters within the epidemiological state machine that impact the outcomes of the model. Here we provide the motivation of our choices of key parameters, the sampled intervals are described in Section 3. The chosen key uncertainties are:

- **Share of asymptomatic population**: Undocumented infections often go unrecognized owing to mild, limited, or lack of symptoms (Li et al., 2020). The share of asymptomatic cases has been widely debated in literature and there is speculation that anywhere between 20-50% of the population that is infected with COVID-19 is asymptomatic due to mild or lack of symptoms (Davies et al., 2020; Ferguson et al., 2020; Nishiura et al., 2020).
- **Initial number of infections in the city:** The initial number of infections in the city has been said to be wildly underreported also owing to the unknown symptoms of COVID-19 and its asymptomatic nature (Day, 2020). The difference this would make to the spread of the disease is how quickly the spread escalates.

- **Contagious Factor:** the contagious factor within this model is considered the base area at which an exposure is probable. The airborne nature of COVID-19 was not confirmed until much after the first few cases (WHO, 2020). 1.5m has come to be believed as an acceptable distance (Setti et al., 2020). However, factors like ventilation have also been shown to have an effect on the spread of the disease (Sun & Zhai, 2020). Hence the choice to sample this parameter.

- **Probability of infection**: The probability of infection makes a difference in how many people get infected and how quickly the disease spreads. This determines how likely a person, when exposed can fall ill. There is a wide range of values that this parameter can take and depends on the health conditions of the person exposed and whether there were masks used in the shared area where exposure took place (Chu et al., 2020). As such, sampling the probability of infection not only has an epidemiological, but also a behavioural component that represents the compliance to hygiene guidelines and recommendations.

- **Decisions, which locations to visit.** To ensure that behavioral pattern is realistic we provided each of the agents a set of probabilities on which type of location to go to when they choose to go to do shopping or social activity. This is a parameter that can be used to change the activity schedules, thus, changing the behavior of the individuals. More comprehensive exploratory analysis of this parameter will be done as part of future work and be described in deliverable D2.3 (see Section 6).

Parameter sampling. Primary to adopting advanced sampling techniques such as Latin hypercube or Monte-carlo sampling, we decided to use non-deterministic iterable over random candidate combinations for hyper- parameter search (Pedregosa, F. et al., 2010). In simple terms, it is a generator of parameters given random distributions. At the first stages of model implementation such an approach is more helpful since it allows to more easily experiment with user-defined combinations of parameters.

2.5.3 Model outcomes

The outcomes of interest used to evaluate the effectiveness of the policies and the impact of the uncertain parameters consist of the following:

- Number of agents per epidemiological state over time

- Number of agents per epidemiological state by age

- Number of agents per epidemiological state by workplace category

These outcomes, based on uncertain parameters and a range of policy implementations, were analyzed in conjunction with known parameters such as total available hospital and ICU beds. The resulting analysis will be used to answer the original research question of how governments can maintain control over the spread of the disease in a city without overloading the healthcare system.

3 Results

The results for the model both The Helsinki and The Hague are evaluated in terms of the people in each epidemiological state as well as their locations and times of infection. The experiments we performed consist of 10 scenarios that were generated by randomly sampling the input parameter space for the following values:

- Infection probability: 0.09-0.38 (Chu et al., 2020)
- Initial number of infected people: 1-50
- Asymptomatic fraction: 0.2-0.5 (Davies et al., 2020)
- Contagious factor: 1-8

Given that one objective of the study is to understand how the mechanisms of virus transmission affects disease statistics under different policies, we tested the policies scenarios that encapsulate a range of uncertainties. As outlined in T1.1, this analysis allows a decision maker to observe the effectiveness of different policies on disease spread dynamics. Furthermore, evaluating the performance of the policies under the different scenarios enables an estimation of the robustness of those policies. Following this analysis, we selected a best case and worst case scenario through visual inspection of the results.

We evaluated the following model outcomes against the known hospital bed and ICU capacities of each city:

- Hospitalizations
- ICU admissions
- Deaths

As outlined in T2.2, policy measures which potentially increase burden on the healthcare system can be identified through this part of the analysis. These results are visualized for both the best and worst case scenario identified in the previous step.

Finally, for both the cities the infection locations are displayed to identify how changes in behavior and movement affects where the disease spreads the most. By identifying where the disease happens most and the social role of people that visit the location most often, policies can be designed to enforce targeted restrictions in different locations.

Lastly, we evaluate the infections and casualties by age group, and represent a geospatial distribution of infection volumes at select steps in time. These time steps are selected to be: Day of implementation, Day 60 (i.e., midway through the simulation period), and Day 120 (i.e., end of the simulation period).

3.1 Results for The Hague

Epidemiological states

The following figures show results from the experiments performed with the uncertainty parameters and policies described above. The graphs in each set of figures represent the number of agents in each of the 12 epidemiological states throughout the simulated 120 days given a policy implementation, with results grouped and color-coded by the time of policy implementations.

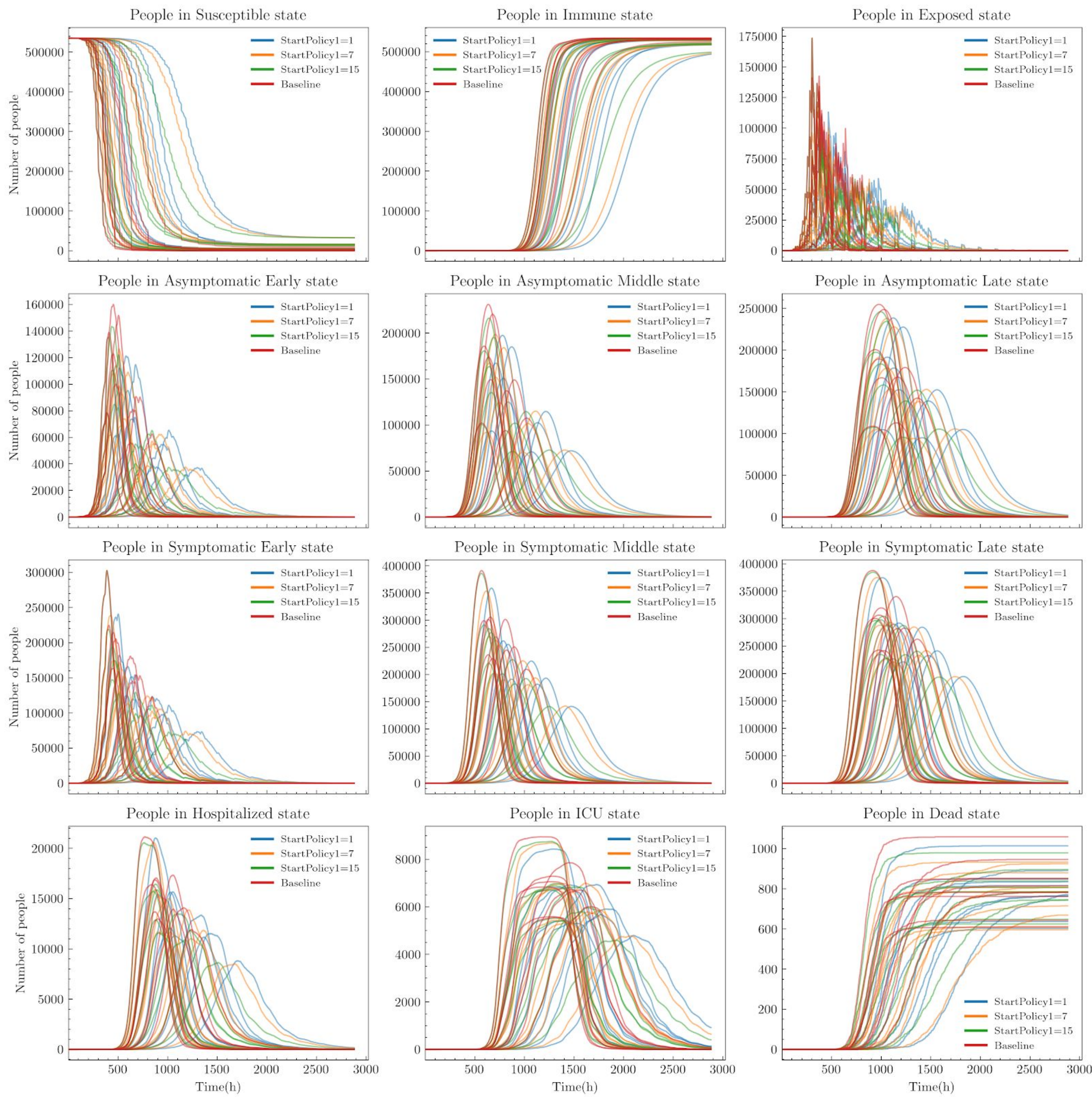

Figure 10. Performance of Policy 1 under 10 scenarios in the model of The Hague.

As noted in Section 2.5.1, Policy 1 entails shutting down schools and imposing a ban on social gatherings. The experiments were run with this policy being enacted on 1, 7 and 15 days after the first reported case of infection in the city. As shown in the graphs, under all scenarios the implementation of Policy 1 is only slightly more effective than not implementing a policy at all in terms of ICU admissions, hospitalizations and deaths. More experiments will be required to confirm whether under specific scenarios (e.g., epidemiological parameters or number of initial cases), Policy 1 can perform better than the baseline.

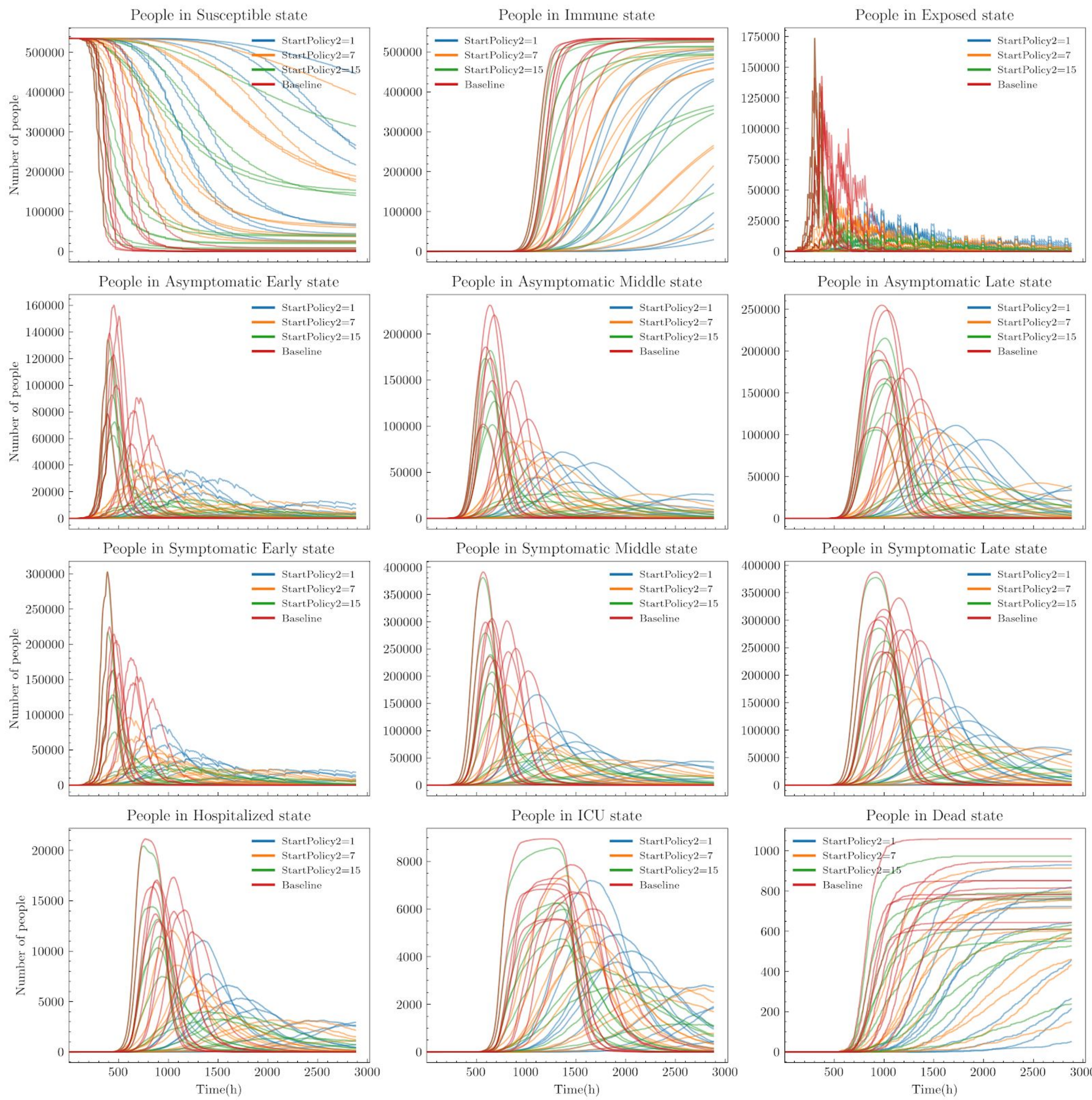

Figure 11. Performance of Policy 2 under 10 scenarios in the model of The Hague.

Policy 2 is the implementation of a full lockdown where only parks, supermarkets and essential services are open. As with Policy 1, the graphs show the effects of Policy 2 being implemented on Days 1, 7 and 15. The graphs indicate clearly that Policy 2 more effectively reduces and delays the initial peak of infections, particularly when it is implemented earlier rather than later. We observed that, while the epidemiological parameters define the dynamics of disease transmission under all policies, Policy 2 outperforms the baseline scenarios in all states. Once again it is observed that the policies implemented early have a higher impact than the ones implemented later.

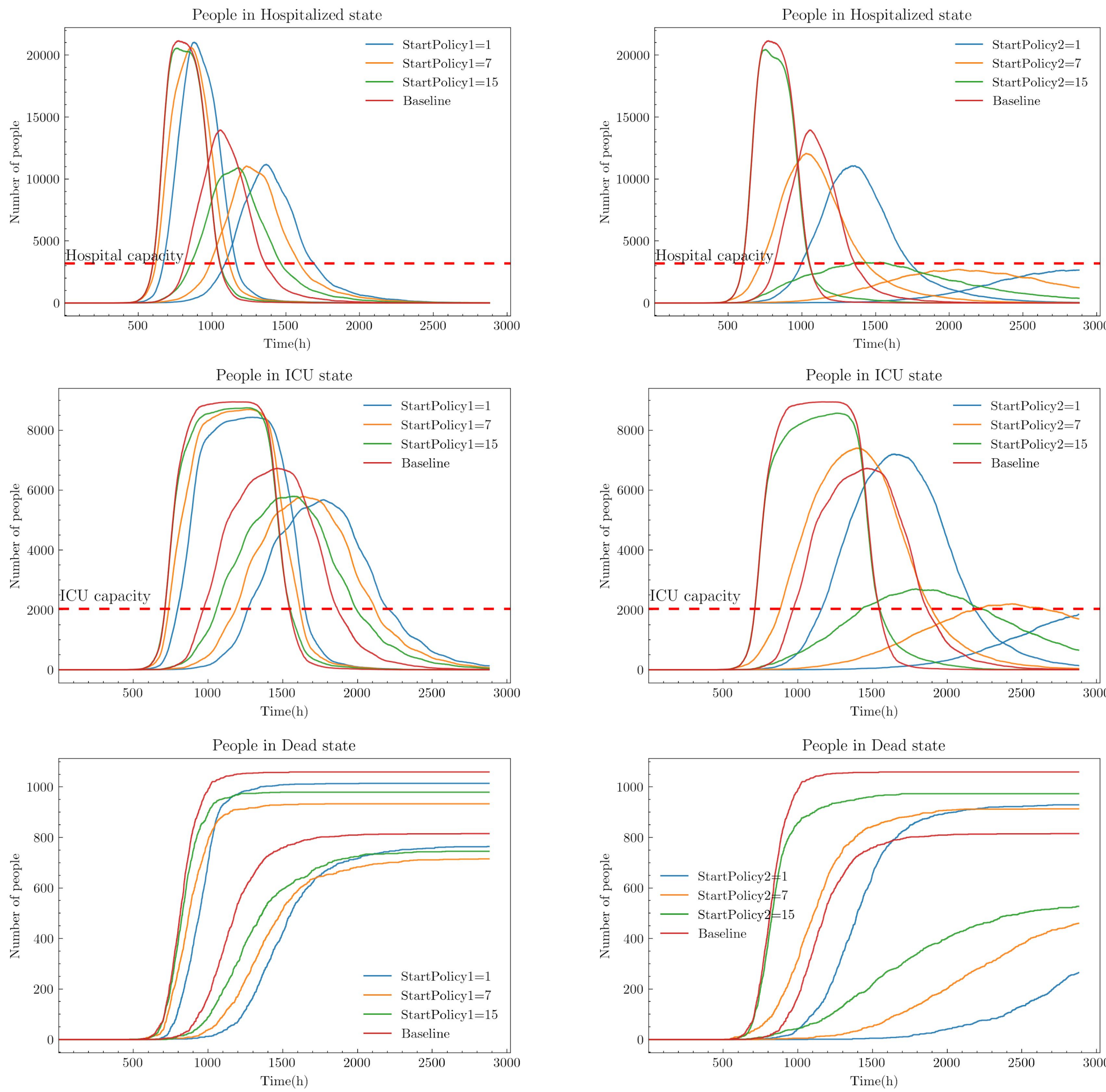

Figure 12. Comparing performance of the policies under the best and worst case scenarios for The Hague.

	AsymptomaticFraction	ContagiousFactor	InfectionProbability	Number of initially infected
Best case	0.356554	3.902634	0.166721	38
Worst case	0.206066	6.828339	0.315665	43

Table 12. Parameter values for best and worst case scenarios for The Hague.

After visually inspecting Figures 10 and 11, we selected the best case and worst case scenarios for each policy and starting date, shown in Figure 12. The epidemiological parameters for these scenarios are represented in Table 12. In the best case scenario, the infection probability is slightly below the mean value considered in the baseline case (Section 2.4 Model verification and validation).

A lower infection probability is a proxy for situations where, for example, face masks are worn. In this case, the contagiousness parameter is approximately 4, which can be conceptualized as one 1 m2 of floor area with two agents maintaining a 2m distance. The worst case (contagiousness >6.8) can be interpreted as, even at more than 2m distance, there remains a chance to be infected. While in the best case, infections happen only under a 2m distance from an infected person.

The worst case scenario is characterized by epidemiological parameters that are almost 1.5 times the best case parameters, which significantly changes the nature of the disease. With a 31% percent chance of getting infected in the worst case scenario, decision-makers must undertake different policies that include reducing the infection rate or contagious factor by mandating use of masks, maintaining social distancing, or other similar measures.

Interestingly, in the best case scenario, the fraction of asymptomatic cases is higher than for the worst case scenario (35 % versus 20 %). This means that although asymptomatic agents have a higher risk of spreading the virus as they may not be recognized as contagious, the increased share of asymptomatic cases reduces the load of severe cases significantly.

In terms of ICU and hospital capacity, only Policy 2 that is implemented within 7 days after the first imported infection ensures that the health system remains within the limits of its maximum capacity. Results also show that this policy, when implemented early on, is effective as it substantially delays the peak onset of patients who are hospitalized, admitted into the ICU, or disease from the virus.

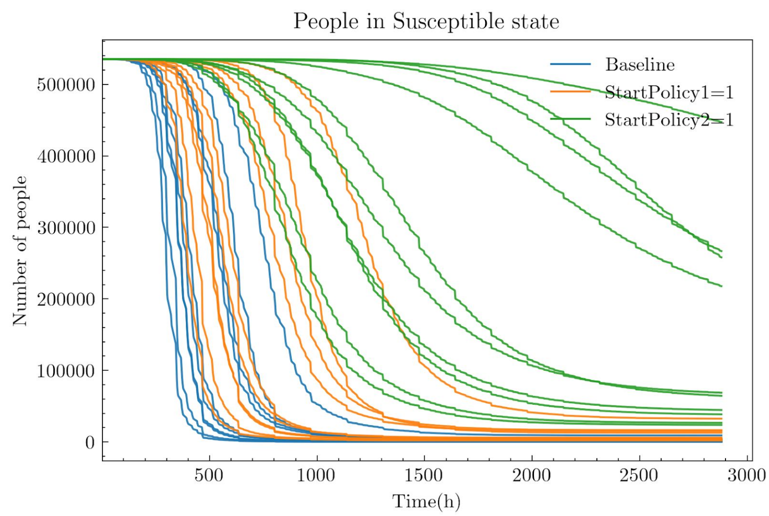

Figure 13. Comparing impact of policies under 10 scenarios on the number of susceptible citizens in The Hague.

Figure 13 provides a direct comparison of the number of people that get infected under each policy when implemented 1 day after the first reported infection. In all of the scenarios under Policy 2, a lesser number of people get infected. However, the difference between Policy 1 and the baseline remains relatively small. Thus far, the analysis shows that Policy 2 is most robust under the range of scenarios considered.

Behavioral patterns and infections at locations

Figure 14 reflects the change in activities that agents take part in after adoption of Policy 1, whereby schools are shut down and social gathering are banned. The graphs show that the number of agents spending time in schools reduces considerably in accordance with the policies. This figure should be evaluated in conjunction with Figure 15 where the number of infections at each location is specified. Evidently, the Policy 1 lockdown has the effect of reducing the number of infections at schools, recreation spots, bars and restaurants. The number of infections in bars and restaurants make up a significant portion of the reduced infections.

Similarly, Figure 16 reflects the change in activities of agents after Policy 2 is adopted. As shown in the graphs, under Policy 2, as time passes, less and less people interact with each other. At Days 7 and 15, we observed in the graphs a marked reduction in the number of infections because of the implementation of the lockdown. Again, Figure 17 is best seen in conjunction with Figure 17, which demonstrates the number of infections that take place at each location type. Policy 2, which constitutes a full lockdown of all except for essential services, reduces the infections in workplaces. This appears to contribute to a significant portion of infections apart from locations that allow for social activity.

A future point of study would be to evaluate what second order effects result from a reduction in infections that occur in specific location types (e.g., workplaces). This is discussed further in Section 6 Future Research.

Figure 14. Amount of time spent by The Hague citizens at different location categories under Policy 1.

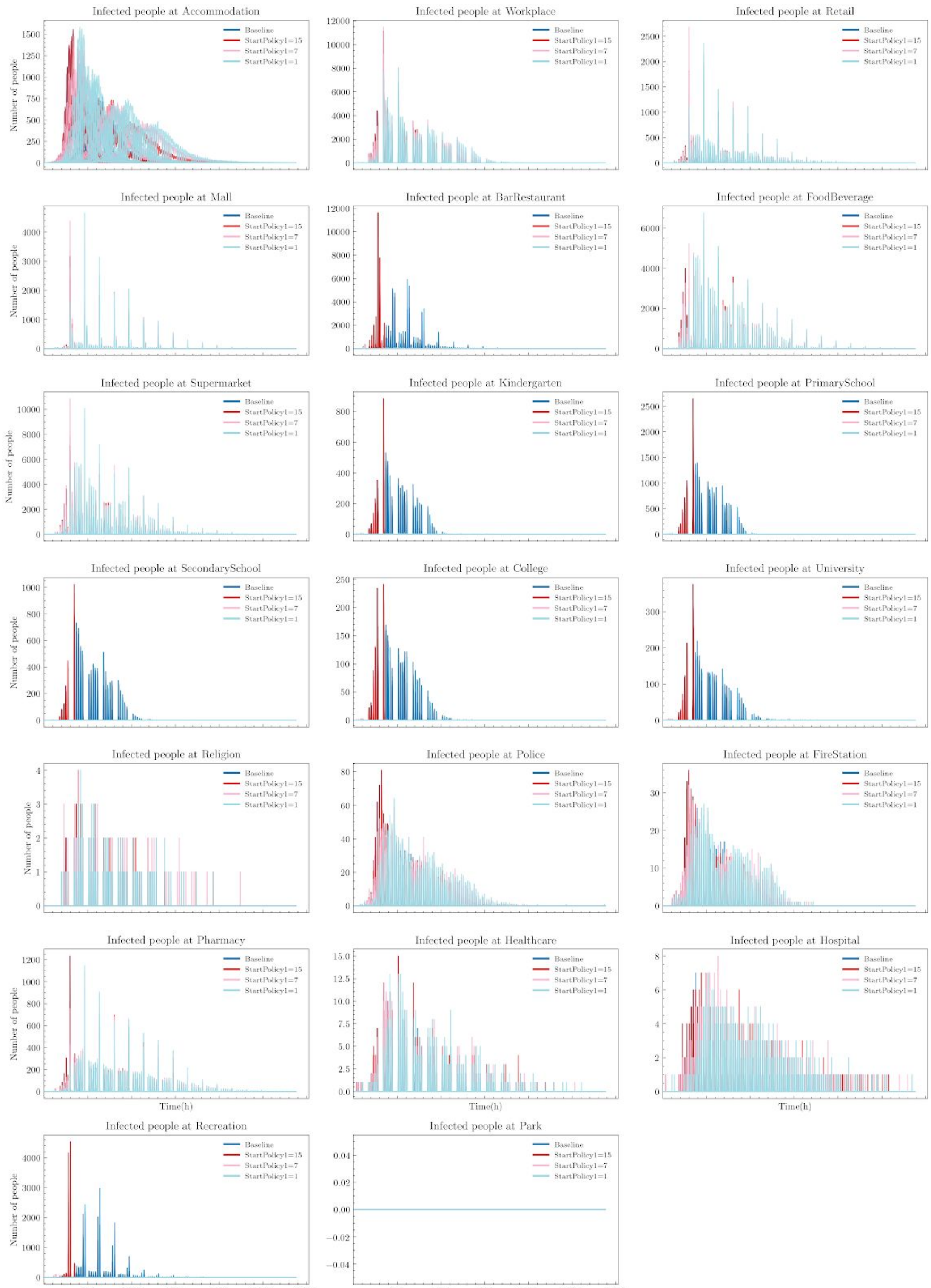

Figure 15. Number of The Hague citizens infected at different location categories under Policy 1.

Figure 16. Amount of time spent by The Hague citizens at different location categories under Policy 2.

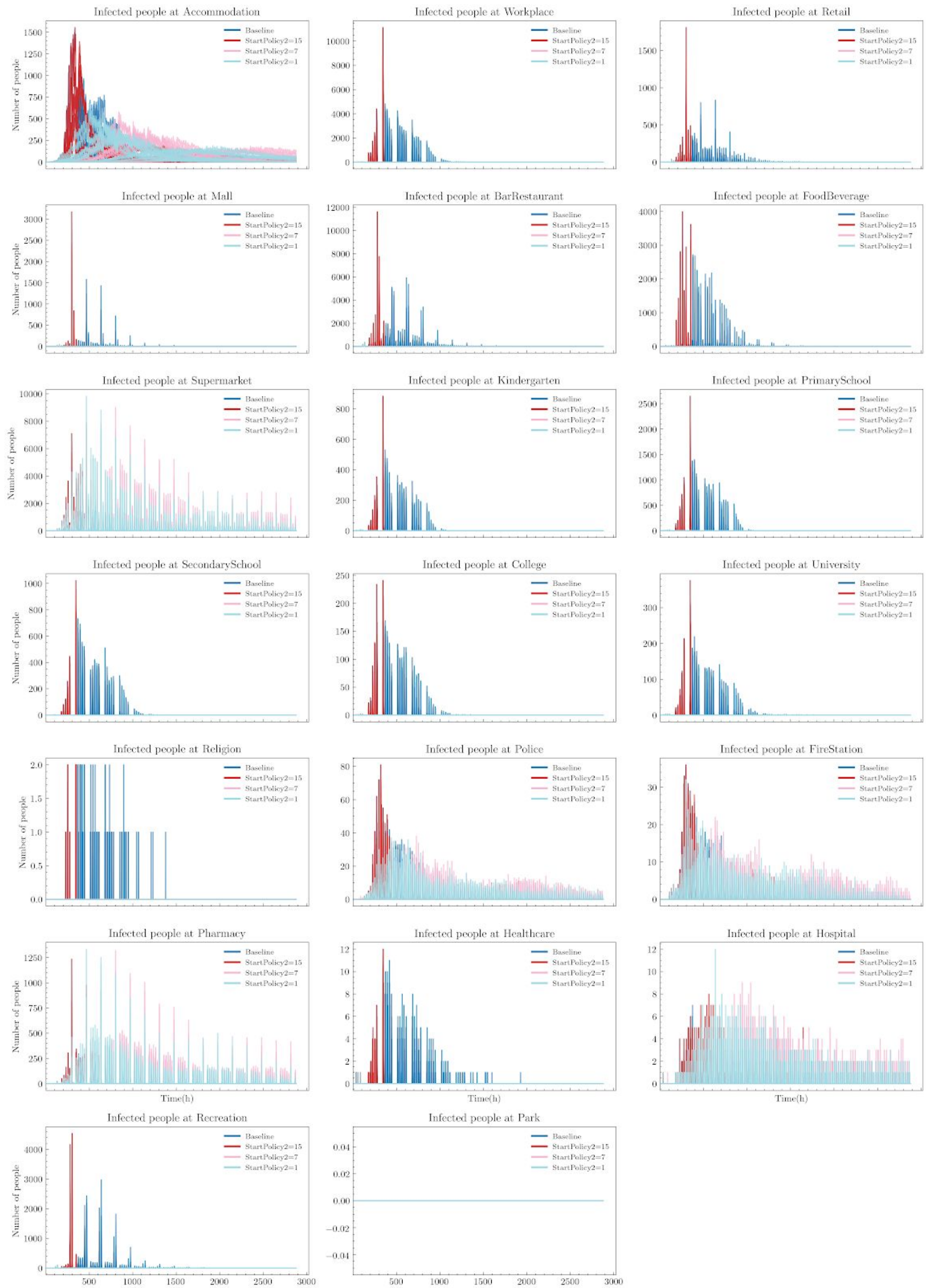

Figure 17. Number of The Hague citizens infected at different location categories under Policy 2.

Infections and casualties by age group

Figures 18 and 19 show infections and casualties by age group of the affected agents. The graphs show that the peaks in infections are associated with a specific activity that a person takes part in. For example, students spend a high amount of time participating in social activities (e.g., at bars), resulting in a higher chance of infection.

The number of deaths in the older age group are less than the expected amount shown in The Hague in Figure . This is the case under both policies. This can be attributed to the fact that nursing homes are not included in this model, and those in the old age (i.e., over 75 years old) group do not go to work. The social network of people and activities performed within the network is excluded from the scope of this version of the model. Therefore, older people often are less likely to meet younger people who are more likely to contract and transmit the disease. This is similarly why the number of infections is different for workers and non-workers, as shown in Figure 18. The number of infections is, however, evened out under the lockdown policy because very few people go to work and everyone is restricted to their homes.

Another reason for the discrepancy in the number of deaths between the model and real life is that the model does not capture the effects of comorbidities and its effects on the COVID-19 infection process. COVID-19 has been reported to have a more severe effect on those with underlying health conditions. Therefore, the results from the model are expected to be lower than in reality, because it does not incorporate the effects of the disease on the population with underlying health conditions.

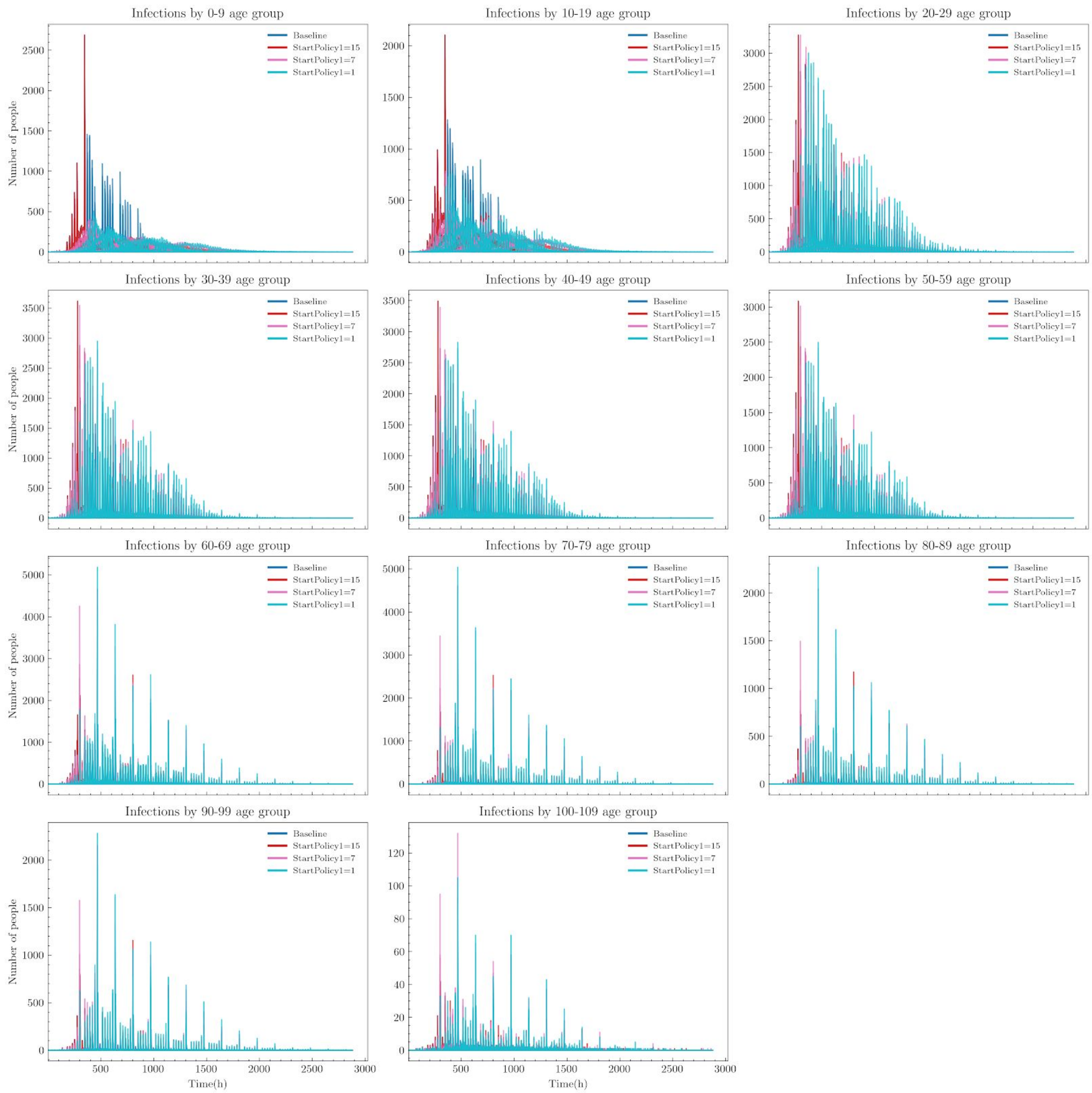

Figure 18. Number of The Hague citizens infected by different age groups under Policy 1.

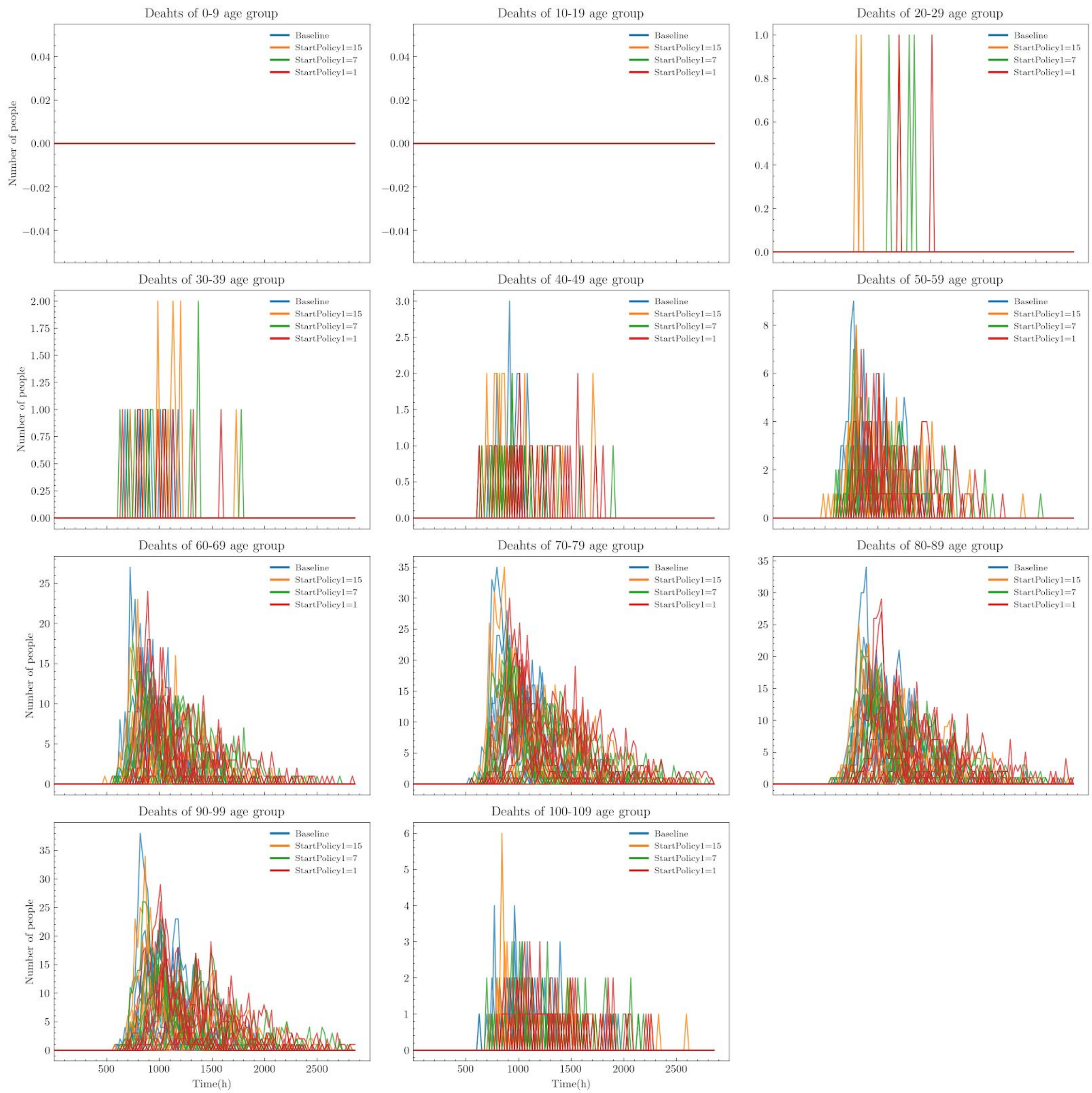

Figure 19. Number of casualties in The Hague by different age groups under Policy 1.

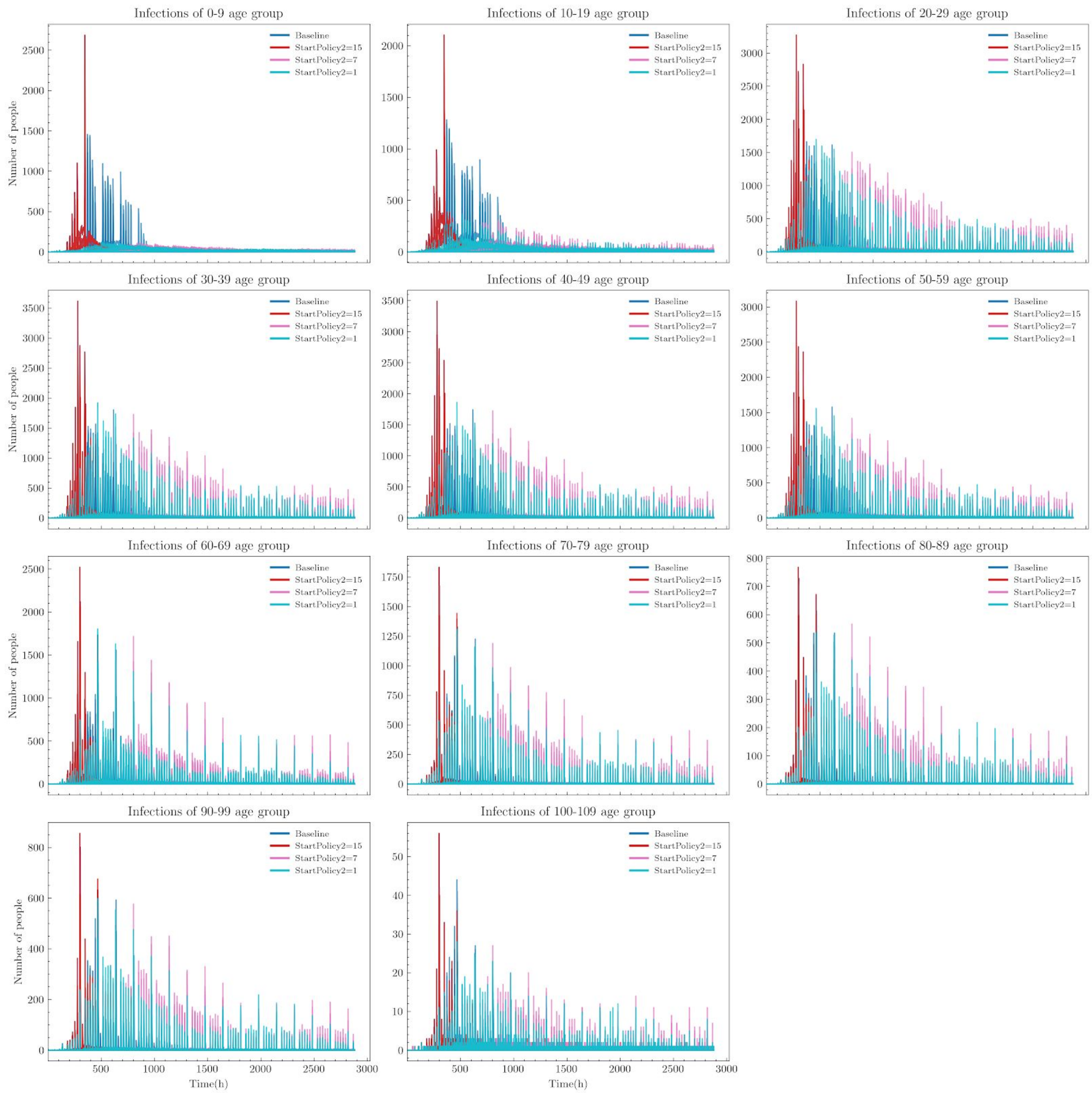

Figure 20. Number of The Hague citizens infected by different age groups under Policy 2.

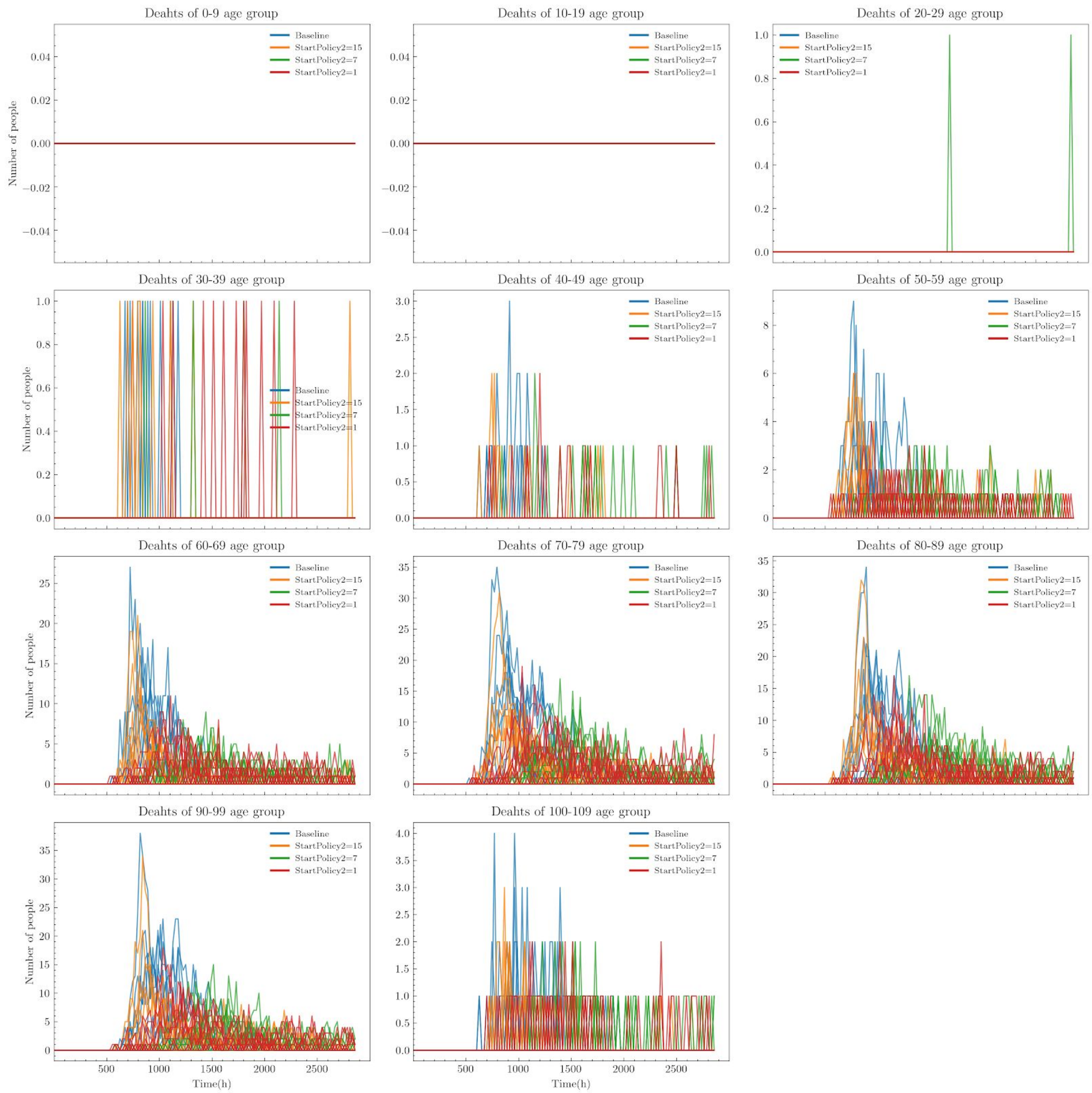

Figure 21. Number of casualties in The Hague by different age groups under Policy 2.

Geospatial distribution of casualties

The maps shown below indicate the spatial distribution of casualties by neighborhood of residence that occurred at three select time steps over the simulation run (Table 13).

	StartPolicy2=1 (days)	StartPolicy2=7 (days)	StartPolicy2=15 (days)
TimeStamp1 (days)	63	63	63
TimeStamp2 (days)	91	91	91
TimeStamp3 (days)	120	120	120

Table 13. Selected timestamps by policy for geospatial visualization of casualties in The Hague.

As shown, the numbers of casualties are higher when the policy is implemented later. This gradual change in number of casualties displays the unequal distribution of infections across the city. Some neighborhoods see more casualties and this could be because of two factors - they are more exposed to infection or they are older communities who are active. It could also be the case that both hold true. This is an opening for future research to delve deeper into.

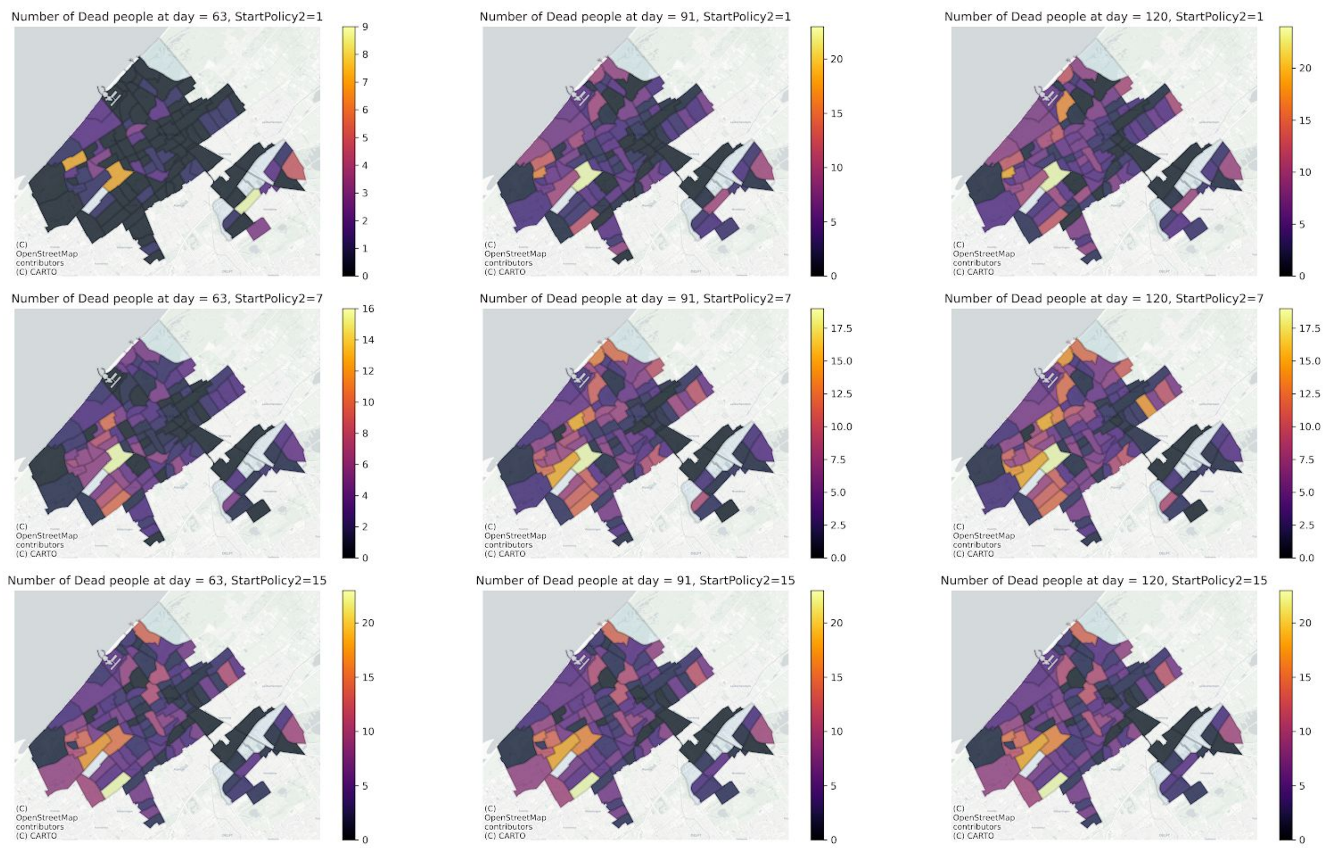

Figure 22. Distribution of casualties in The Hague over time and space based on time of Policy 2 implementation and TimeStamp.

3.2 Results for Helsinki

The structure of this subsection follows the section 3.1.

Epidemiological states

The following figures show results from the experiments performed with the uncertainty parameters and policies described in subsection 2.5. The graphs in each set of figures represent the number of agents in each of the 12 epidemiological states throughout the simulated 120 days given a policy implementation, with results grouped and color-coded by the time of policy implementations.

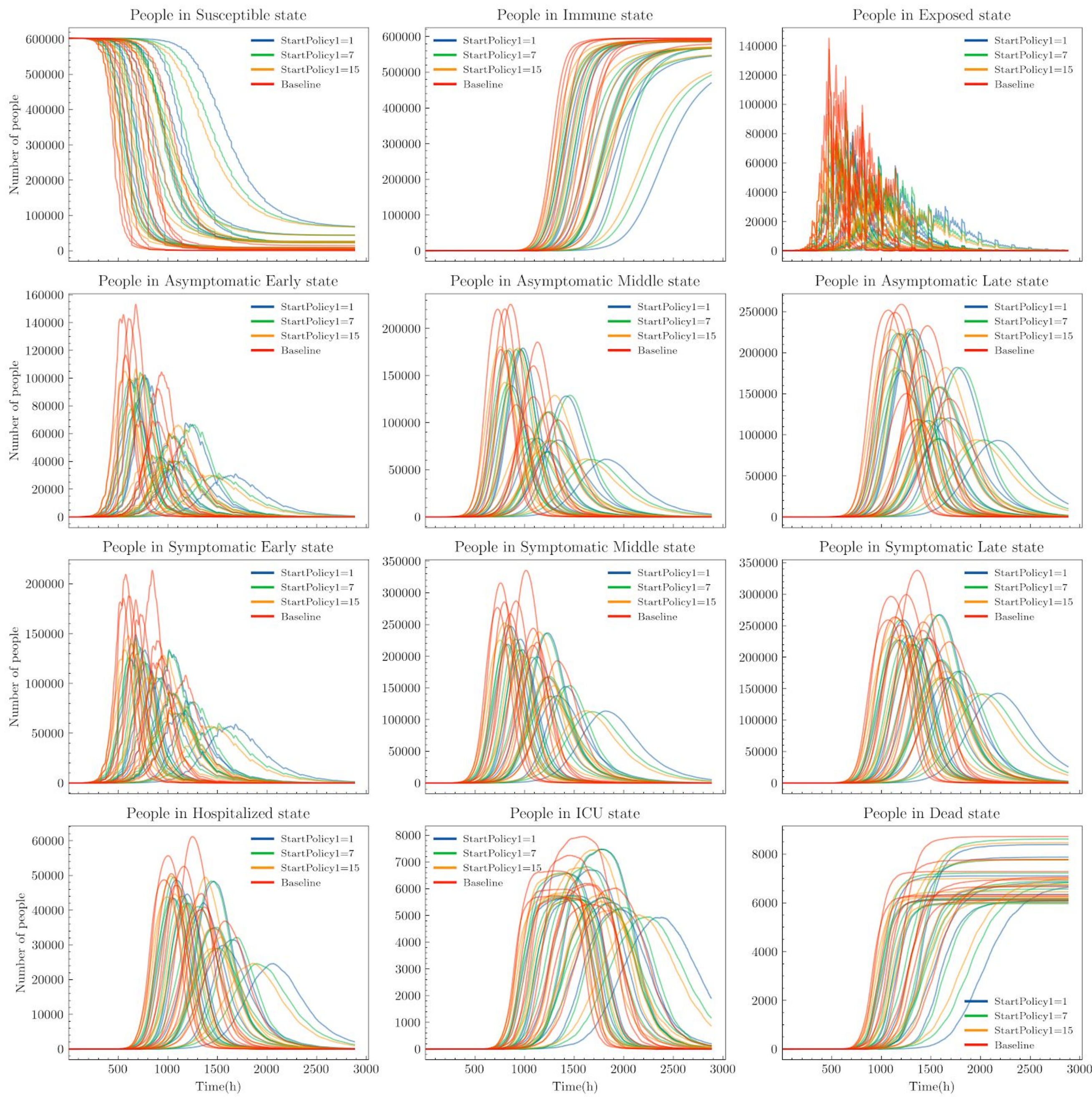

Figure 23. Performance of Policy 1 under 10 scenarios in the model of Helsinki.

As noted in Section 2.5.1, Policy 1 entails shutting down schools and imposing a ban on social gatherings. The experiments were run with this policy being enacted on 1, 7 and 15 days after the first reported case of infection in the city. The graphs show that under the majority of scenarios the implementation of Policy 1 is only slightly more effective than not implementing a policy at all in terms of ICU admissions, hospitalizations and deaths. There are very few scenarios where Policy 1 is delaying the outbreak, but as can be seen from the first plot of the grid, the number of susceptible individuals at the end of the model run is very low under all scenarios. More experiments will be required to confirm whether under specific scenarios (e.g., epidemiological parameters or number of initial cases), Policy 1 can perform better than the baseline.

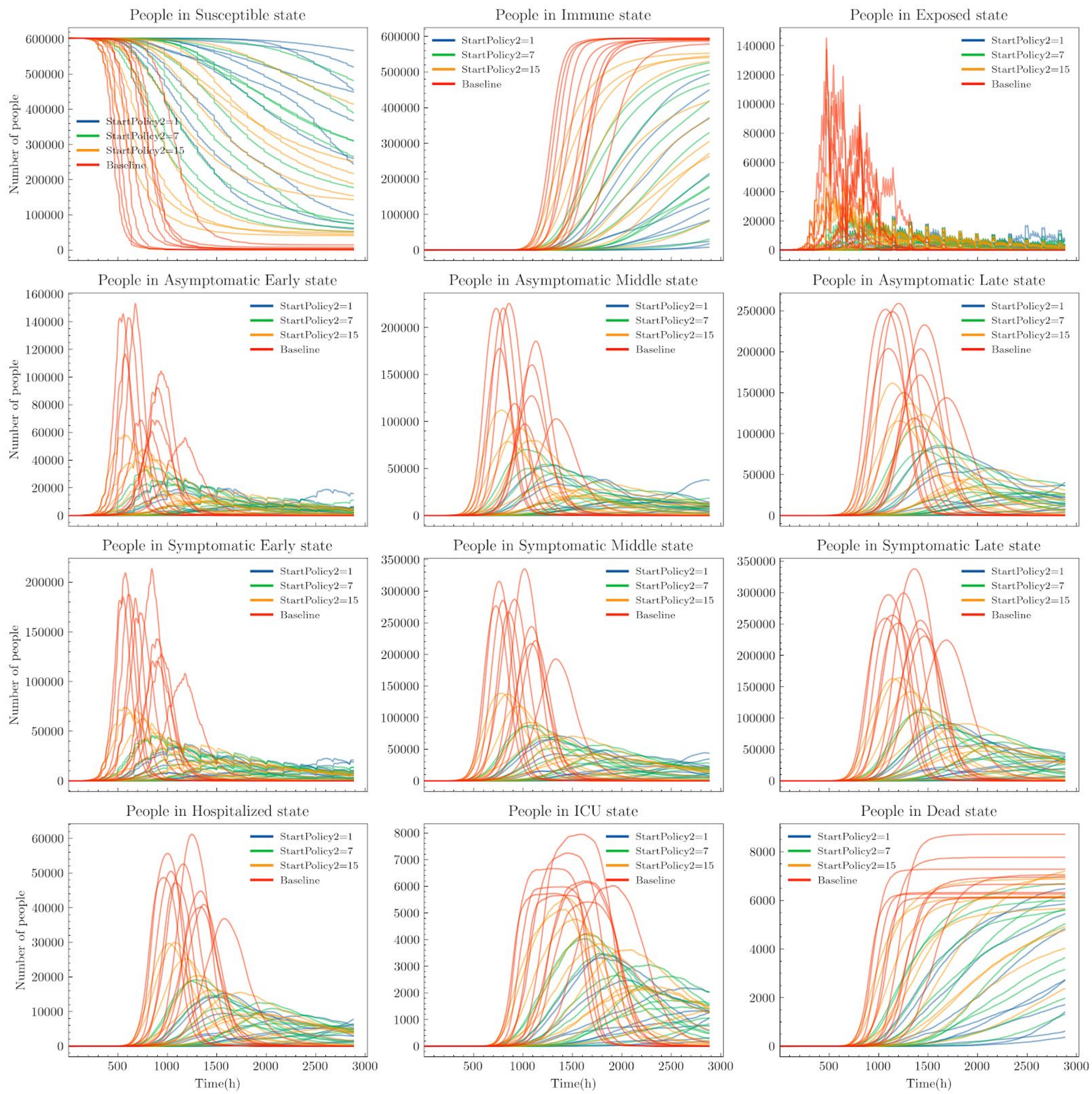

Figure 24. Performance of Policy 2 under 10 scenarios in the model of Helsinki.

Policy 2 is the implementation of a full lockdown where only parks, supermarkets and essential services are open. As with Policy 1, the graphs show the effects of Policy 2 being implemented on Days 1, 7 and 15. The graphs indicate clearly that Policy 2 more effectively reduces and delays the initial peak of infections, particularly when it is implemented earlier rather than later. We observed that, while the epidemiological parameters define the dynamics of disease transmission under all policies, Policy 2 outperforms the baseline scenarios in all states. Once again it is observed that the policies implemented early have a higher impact than the ones implemented later.

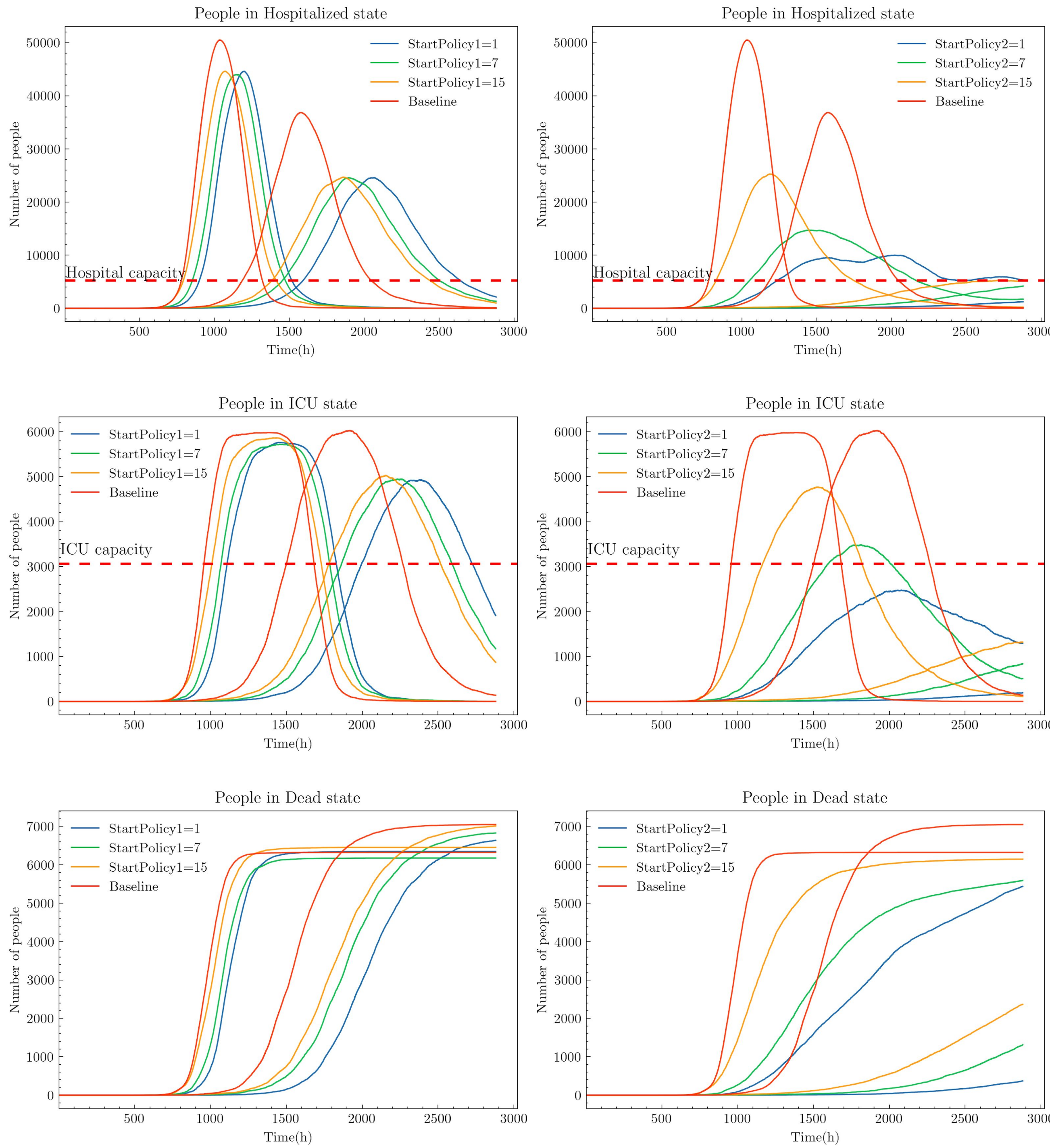

Figure 25. Comparing performance of the policies under the best and worst case scenarios for Helsinki.

	AsymptomaticFraction	ContagiousFactor	InfectionProbability	Number of initially infected
Best case	0.3433	2	0.203908	15
Worst case	0.43227	6	0.254846	5

Table 14. Parameter values for best and worst case scenarios for Helsinki.

From the experimental setup (see Annexes C) we have selected the best case and worst case scenarios for each policy and starting date, shown in Figure 25. The epidemiological parameters for these scenarios are represented in Table 14. In the best case scenario, the infection probability is around the mean value considered in the baseline case. The worst case scenario has significantly higher contagious factor which can be interpreted as, even at more than 2m distance, a chance to be infected remains.

In terms of ICU and hospital capacity, only Policy 2 implemented at the 1 day after the first imported infection has a chance to be if not below but at least close to the capacity.

Important to mention the values of the outcomes are not necessarily fit to the historical data. As it was explained in Introduction, the proposed simulation model is exploratory and the model was not fine tuned to exactly meet the values reported by the Helsinki healthcare system. One of the potential explanations of such a mismatch is that Helsinki citizens behave much more consciously then our model currently accounts for. For example, people kept social distance, or were much more spread throughout the week while visiting supermarkets etcetera.

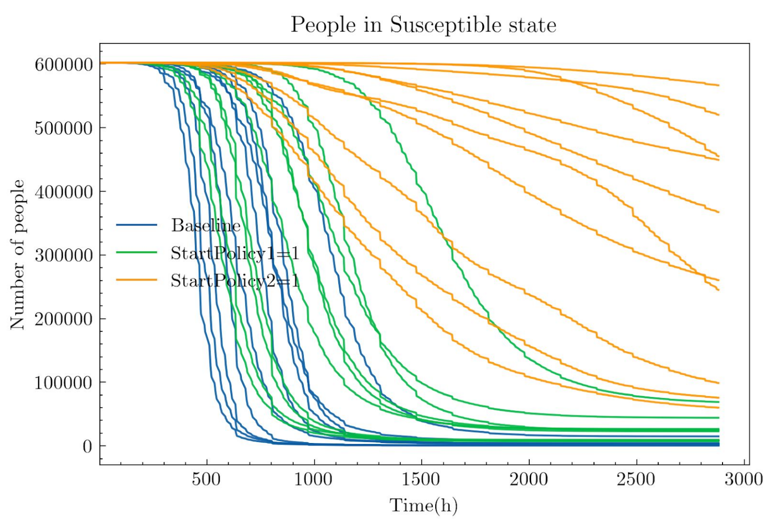

Figure 26. Comparing impact of policies under 10 scenarios on the number of susceptible citizens in Helsinki.

Figure 26 provides a direct comparison of the number of people that get infected under each policy when implemented 1 day after the first reported infection. In all of the scenarios under Policy 2, a lesser number of people get infected. However, the difference between Policy 1 and the baseline remains relatively small. Thus far, the analysis shows that Policy 2 is most robust under the range of scenarios considered.

Behavioral patterns and infections at locations

Figure 27 reflects the change in activities that agents take part in after adoption of Policy 1, whereby schools are shut down and social gathering are banned. The graphs show that the number of agents spending time in schools reduces considerably in accordance with the policies. This figure should be evaluated in conjunction with Figure 28 where the number of infections at each location is specified. Evidently, the Policy 1 lockdown has the effect of reducing the number of infections at schools, recreation spots, bars and restaurants. The number of infections in bars and restaurants make up a significant portion of the reduced infections.

Similarly, Figure 29 reflects the change in activities of agents after Policy 2 is adopted. As shown in the graphs, under Policy 2, as time passes, less and less people interact with each other. At Days 7 and 15, we observed in the graphs a marked reduction in the number of infections because of the implementation of the lockdown. Again, Figure 30 is best seen in conjunction with Figure 30, which demonstrates the number of infections that take place at each location type. Policy 2, which constitutes a full lockdown of all except for essential services, reduces the infections in workplaces. This appears to contribute to a significant portion of infections apart from locations that allow for social activity.

A future point of study would be to evaluate what second order effects result from a reduction in infections that occur in specific location types (e.g., workplaces). This is discussed further in Section 6 Future Research.

Figure 27. Amount of time spent by Helsinki citizens at different location categories under Policy 1.

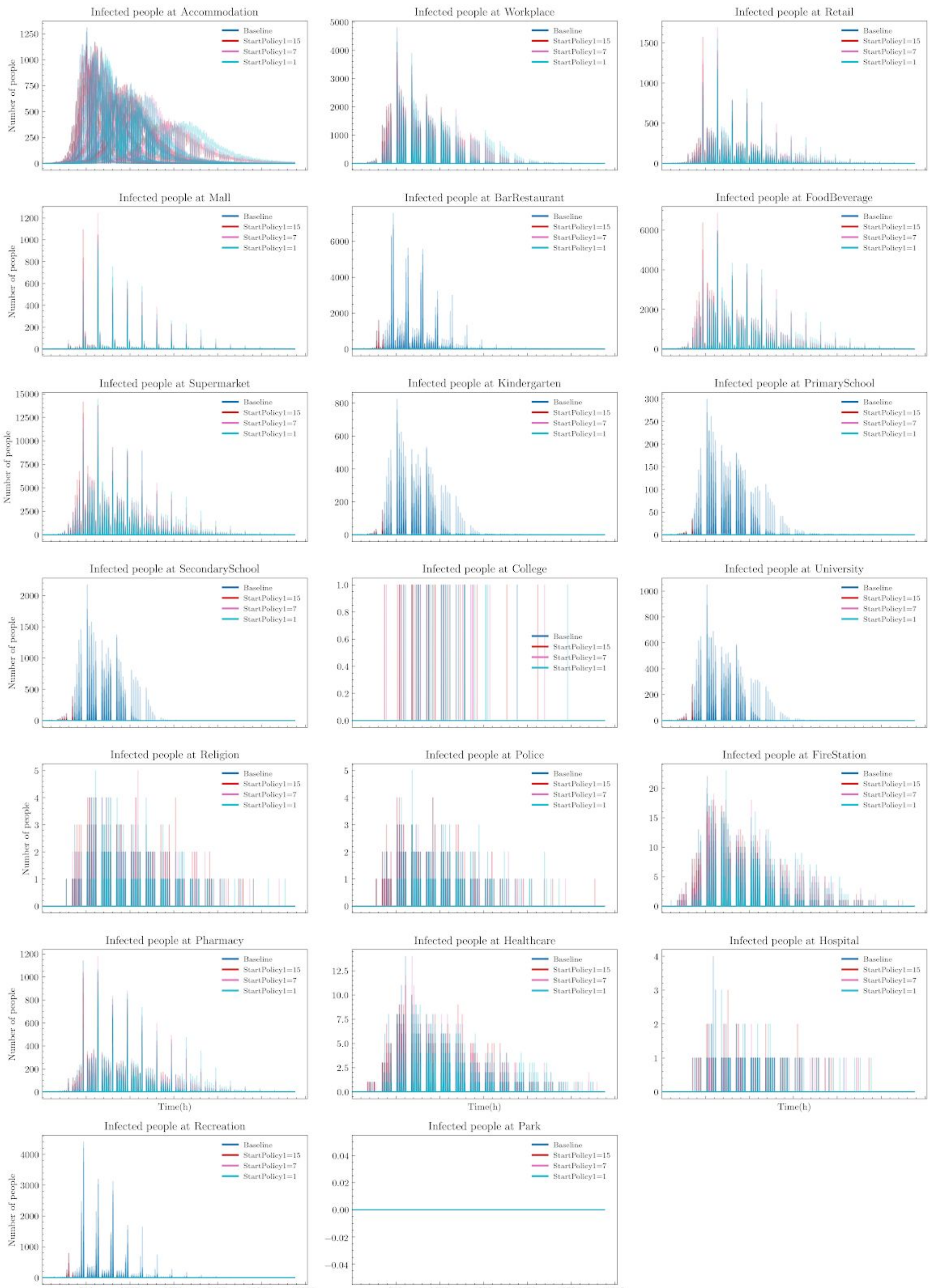

Figure 28. Number of Helsinki citizens infected at different locations under Policy 1.

Figure 29. Amount of time spent by Helsinki citizens at different location categories under Policy 2.

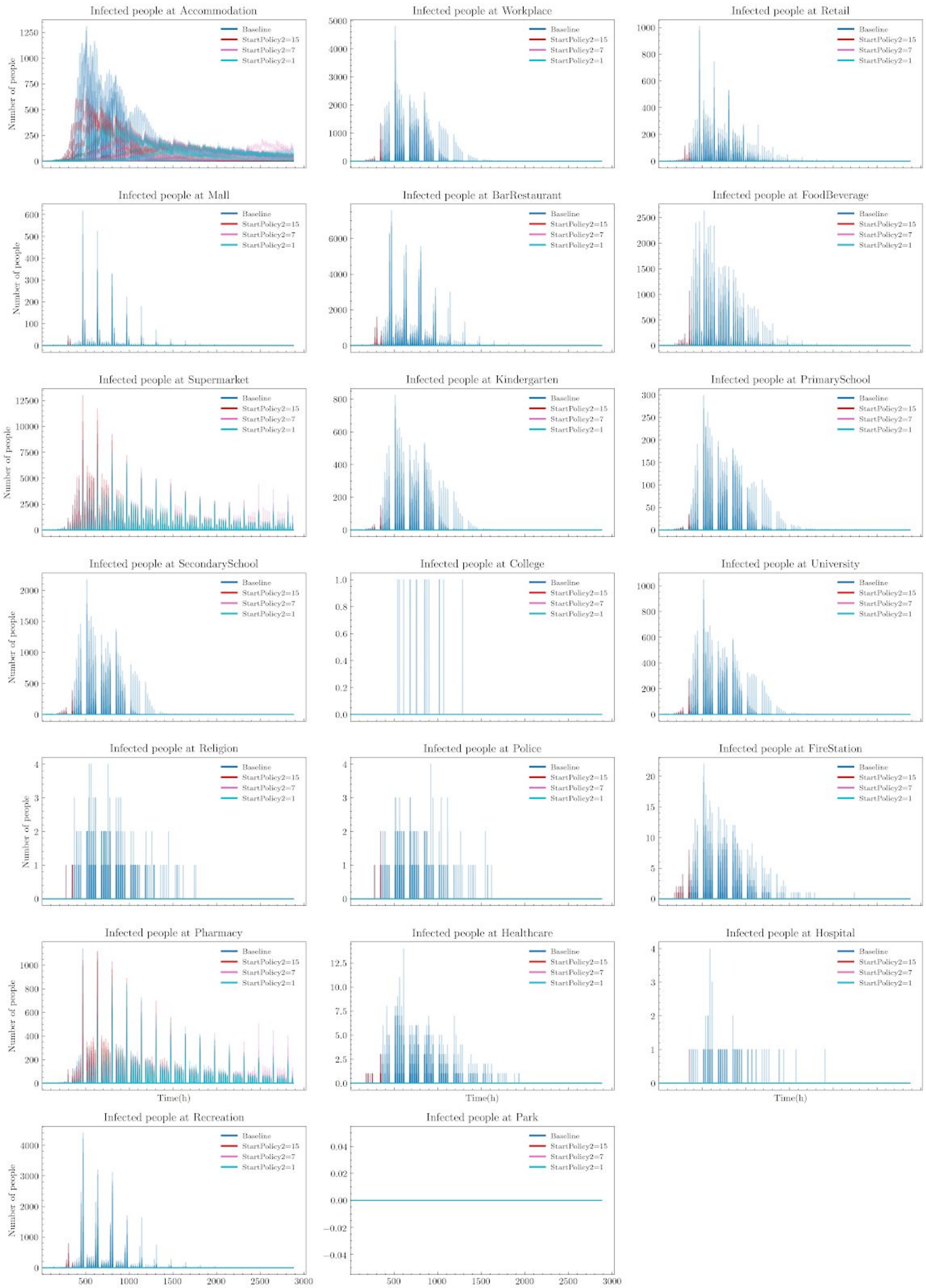

Figure 30. Number of Helsinki citizens infected at different locations under Policy 2.

Infections and casualties by age

Figures 31, 32, 33, 34 show infections and casualties by age group of the affected agents. The graphs show that the peaks in infections are associated with a specific activity that a person takes part in. For example, students spend a high amount of time participating in social activities (e.g., at bars), resulting in a higher chance of infection.

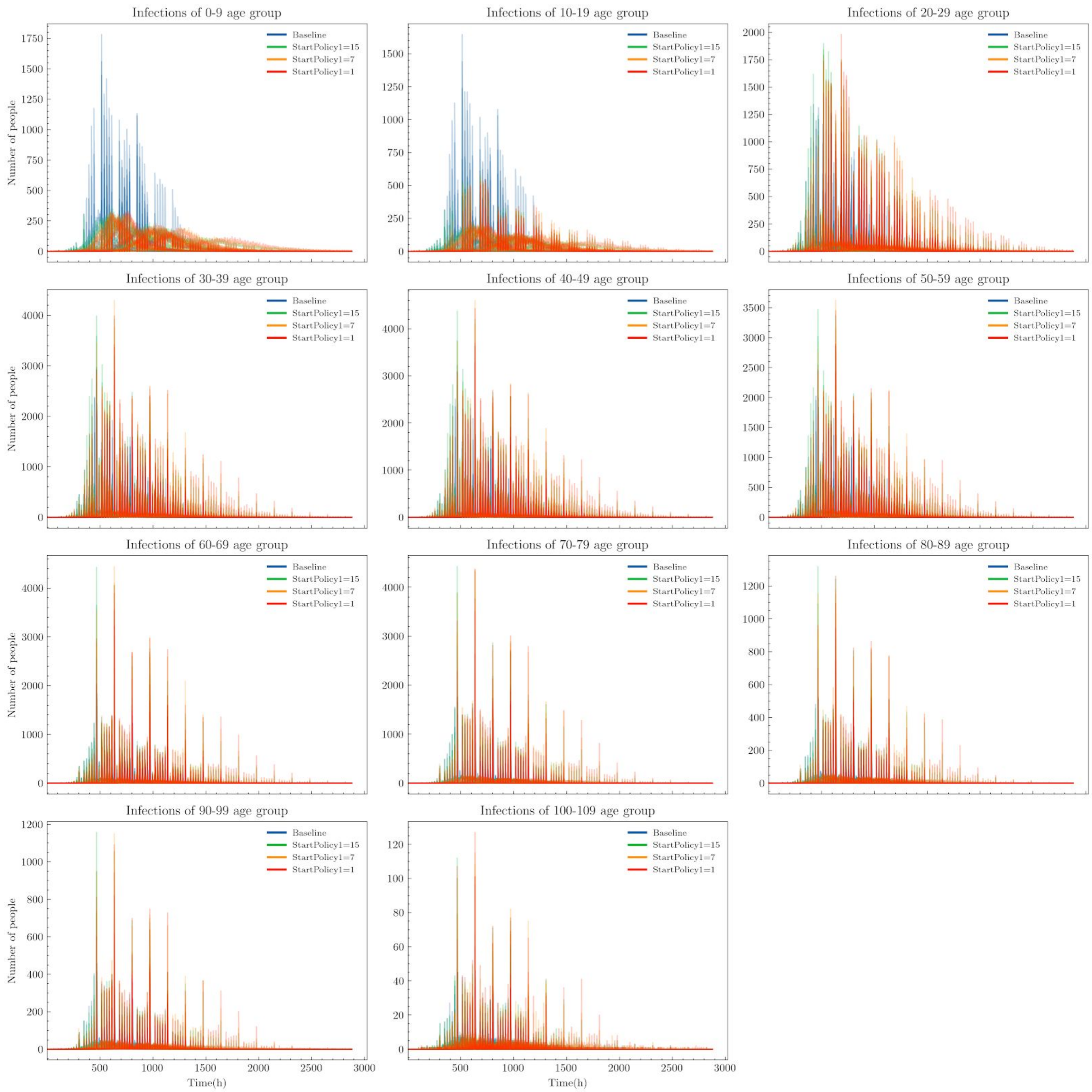

Figure 31. Number of Helsinki citizens infected by different age groups under Policy 1.

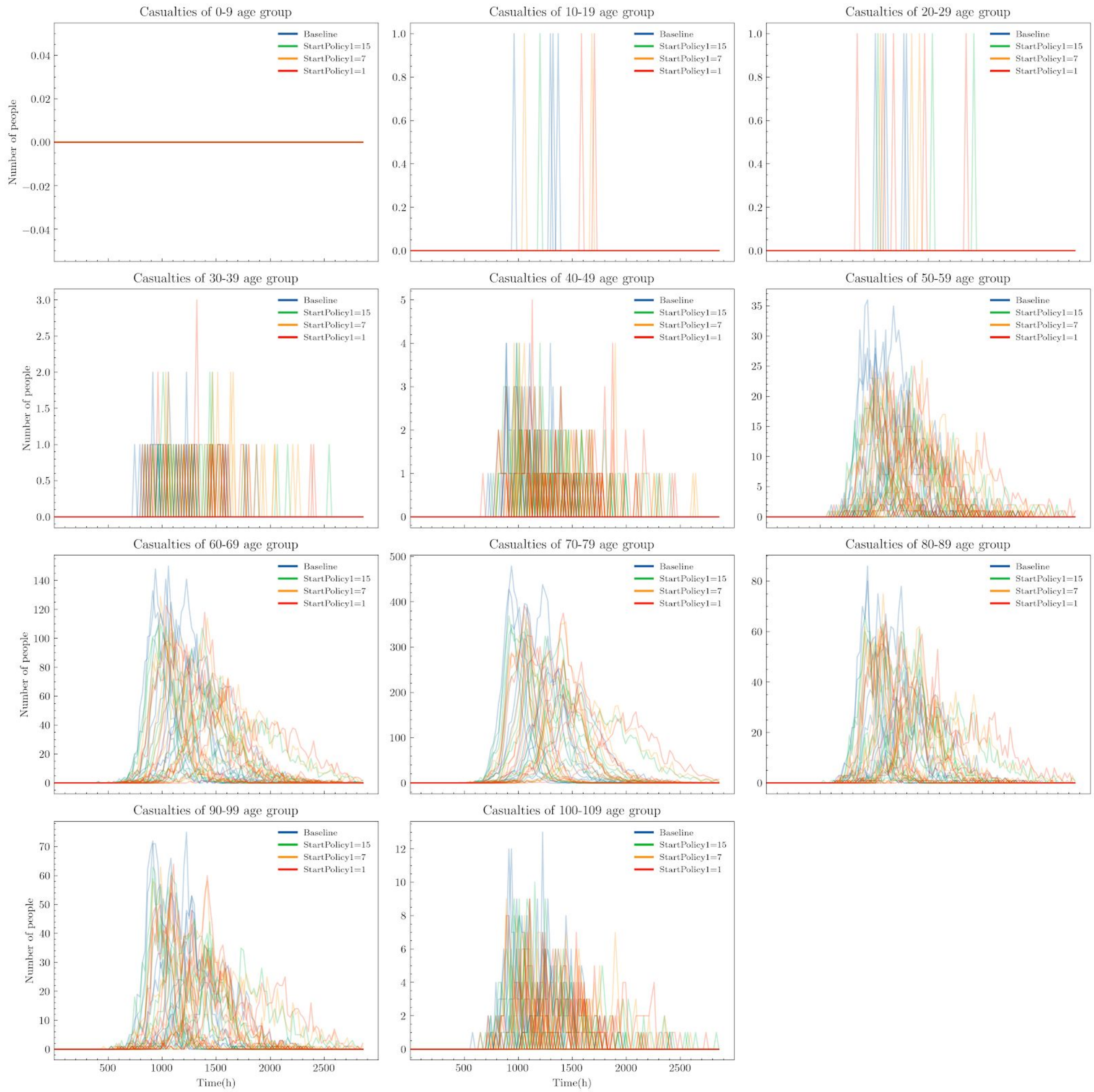

Figure 32. Number of casualties in Helsinki by different age groups under Policy 1.

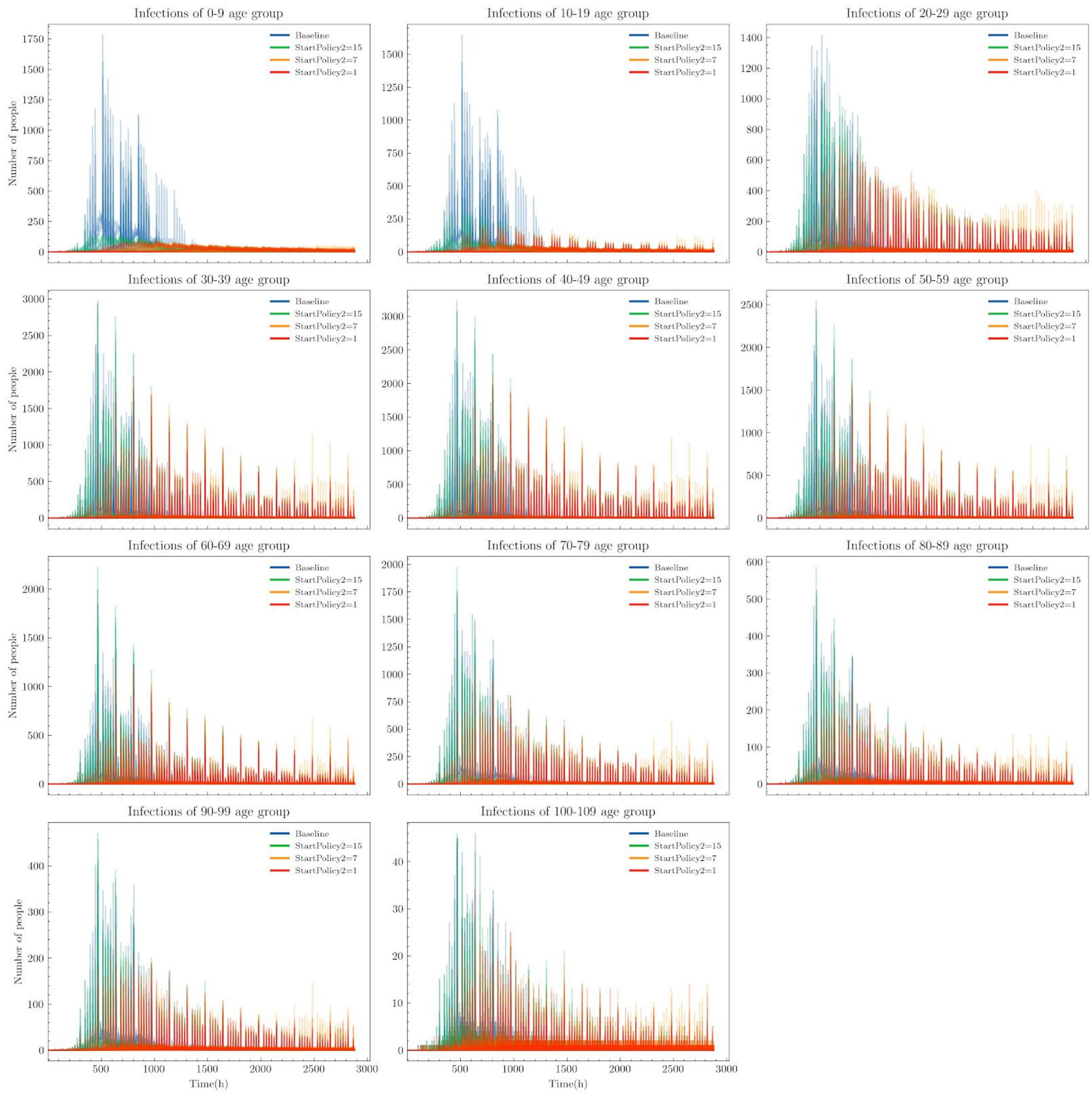

Figure 33. Number of Helsinki citizens infected by different age groups under Policy 2.

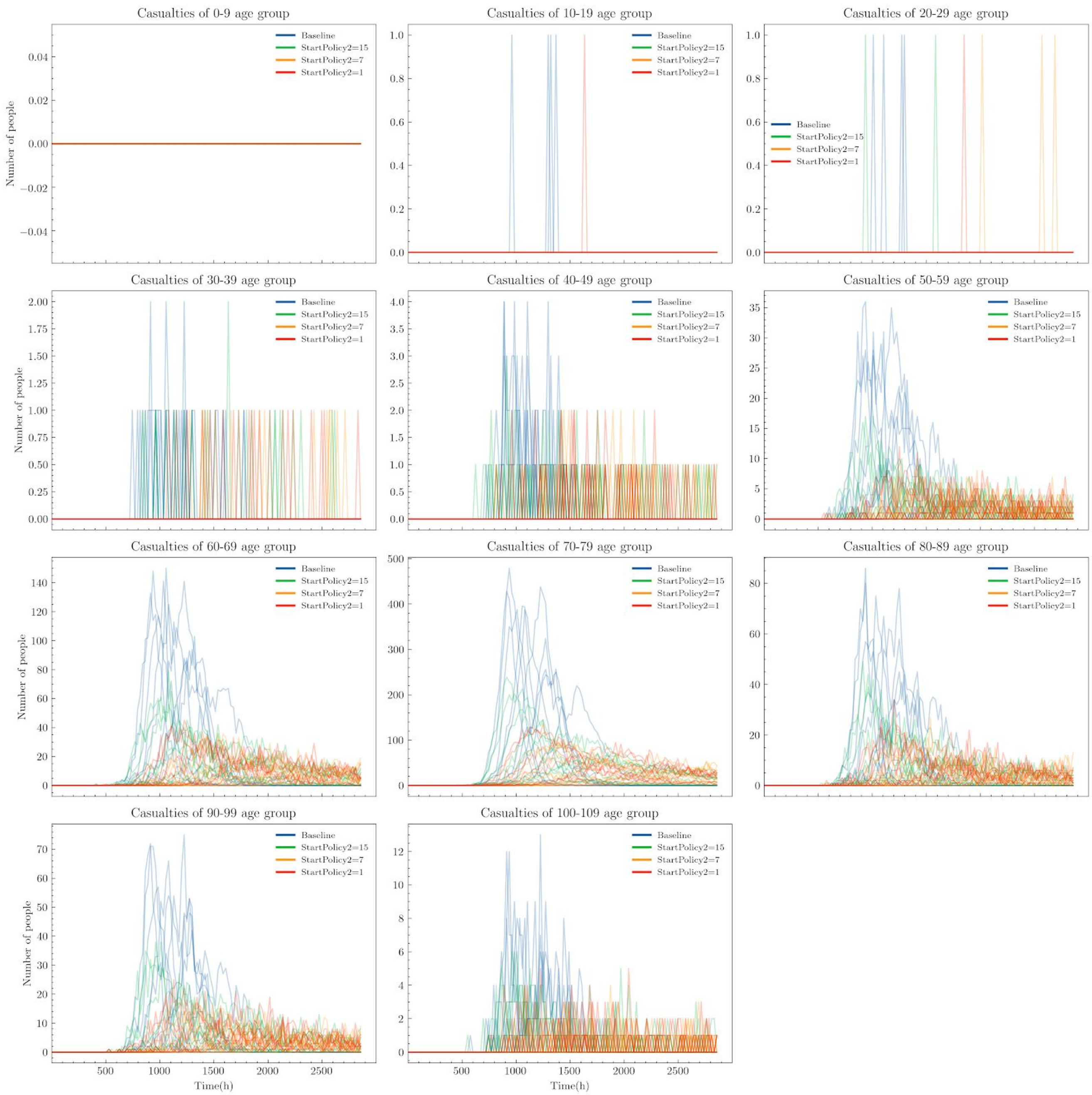

Figure 34. Number of casualties in Helsinki by different age groups under Policy 2.

Geospatial distribution of casualties

The maps shown below indicate the spatial distribution of casualties by neighborhood of residence that occurred at three select time steps over the simulation run (Table 15).

	StartPolicy2=1 (days)	StartPolicy2=7 (days)	StartPolicy2=15 (days)
TimeStamp1 (days)	63	63	63
TimeStamp2 (days)	91	91	91
TimeStamp3 (days)	120	120	120

Table 15. Selected timestamps by policy for visualization of casualties in Helsinki.

Similarly to The Hague case, the numbers of casualties are higher when the policy is implemented later. And again, the gradual change in number of casualties displays the unequal distribution of infections across the city. Some neighborhoods see more casualties and this could be because of two factors - they are more exposed to infection or they are older communities who are active. It could also be the case that both hold true. This is an opening for future research to delve deeper into.

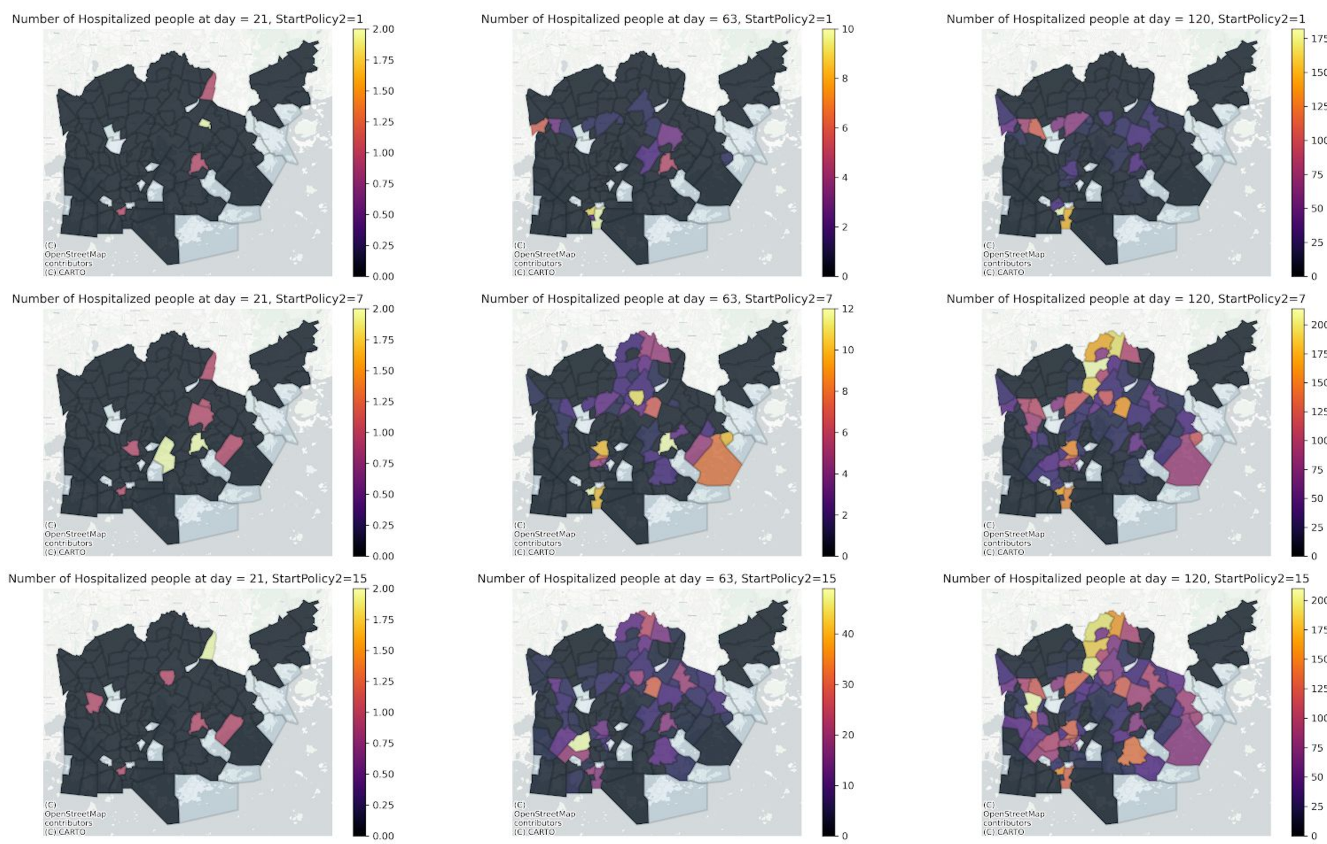

Figure 35. Distribution of casualties in Helsinki over time and space based on time of Policy 2 implementation and TimeStamp.

3.3 Cross-case comparison

This subsection aims to compare the main epidemiological indicators under a set of policies and scenarios for two case cities: The Hague, The Netherlands and Helsinki, Finland.

The first pair of graphs (Figure 36) shows that The Hague and Helsinki react similarly to the baseline policy, Policy 1 activated at day 1 and Policy 2 activated on day 1, under all scenarios. In the baseline, by the end of the simulation run the complete population of both cities got infected. Similarly to the baseline case, Policy 1 even implemented early (at day 1) has a relatively muted effect on mitigating disease spread. In contrast, under Policy 2 implemented on day 1, the number of infections does not increase as rapidly and appears to stabilize earlier. Thus, for the both cities, Policy 2 is more robust and has the potential to lower the number of infections under the majority of the tested scenarios.

The next pair of graphs on Figure 37 presents the change in number of hospital admission in The Hague and Helsinki on the baseline policy, as well as Policy 2 activated at day 1, 7, 15 under all scenarios. Model results showed that for Helsinki, under the worst case scenario and Policy 2 even at day 1, hospitalizations still exceeded hospital capacity. This indicates that extra hospital beds may be required in scenarios where the virus has an extremely high rate of infection. Alternatively, this could suggest that more effective policy measures should be introduced to reduce disease spread. As explained earlier, even though the majority of establishments were shut down under Policy 2, supermarkets continued to function in a business-as-usual mode. At the same time, agents did not adjust their individual activity schedules when it came to the 'Shopping' activity type, and therefore continued to visit supermarkets as they did before the pandemic. Therefore, one potential improvement of Policy 2 that can potentially lower infections in Helsinki is to introduce longer working times for essential retail establishments, alongside limiting the maximum number of visitors at any one time.

The final pair of graphs compares ICU admissions. While Policy 2 activated at day 1 performs relatively well in Helsinki under both the best and worst case scenario, The Hague appears to endure a relatively higher impact on its ICU admissions in the worst case scenario. This suggests that improving preparedness for a variety of plausible uncertain futures may require increasing ICU capacity in the healthcare system.

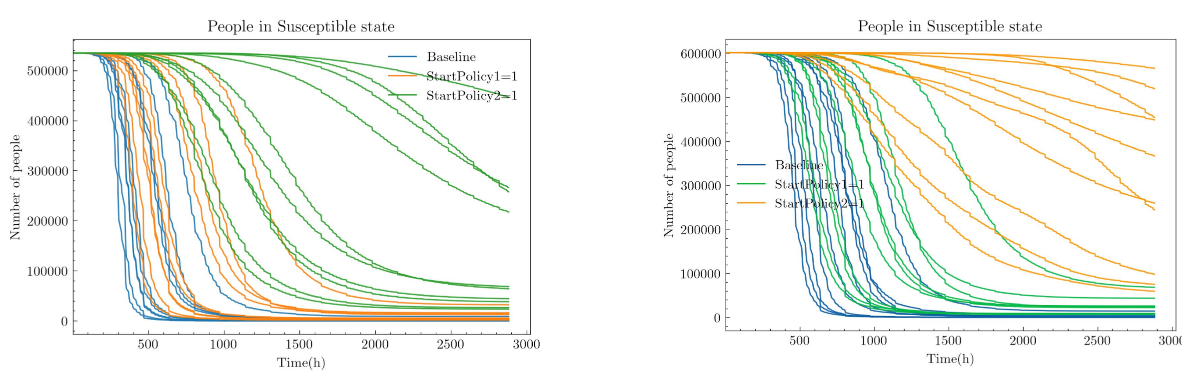

Figure 36. Comparison of changes in susceptible states in The Hague (left) and Helsinki (right) population given best and worst case scenarios.

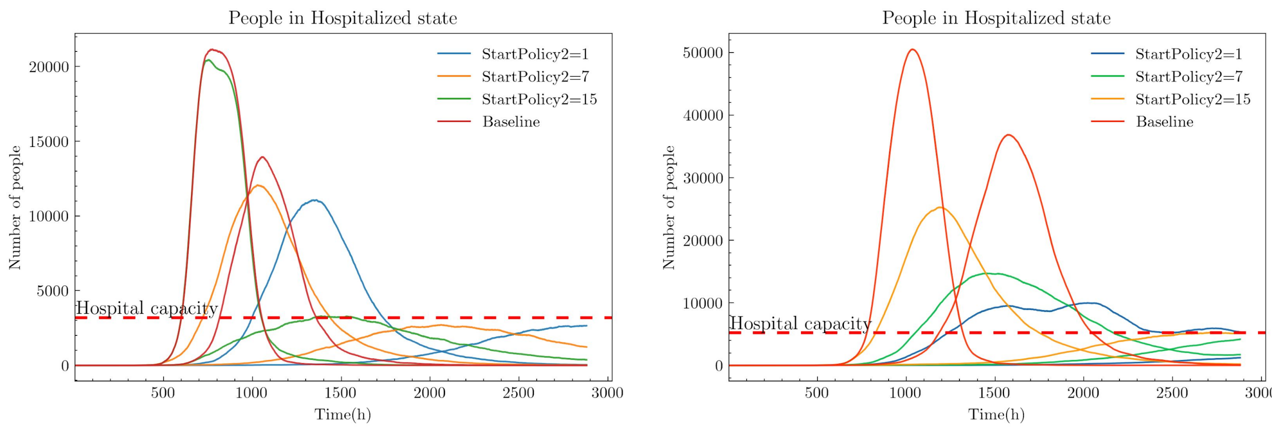

Figure 37. Comparison of hospital admission in The Hague (left) and Helsinki (right) given best and worst case scenarios.

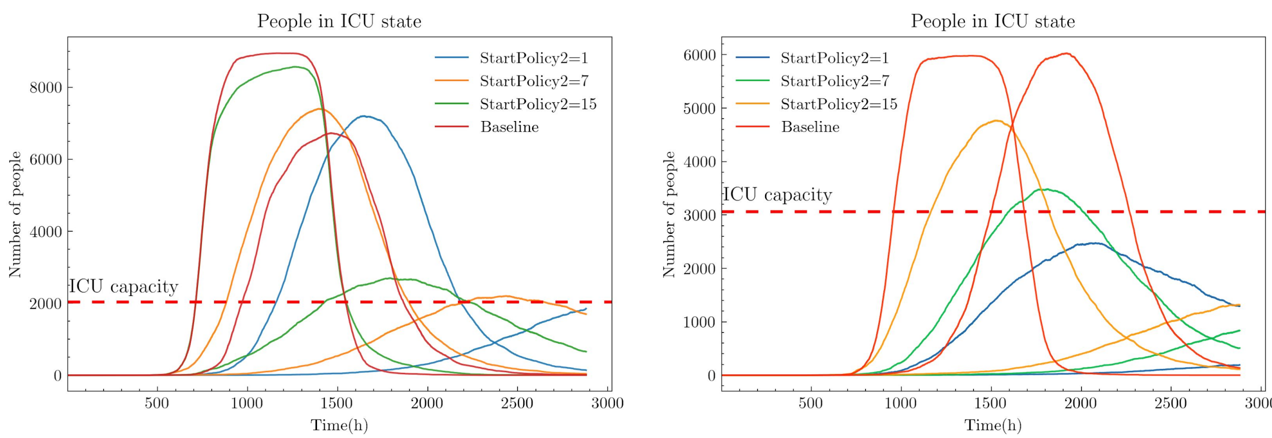

Figure 38. Comparison of ICU admission in The Hague (left) and Helsinki (right) given best and worst case scenarios.

3.4 Implications for international mobility

The proposed simulation model is a closed system: no inflow or outflow modelled neither from the neighboring cities (daily commuters) nor from other countries (flight, train, car travellers). The immediate limitation of such an approach is that we cannot keep track of potential impact of the disease on a larger scale: cross-border infections. One of the ways to address is to use estimated international mobility data.

EpiRisk is a computational platform designed to allow a quick estimate of the probability of exporting infected individuals from sites affected by a disease outbreak to other areas in the world through the airline transportation network and the daily commuting patterns. We used EpiRisk to come with first estimates of the impact of the local infections on the international ones.

We assumed that given a very dense domestic transportation network in the Netherlands we can start from Amsterdam as an infected basin instead of The Hague. For both cities we consider two scenarios 100 and 1000 infected individuals. These numbers reflect on the different times of implementing the local policy measures.

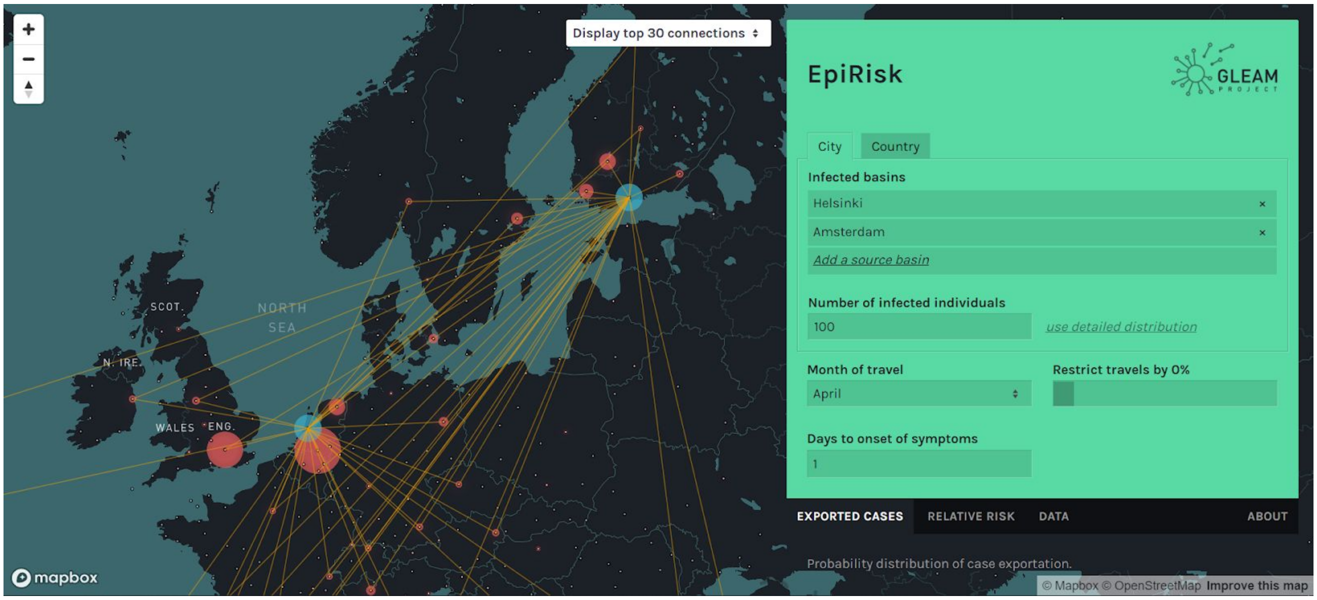

Figure 39. Top 30 connections between The Hague and Helsinki.

Map below highlights 30 connections between The Hague and Helsinki. With such intense passenger flow even such a relatively small number of infections has a change to spread out across neighboring cities (see Figure 41). In the case of 1000 infected individuals this risk significantly intensifies.

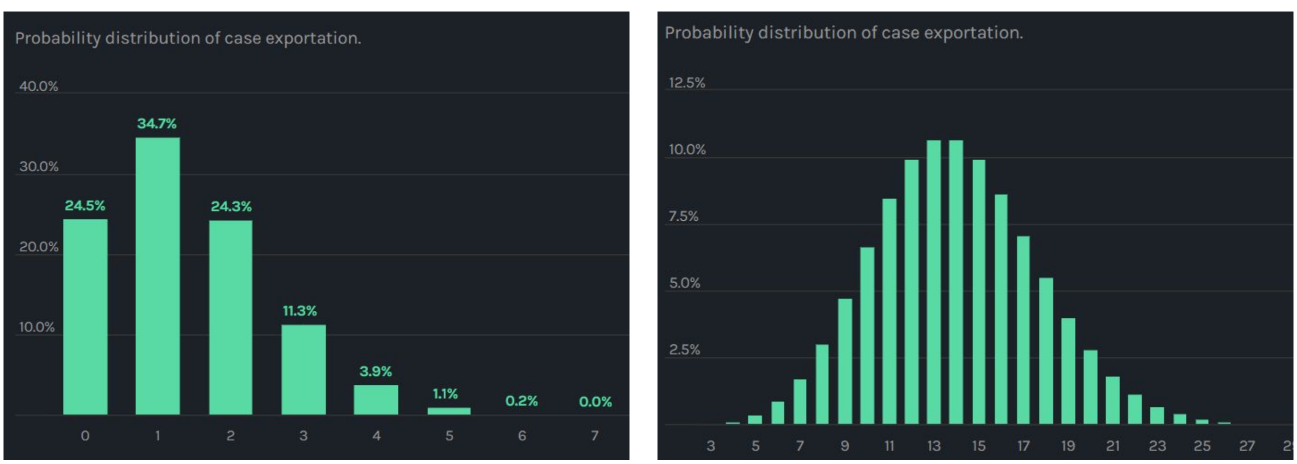

Figure 40. Probability distribution of case exportation for 100 and 1000 initial cases respectively.

Finally, the last figure presents cities ranked by relative risk of case importation.

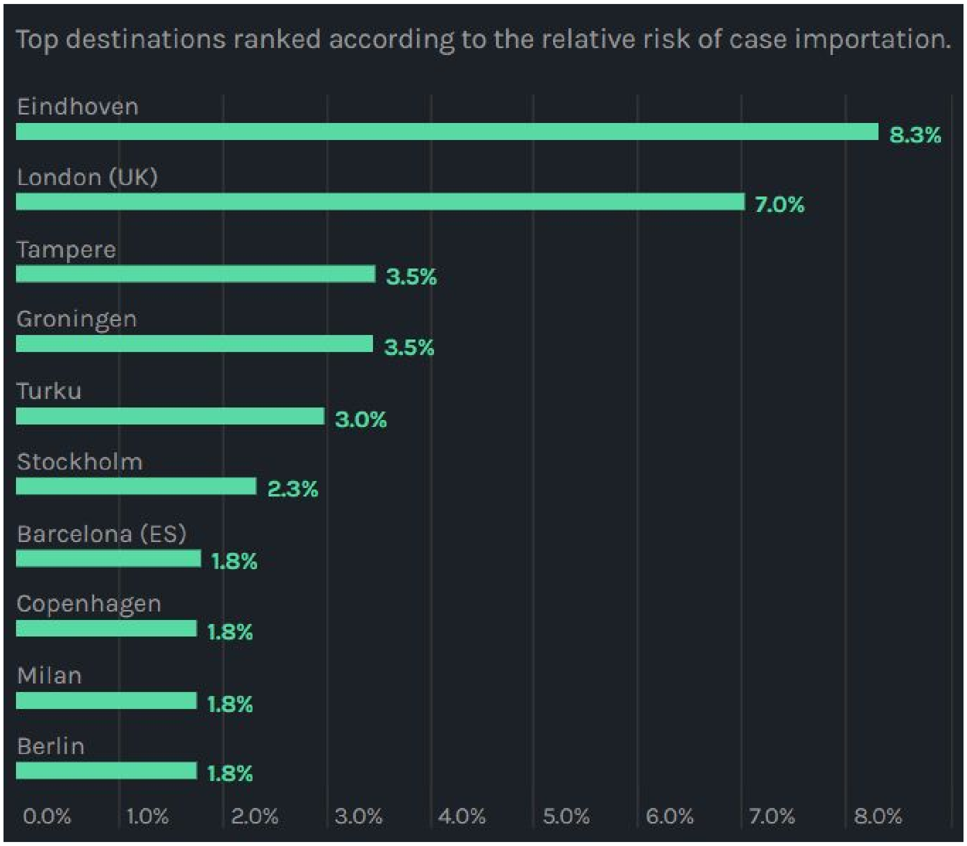

Figure 41. Top destinations ranked according to the relative risk of case importation.

4 Assumptions and limitations

The limitations of this study can be categorized into conceptual limitations, which relate to how a real system is represented in a model, and implementation limitations, which concern how the conceptualized model is constructed.

The first conceptual limitation is the boundary of the system, which was chosen to be the city administrative boundary. This limitation implies that all agents who live in this city live, work and play in the same city, and that no one from outside of the city boundary comes into the city. This does not reflect reality as statistics for both modeled cities indicate that many citizens travel into these cities for educational, occupational and recreational activities. In a city like The Hague, multiple people visit and leave the city for work to neighbouring cities like Zoetermeer. The number of people that enter the city for work or school could be more than the number that leave the city, thereby increasing workplace infections but decreasing accommodation infections. This limitation is something that can be addressed in future iterations of the model.

Another conceptual limitation is that all agents that enter the same state in the epidemiological model are ascribed the same rate of infection. Multiple studies have suggested that this is not the case, and that women, for example, are more resistant to contracting and more likely to recover from COVID-19. However, the gender of individuals is not represented in the model. Additionally, every person is as equally likely to get infected.

Lastly, the model does not include a public transportation system. Studies have shown that the public transit system in a city may act as a major facilitator of disease transmission during a pandemic (Harris, 2020). However, in this study, people select only from walking, cycling and driving as travel modes to their destinations. An implication of this limitation is that the effect of infections that potentially occur on public transit modes of travel are not captured in the model. This is a submodel that can be incorporated in the future versions of this model.

An implementation limitation is that the data used to construct the built environment in the artificial city is largely based on OpenStreetMaps data. The OSM database, while large and comprehensive, is built on crowd-sourced data, and is inconsistent in terms of its syntactic and semantic quality. As defined by Price and Shanks (2005), the former refers to how the data conforms to database rules, while the latter refers to how the stored data corresponds to the represented referents for which the data describes. OSM data is often syntactically inconsistent, where for example the "Building" tag for each building may either describe the use case (e.g., museum, college) of the building, or simply contain an affirmative 'Yes' (i.e., that the building is indeed a building). The data is further semantically inconsistent, mainly because the database is crowdsourced and multiple bars that present the same use functions may each be tagged differently (e.g., "bar", "brewery", "pub", etc.). To cope with these data quality issues, we were required to make extrapolating assumptions or to omit incomplete data points entirely.

Additionally, the scope of creating an agent-based model of a specific city where an agent represents a citizen of that city requires large amounts of individual level data that we were unable to access for this study. The process of generating a synthetic population to approximate the individual attributes of agents was based on neighborhood level data and thus has a margin of error.

Lastly, people within the model continue to make choices rationally about their commuting patterns and work schedules. This has been discussed wildly not to be the case. While greater resolution of data can allow for more complex decision making, the irrational component can be incorporated by modeling fear (Epstein et al., 2008). This will be done as a future model addition for the second phase of the project (Task 2.3, see Section 6 Future Research).

Taken altogether these limitations do not invalidate the model findings, but they needed to be approached carefully. Opposite to conventional modeling, the approach that we have chosen is exploratory. The aim of an exploratory simulation model is not to predict but rather explore the set of plausible scenarios to find out what are the best ways to act given uncertain futures. Therefore, model results should not be taken as ultimately truth, but instead inform policy makers about the potential impacts and consequences of not taking an action. Model users can think about the model results as follows: given all assumptions that were made what are potential consequences? For example, what if my The Hague has 100 infected individuals randomly distributed all over the city and these individuals visit overcrowded supermarkets? Such a scenario sounds reasonable and worth exploring even though it does not incorporate all potential details. To conclude, the validity of an exploratory simulation model is defined by whether or not it fits for the intended purpose.

5 Recommendations

Our model results showed that **time of implementing the policy** significantly influences model outcomes. Policy 2 implemented on day 1 in comparison to that implemented on day 15 resulted in a much lower number of infections and did not overwhelm the healthcare system under the majority of scenarios.

Given epidemiological parameters, we found that **activities** in combination with **locations** are one of the key drivers of the disease spread. Places with high passability (e.g. bars, supermarkets) or locations where a person spends a large amount of time (e.g. workplaces) are the hotspots of the disease spread. Therefore, to combat COVID-19, a set of actions should be tatke aimed at **limiting citizens' interactions**.

Model findings also indicate the importance of the **right closures, scheduling** and **overcrowding.** Which establishment types to shut down, or what working hours should those establishments be limited to? These are questions that should be addressed before implementing policies aimed at shutting down businesses. Initially, the model simulated locations and their visitors in a relative balance whereby supply (volume of visitors) satisfied demand (capacity of locations visited). However, when a certain location type becomes unavailable, client flow redirects to locations with either similar or sometimes with a different function. For example, by shutting down food and beverage establishments, we potentially increase the load on supermarkets. If no effort is taken to manage opening hours and the number of visitors, supermarkets can easily become the main hotspots, especially under Policy 2, when these are the only places of mass gatherings along with pharmacies.

Day of the week. The behavioral pattern of a citizen during the weekday and weekend differs. Typically citizens spend more time at locations with a higher number of visitors over the weekend than on a weekday (e.g., shopping mall). This is why our model showed certain regularities: the number of exposed people spiked during the weekend. Knowing this can help to account and **monitor** for the **delayed effect of weekend activities and gatherings**.

Area and the number of personnel. We found out that the area of a location and the number of associated sublocations played an important role. Similarly to scheduling of supermarkets, efforts can be taken to limit the number of workers visiting their workplaces at the same time.

Essential workers. Essential workers are those who work at supermarkets, pharmacies, hospitals, fire stations and police stations. Since these types of locations remain open under Policy 2 (i.e., the most robust policy), they continue to face elevated risk of infection than the average stay-at-home citizen. Thus, extra effort should be taken to protect this group of citizens from infections in their workplaces.

6 Future research

This section discusses the additions that can be incorporated for further refinement of the simulation model. We divide these additions into two categories: structural additions and policy and experimental additions. The former discusses specific aspects that can be further improved to capture urban dynamics. The latter describes additional policy and uncertainty experiments that may be implemented to derive more robust and effective designs of policies as well as an understanding of the impacts of uncertainties.

The structural additions are:

1. Introduce a **layered social network** for each of the agents: friends, family, colleagues and neighbors. This social network may incorporate a power law distribution for the number of friends each person has (Hamill & Gilbert, 2009). The implementation of the social network and subsequent modeling of choice to meet people can follow the approach of (Zhang et al., 2016).

2. Add a **transportation submodel**. Multiple studies have shown that public transport acts as a source of COVID-19 spread due to long exposure times in suboptimal ventilation conditions (Sun & Zhai, 2020). Shutdown of a public transport system also has a complex non-linear effect on people’s choice of transport as well as choice of an activity itself.

3. Incorporate **psychological factors** into the coding of agents’ behaviors. Human behavior and compliance with the mitigation policies is not merely dependent on the social role and health condition but additional psychological effects such as **fear** or more formally **concerned awareness**. A person’s fear will be potentially modelled as a combination of: internal fear: due to age, preexistent health conditions; external fear: influenced by the number of people sick within their social network and how close they are within the social network (Epstein et al., 2008). Important to mention that fear does not remain constant over time from the first event to the end of one's life. Instead, it reduces over time creating an effect of forgetting (Bi et al., 2019).

4. Make activities of individuals more dynamic by **spreading out time spent on activities** over the corresponding activity time slots. One example would be to include an activity that models an agent spending a randomly selected amount of time at a Mall location, within the time period scheduled for a “Shopping” activity. The random selection may be a fixed or a stochastic distribution of time and can be included for all social and shopping activities.

5. **Modify** activity **schedules** of agents based **on** their **epidemiological state**. Currently, an agent’s activity schedule changes when they are in the symptomatic middle stage state (i.e., they stay in the hospital or at home only). Future iterations of the model will include testing, whereby people stay at home without participating in any activity while waiting for a test result or after testing positive. Further changes may include people choosing to stay home or change their activity patterns based on current state. This can be incorporated by fine-tuning the activity schedule, with details informed by literature and reports (e.g., interviews with patients of COVID-19).

6. Gather **more detailed data** and incorporate extra socio-demographic parameters into the synthetic population (e.g., gender, connection between income and occupation) and improve locations data set (e.g. number of sublocations, total area).

7. Include **commuter agents** whose place of residence are not in the same city as their place of work or study. These commuters may travel in and out of the city for educational, occupational, or recreational activities, which changes disease transmission.

The policy and experimental additions include:

1. Incorporate **scenario discovery** and **multi-objective robust optimization** techniques to determine policy designs that are robust and optimum. This may be done by running a high volume of experiments on a wide range of uncertainty parameters and policies, which will require extensive time and computational resources.

2. Simulate the impacts of **mask-wearing and social distancing** practices between agents on disease transmission. This can be incorporated by fine-tuning the contagiousness parameter, and may be differentiated based on the types of locations (e.g., outdoors vs. indoors).

3. Allow **cross infections across sublocations** at the same location. Cross-infections often occur in large office buildings (i.e., a single location) that contains multiple offices (i.e., several sublocations), particularly in common areas such as lobbies and elevators. This can be incorporated into the model by fine-tuning the contagiousness parameter.

7 Conclusion

The SARS-CoV-2 virus (COVID-19), first identified in December 2019, spread across the globe and resulted in over 35 million confirmed infections and over 1 million deaths. To mitigate the spread of the virus, governments across the globe were put in a position to take measures without complete knowledge of the epidemiological characteristics of the disease. With no vaccine in sight and overburdened healthcare systems, the situation pushed countries to resort to non-pharmaceutical interventions that involved changing human behavior. Under the uncertainties of disease characteristics and unpredictable human behavior, a policy is meaningfully impactful when it is robust.

The purpose of this study is to understand the effect that human behavior and interactions have on disease spread in a city. The problem under investigation in this study is how the government can control the spread of COVID-19. The aim was to understand the effect of human behavior and interactions on the outcomes of different policies taking into account the uncertainty around the epidemiological characteristics of the disease, and the cultural and contextual characteristics of a city. The different policies are then analysed to identify robust policies that can contain the spread of the disease under different possible scenarios.

For this purpose, we built an agent-based model of an artificial city. This artificial city was used to model two case cities - The Hague, Netherlands and Helsinki, Finland with 535144 and 602128 individual agents respectively. To create these cities we generated synthetic population from available open data, spatial data and locations of points of interest from OpenStreetMaps and literature. The model consists of people, locations, activity schedules and epidemiological state transitions. The temporal scale of the model is 120 days after the first infected case. The spatial scale of the model is up to individual building and persons. The model is analysed using techniques of decision making under deep uncertainty where policies were stress tested against a set of scenarios.

The model was tested under 3 policies. The baseline (no policy is implemented), a ‘soft’ lockdown policy (closure of only restaurants, bars, and recreational and educational institutions, Policy 1) and a strict policy of complete lockdown where only essential services and parks remain open (Policy 2). These policies are analysed against 10 scenarios sampled for four uncertain parameters within the model - infection probability, contagious factor, initial number of infected people and fraction of people that are asymptomatic.

Findings from analysis of the model showed that Policy 1 is not substantially different than the baseline of not taking action. Furthermore, the analysis shows that Policy 2 is more effective than Policy 1 and the baseline at delaying and reducing the peak of infections, which ultimately alleviates the burden on the healthcare system and reduces the risk of overloading hospitals. The efficacy of Policy 2 may be attributed to the reduced number of spatial contacts directly resulting from reduced movement and activity of citizens.

Results from the model even more pertinently demonstrate the importance of taking action to mitigate disease spread as soon as possible. Across all scenarios, policies that were implemented later yielded worse performance on numbers of infections, hospitalizations, ICU admissions, and deaths compared to policies implemented earlier. Thus, the model showed that delaying actions can push a city to a point of “no-return” and overload the healthcare system.

Furthermore, the model shows that locations with a high turnover of visitors over a short period of time have the potential to become hotspots for disease spread. Thus, spreading out visitor load on locations can potentially reduce the risk of infections. Similarly, limiting the number of workers at a workplace can also reduce risk of infections. Finally, essential workers who cannot comply with a lockdown and must still go to work face an elevated risk of exposure to the virus as they continue to experience a high volume of spatial contacts. This category of citizens therefore risk becoming vectors of disease spread in their homes, demonstrating the criticality of additional action to ensure their safety.

In reviewing the variations in patterns of disease spread resulting from different scenarios, it is clear that the epidemiological parameters used as inputs into the model meaningfully influence model outcomes. For this study, the range of parameters used in the experiments were defined based on currently available information and research on the characteristics of COVID-19 transmission.

This study resulted in the development of a model that captures how the system responds to different policy measures. This model was used to stress test different policies under a range of scenarios sampled for contested epidemiological parameters. The study resulted in a powerful scalable tool that can be used to inform policy makers on robust decision-making for policies to mitigate an epidemic. It can be used to stress test fine grained policies in future iterations. Some such policies can include identifying specific types of establishments for shut down, or changing the times for shutting down establishments. Future iterations may also include incorporation of distributed activity schedules, as well as psychological components (e.g., fear) that influence how agents make decisions. In addition to that, the set of algorithms designed for creating the synthetic population is flexible enough to be adjusted for other cities of interest given the relatively low input data requirements. Thus, the model may be applied to other cities in the future.

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Annexes A: Healthcare Parameters

State	Related variable	Age	Range	Mean	Distribution	Source
Infected contagious early stage	Correction factor for transmissibility in state			0.75		(X. He at al., 2020)
	Probability of infection at less than 1m		0.09-0.38			(Chu et al., 2020)
	Percentage of people showing symptoms		40-50			(Nishiura et al., 2020), (Ferguson et al., 2020)
	Incubation period		2-14	5	Lognormal	(Linton et al., 2020)
Symptomatic Contagious middle stage	Correction factor for transmissibility in state			1		(X. He at al., 2020)
	Recovery period			24.7		(Verity et al., 2020)
	Duration before hospitalization		7-11			(van Wees et al., 2020)
Symptomatic Contagious late stage	Correction factor for transmissibility in state			0.25		(X. He at al., 2020)
Asymptomatic Contagious middle stage	Correction factor for transmissibility in state			1		
	Relative transmissibility			1.5		(D. He et al., 2020)
Asymptomatic Contagious late	Correction factor for transmissibility in state			0.25		(X. He at al., 2020)

stage						
	Relative transmissibility			1		
Hospitalized	Correction factor for transmissibility in state			0		
	Percentage of people being hospitalized	0-9		0.001		(Ferguson et al., 2020)
	Percentage of people being hospitalized	10-19		0.003		(Ferguson et al., 2020)
	Percentage of people being hospitalized	20-29		0.012		(Ferguson et al., 2020)
	Percentage of people being hospitalized	30-39		0.032		(Ferguson et al., 2020)
	Percentage of people being hospitalized	40-49		0.049		(Ferguson et al., 2020)
	Percentage of people being hospitalized	50-59		0.102		(Ferguson et al., 2020)
	Percentage of people being hospitalized	60-69		0.166		(Ferguson et al., 2020)
	Percentage of people being hospitalized	70-79		0.243		(Ferguson et al., 2020)
	Percentage of people being hospitalized	80+		0.273		(Ferguson et al., 2020)
	Infection Mortality Rate	0-9		0		(Ferguson et al., 2020)
	Infection Mortality Rate	10-19		0.0001		(Ferguson et al., 2020)
	Infection Mortality Rate	20-29		0.0003		(Ferguson et al., 2020)
	Infection Mortality Rate	30-39		0.0008		(Ferguson et al.,

						2020)
	Infection Mortality Rate	40-49		0.0015		(Ferguson et al., 2020)
	Infection Mortality Rate	50-59		0.006		(Ferguson et al., 2020)
	Infection Mortality Rate	60-69		0.022		(Ferguson et al., 2020)
	Infection Mortality Rate	70-79		0.051		(Ferguson et al., 2020)
	Infection Mortality Rate	80+		0.093		(Ferguson et al., 2020)
	Duration before recovery		12-14			(van Wees et al., 2020)
	Duration before death		1-4			(van Wees et al., 2020)
	Duration before ICU			3		(van Wees et al., 2020)
ICU	Correction factor for transmissibility in state			0		
	Probability of people who went to the ICU	0-9		0		(Ferguson et al., 2020)
	Probability of people who went to the ICU	10-19		0.0001		(Ferguson et al., 2020)
	Probability of people who went to the ICU	20-29		0.0003		(Ferguson et al., 2020)
	Probability of people who went to the ICU	30-39		0.0008		(Ferguson et al., 2020)
	Probability of people who went to the ICU	40-49		0.0015		(Ferguson et al., 2020)

	Probability of people who went to the ICU	50-59		0.006		(Ferguson et al., 2020)
	Probability of people who went to the ICU	60-69		0.022		(Ferguson et al., 2020)
	Probability of people who went to the ICU	70-79		0.051		(Ferguson et al., 2020)
	Probability of people who went to the ICU	80+		0.093		(Ferguson et al., 2020)
	Duration before recovery		28-32			(van Wees et al., 2020)
	Duration before death		3-7			(van Wees et al., 2020)

Table 16. Healthcare parameters input data.

Data for hospital beds and ICU capacity for The Hague and Helsinki was obtained from OECD (2012) and Trading Economics (2012).

Annexes B: Model verification and validation

Policies

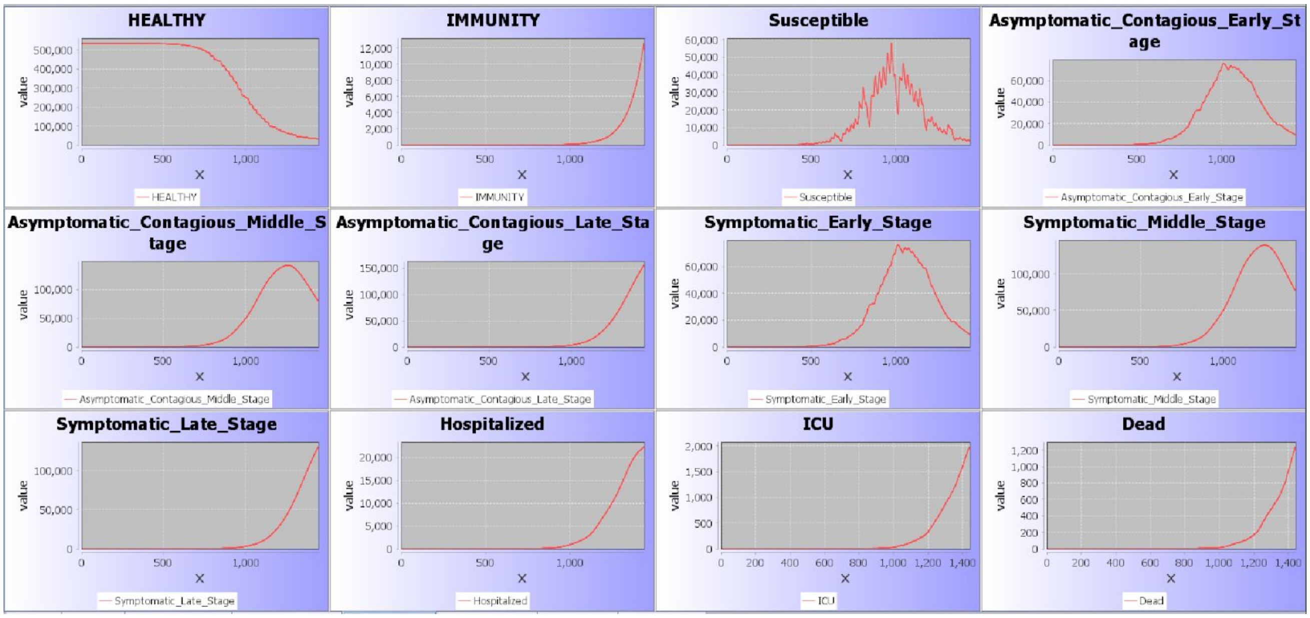

Figure 43. Disease spread under baseline

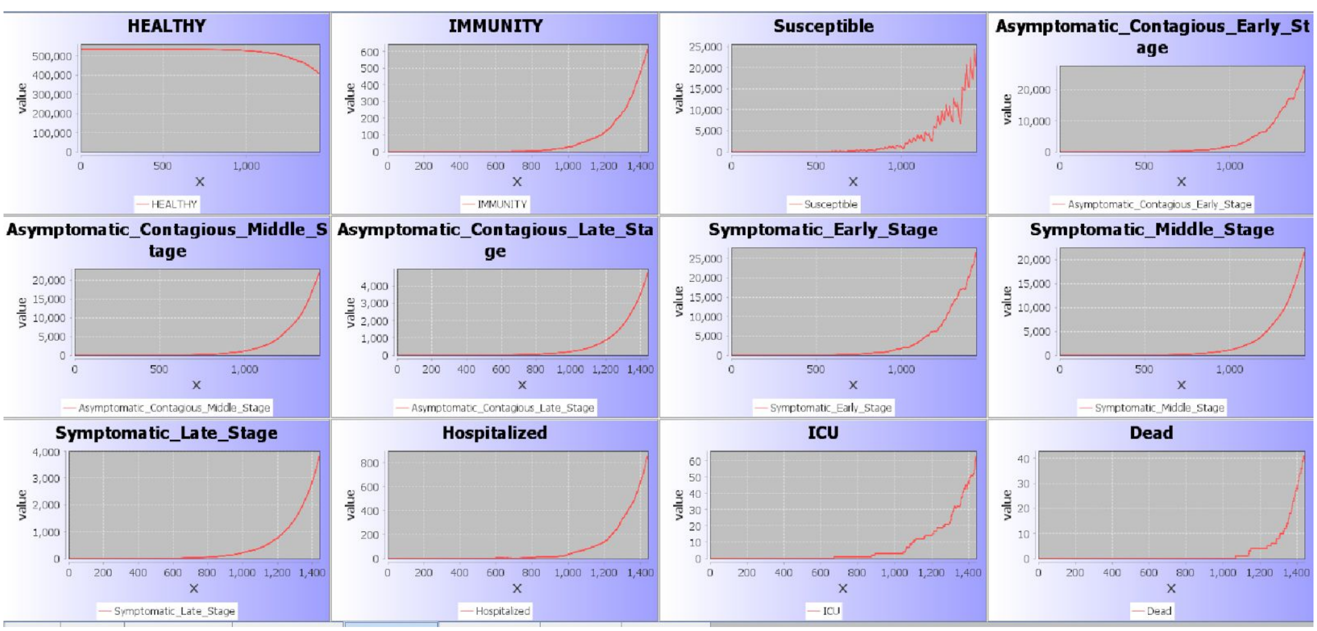

Figure 44. Disease spread under school shut down and social gathering ban policy

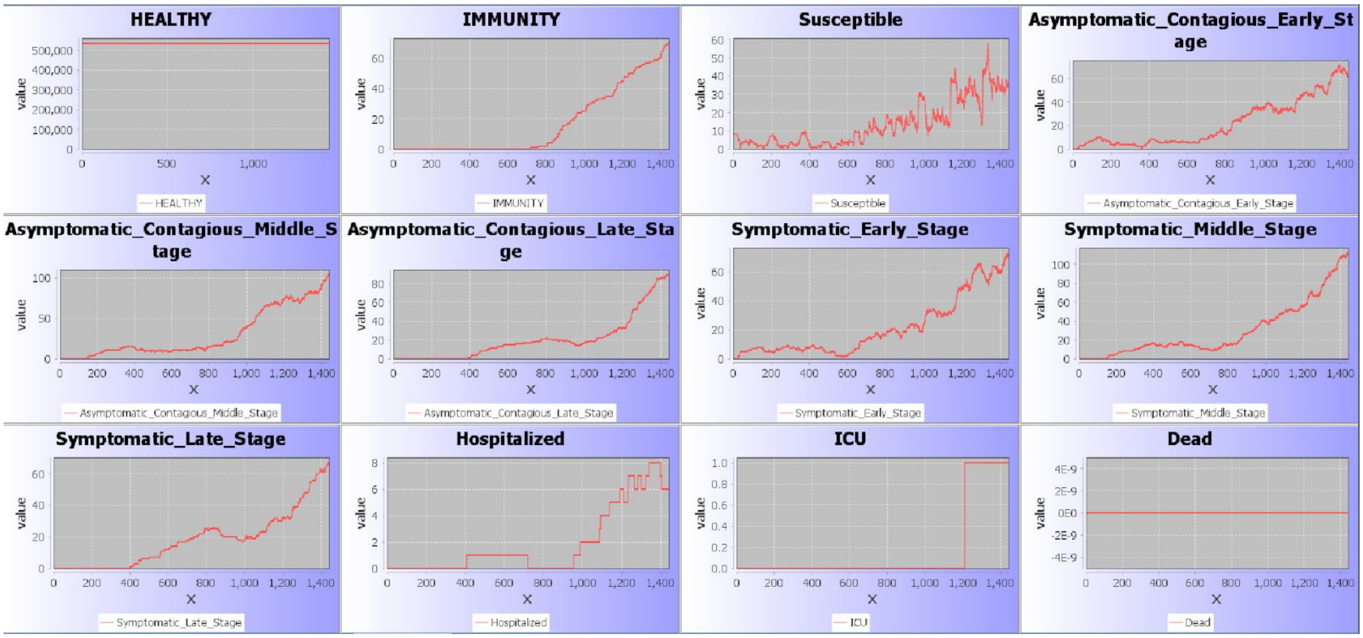

Figure 45. Disease spread under full lockdown

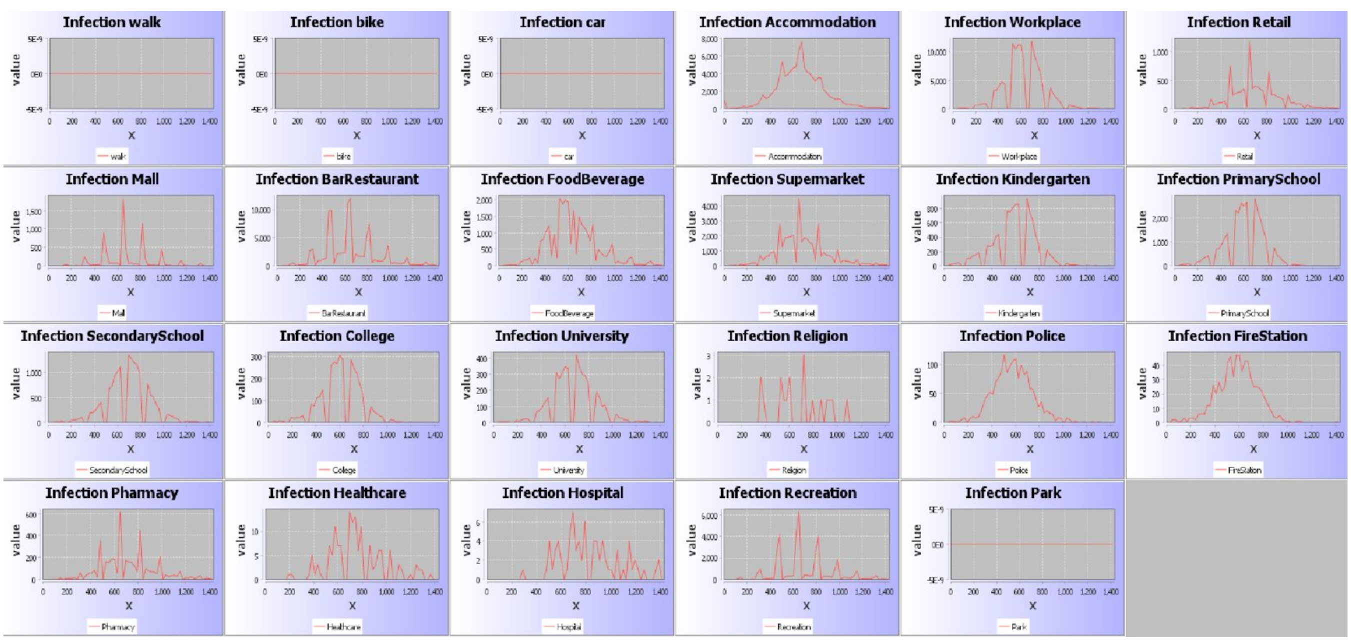

Figure 46. Disease spread in different location types under baseline

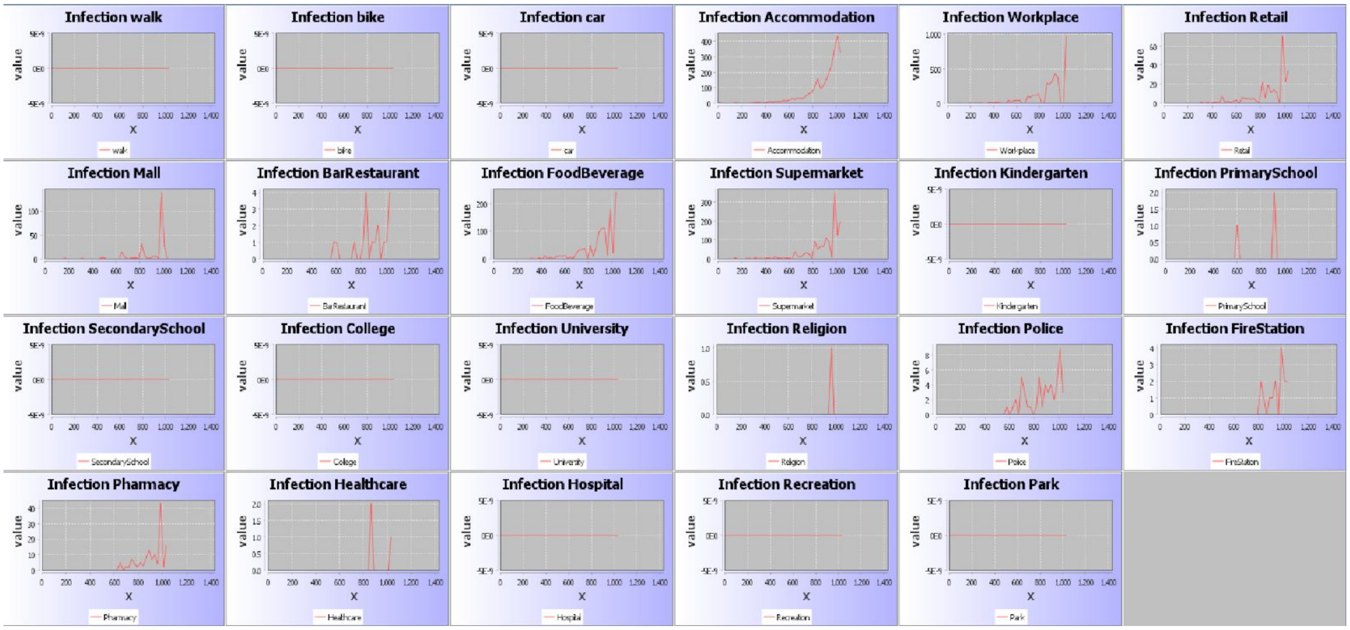

Figure 47. Disease spread in different location types under school shut down and social gathering ban policy

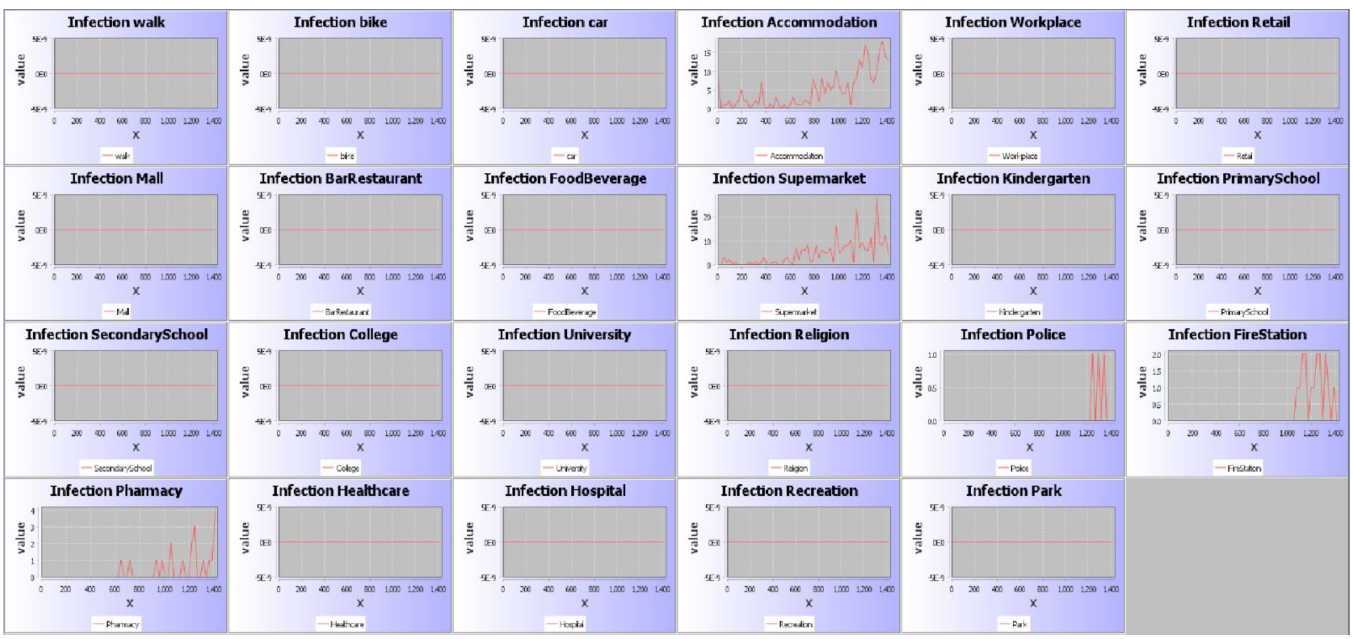

Figure 48. Disease spread in different location types under full lockdown

Minimal interaction test

Disease spread with no cross infections. It can be observed that there are no new infections

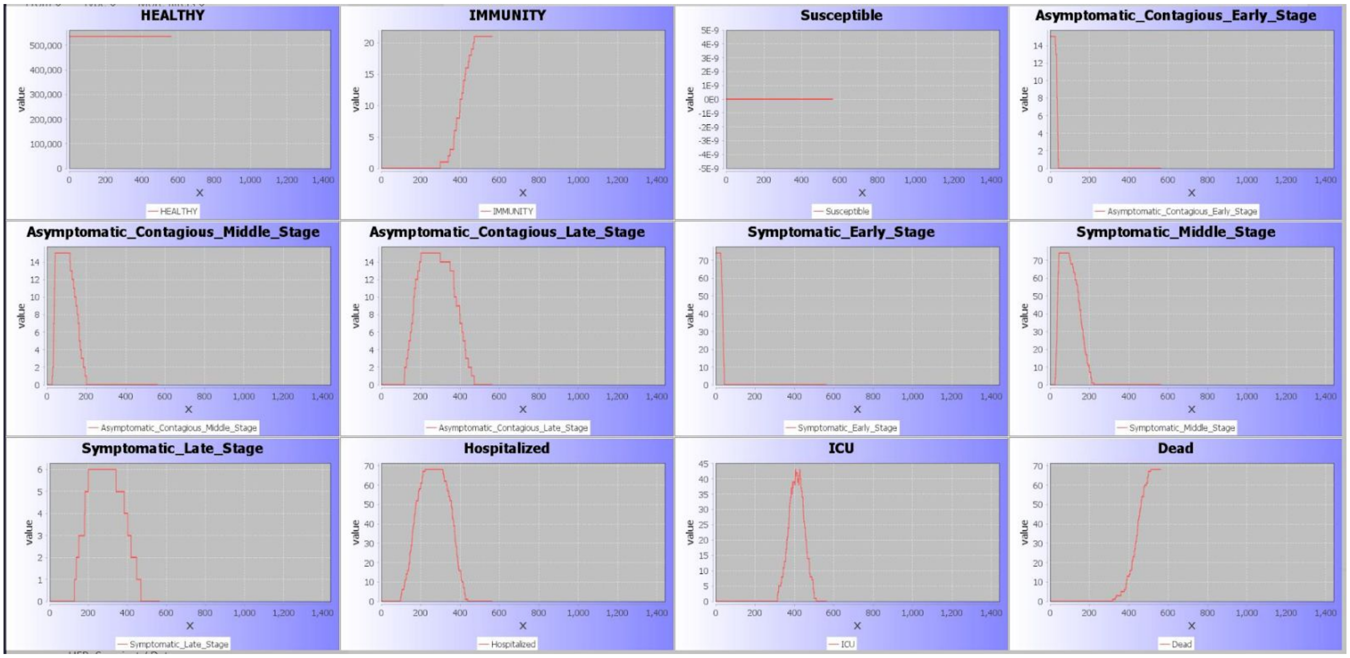

Figure 49. Disease spread when no cross infections are allowed to happen

Extreme values

1000 people infected in the beginning and all of them were modelled to be asymptomatic. This should include no deaths or hospitalizations. This can be seen in Figure 50.

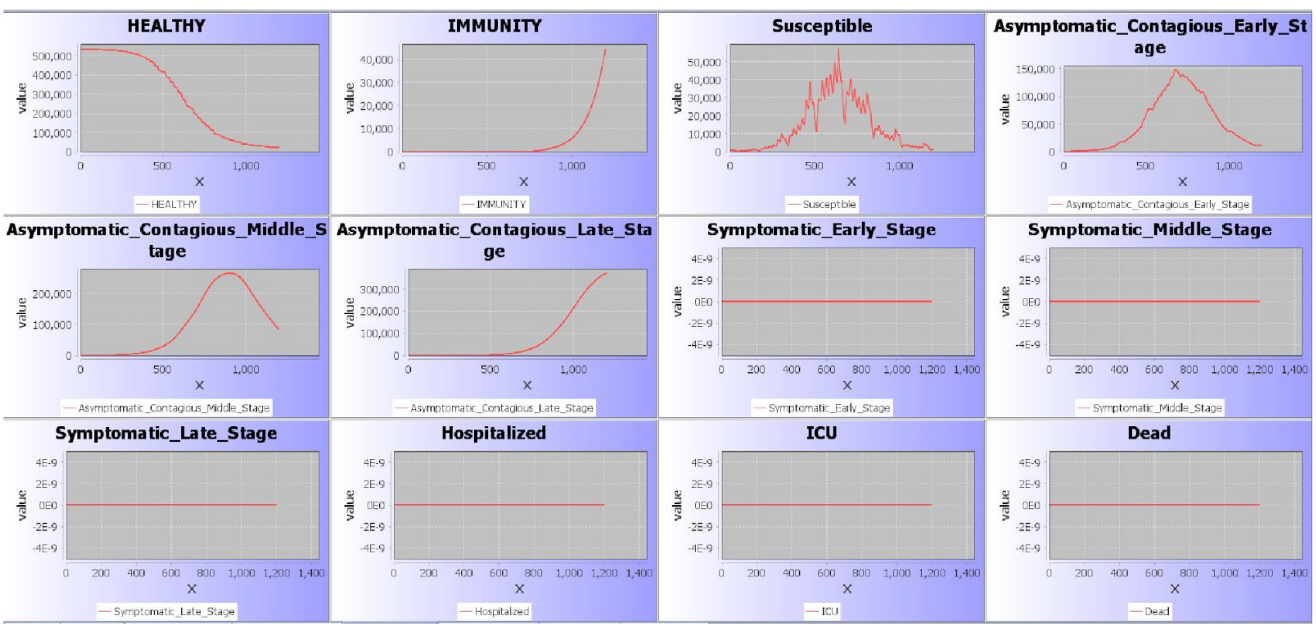

Figure 50. 1000 infected people with asymptomatic fraction set to 1

Mortality

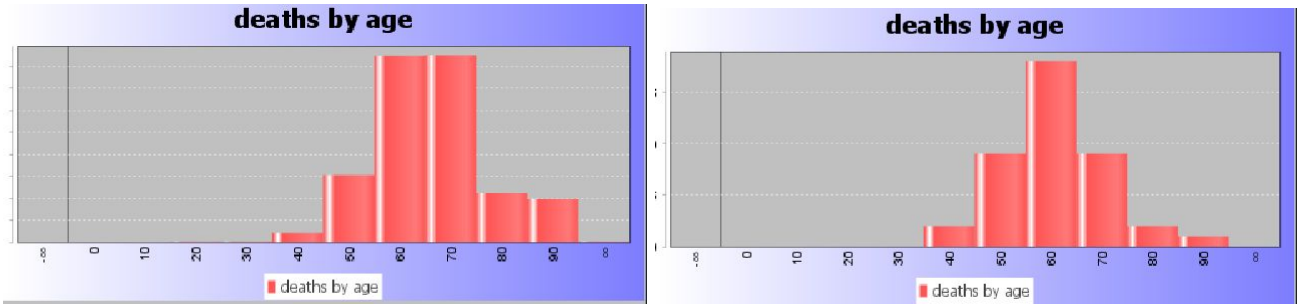

Figure 51. Death by age under baseline (left) and school shut down and social gathering ban policy (right)

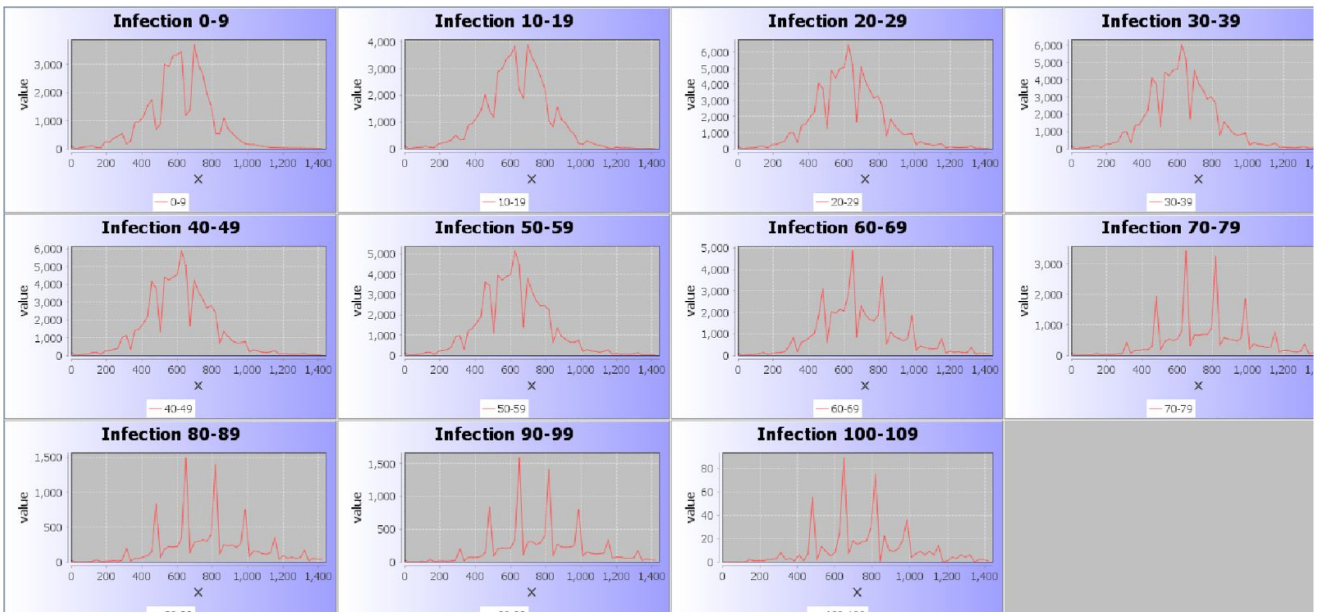

Figure 52. Number of infections by age group under baseline

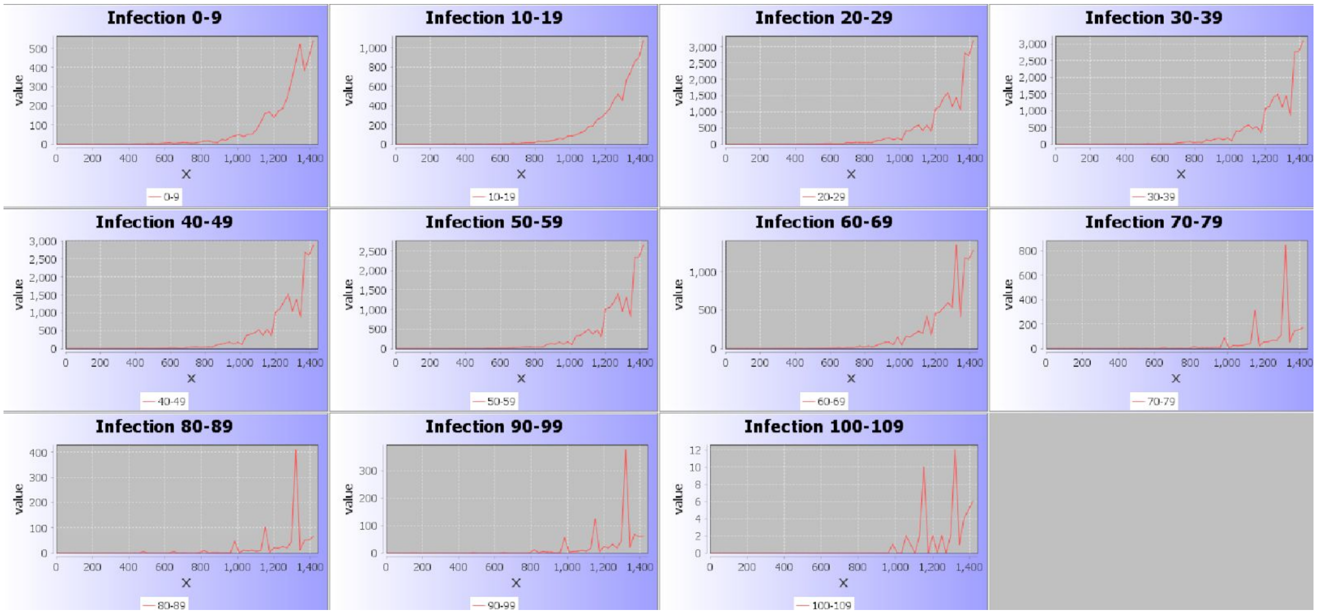

Figure 53. Number of infections by age group under school shut down and social gathering ban policy

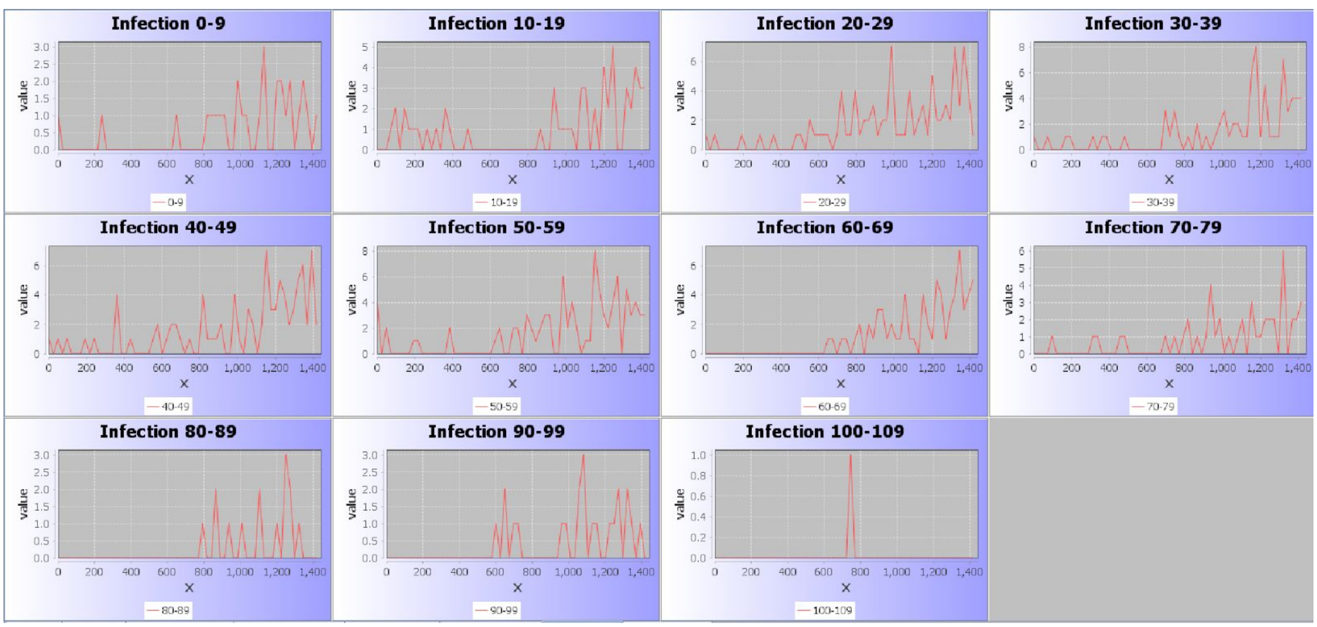

Figure 54. Number of infections by age group under full lockdown

Reproducibility

Model reproducibility check in different sublocations

name	reproducible
Accommodation	TRUE
Workplace	TRUE
Retail	FALSE
Mall	FALSE
BarRestaurant	FALSE
FoodBeverage	FALSE
Supermarket	FALSE
Kindergarten	TRUE
PrimarySchool	TRUE
SecondarySchool	TRUE
College	TRUE
University	TRUE
Religion	TRUE
Police	TRUE
FireStation	TRUE
Pharmacy	FALSE

Healthcare	FALSE
Hospital	FALSE
Recreation	FALSE
Park	FALSE

Table 17. Reproducibility of sublocation specification file

Annexes C: Experimental setup

The Hague

scenario	policy	Asymptomatic Fraction	Contagious Factor	Infection Probability	Number of infected initially	Policy Measure
0	0	0.364644	6.006326	0.264801	27	policies.DayStartPolicy1 = 1
1	0	0.327096	5.521259	0.2169	44	policies.DayStartPolicy1 = 1
2	0	0.489099	3.684091	0.3196	26	policies.DayStartPolicy1 = 1
3	0	0.370413	7.479176	0.1106	4	policies.DayStartPolicy1 = 1
4	0	0.206066	6.828339	0.315665	43	policies.DayStartPolicy1 = 1
5	0	0.493586	6.59411	0.223829	39	policies.DayStartPolicy1 = 1
6	0	0.235482	5.479447	0.131572	47	policies.DayStartPolicy1 = 1
7	0	0.356554	3.902634	0.166721	38	policies.DayStartPolicy1 = 1
8	0	0.336845	4.979038	0.095449	30	policies.DayStartPolicy1 = 1
9	0	0.383629	5.318538	0.363687	34	policies.DayStartPolicy1 = 1
0	1	0.364644	6.006326	0.264801	27	policies.DayStartPolicy1 = 7
1	1	0.327096	5.521259	0.2169	44	policies.DayStartPolicy1 = 7

2	1	0.489099	3.684091	0.3196	26	policies.DayStartPolicy1 = 7
3	1	0.370413	7.479176	0.1106	4	policies.DayStartPolicy1 = 7
4	1	0.206066	6.828339	0.315665	43	policies.DayStartPolicy1 = 7
5	1	0.493586	6.59411	0.223829	39	policies.DayStartPolicy1 = 7
6	1	0.235482	5.479447	0.131572	47	policies.DayStartPolicy1 = 7
7	1	0.356554	3.902634	0.166721	38	policies.DayStartPolicy1 = 7
8	1	0.336845	4.979038	0.095449	30	policies.DayStartPolicy1 = 7
9	1	0.383629	5.318538	0.363687	34	policies.DayStartPolicy1 = 7
0	2	0.364644	6.006326	0.264801	27	policies.DayStartPolicy1 = 15
1	2	0.327096	5.521259	0.2169	44	policies.DayStartPolicy1 = 15

2	2	0.489099	3.684091	0.3196	26	policies.DayStartPolicy1 = 15
3	2	0.370413	7.479176	0.1106	4	policies.DayStartPolicy1 = 15
4	2	0.206066	6.828339	0.315665	43	policies.DayStartPolicy1 = 15
5	2	0.493586	6.59411	0.223829	39	policies.DayStartPolicy1 = 15
6	2	0.235482	5.479447	0.131572	47	policies.DayStartPolicy1 = 15
7	2	0.356554	3.902634	0.166721	38	policies.DayStartPolicy1 = 15
8	2	0.336845	4.979038	0.095449	30	policies.DayStartPolicy1 = 15

9	2	0.383629	5.318538	0.363687	34	policies.DayStartPolicy1 = 15
0	3	0.364644	6.006326	0.264801	27	policies.DayStartPolicy2 = 1
1	3	0.327096	5.521259	0.2169	44	policies.DayStartPolicy2 = 1
2	3	0.489099	3.684091	0.3196	26	policies.DayStartPolicy2 = 1
3	3	0.370413	7.479176	0.1106	4	policies.DayStartPolicy2 = 1
4	3	0.206066	6.828339	0.315665	43	policies.DayStartPolicy2 = 1
5	3	0.493586	6.59411	0.223829	39	policies.DayStartPolicy2 = 1

6	3	0.235482	5.479447	0.131572	47	policies.DayStartPolicy2 = 1
7	3	0.356554	3.902634	0.166721	38	policies.DayStartPolicy2 = 1
8	3	0.336845	4.979038	0.095449	30	policies.DayStartPolicy2 = 1
9	3	0.383629	5.318538	0.363687	34	policies.DayStartPolicy2 = 1
0	4	0.364644	6.006326	0.264801	27	policies.DayStartPolicy2 = 7
1	4	0.327096	5.521259	0.2169	44	policies.DayStartPolicy2 = 7
2	4	0.489099	3.684091	0.3196	26	policies.DayStartPolicy2 = 7

3	4	0.370413	7.479176	0.1106	4	policies.DayStartPolicy2 = 7
4	4	0.206066	6.828339	0.315665	43	policies.DayStartPolicy2 = 7
5	4	0.493586	6.59411	0.223829	39	policies.DayStartPolicy2 = 7
6	4	0.235482	5.479447	0.131572	47	policies.DayStartPolicy2 = 7
7	4	0.356554	3.902634	0.166721	38	policies.DayStartPolicy2 = 7
8	4	0.336845	4.979038	0.095449	30	policies.DayStartPolicy2 = 7
9	4	0.383629	5.318538	0.363687	34	policies.DayStartPolicy2 = 7

0	5	0.364644	6.006326	0.264801	27	policies.DayStartPolicy2 = 15
1	5	0.327096	5.521259	0.2169	44	policies.DayStartPolicy2 = 15
2	5	0.489099	3.684091	0.3196	26	policies.DayStartPolicy2 = 15
3	5	0.370413	7.479176	0.1106	4	policies.DayStartPolicy2 = 15
4	5	0.206066	6.828339	0.315665	43	policies.DayStartPolicy2 = 15
5	5	0.493586	6.59411	0.223829	39	policies.DayStartPolicy2 = 15
6	5	0.235482	5.479447	0.131572	47	policies.DayStartPolicy2 = 15

7	5	0.356554	3.902634	0.166721	38	policies.DayStartPolicy2 = 15
8	5	0.336845	4.979038	0.095449	30	policies.DayStartPolicy2 = 15
9	5	0.383629	5.318538	0.363687	34	policies.DayStartPolicy2 = 15
0	6	0.364644	6.006326	0.264801	27	Baseline
1	6	0.327096	5.521259	0.2169	44	Baseline
2	6	0.489099	3.684091	0.3196	26	Baseline
3	6	0.370413	7.479176	0.1106	4	Baseline

4	6	0.206066	6.828339	0.315665	43	Baseline
5	6	0.493586	6.59411	0.223829	39	Baseline
6	6	0.235482	5.479447	0.131572	47	Baseline
7	6	0.356554	3.902634	0.166721	38	Baseline
8	6	0.336845	4.979038	0.095449	30	Baseline
9	6	0.383629	5.318538	0.363687	34	Baseline

Table 18. Experimental setup The Hague.

Helsinki

scenario	policy	AsymptomaticFraction	ContagiousFactor	InfectionProbability	Number of initially infected	PolicyMeasure
0	0	0.364644	2	0.264801	50	policies.DayStartPolicy1 = 1
1	0	0.454176	5	0.277309	5	policies.DayStartPolicy1 = 1
2	0	0.28926	2	0.369462	30	policies.DayStartPolicy1 = 1
3	0	0.3433	2	0.203908	15	policies.DayStartPolicy1 = 1
4	0	0.221311	3	0.27797	5	policies.DayStartPolicy1 = 1
5	0	0.449786	2	0.373799	5	policies.DayStartPolicy1 = 1

6	0	0.440273	5	0.286875	50	policies.DayStartPolicy1 = 1
7	0	0.391976	3	0.245838	5	policies.DayStartPolicy1 = 1
8	0	0.356554	6	0.227344	30	policies.DayStartPolicy1 = 1
9	0	0.43227	6	0.254846	5	policies.DayStartPolicy1 = 1
0	1	0.364644	2	0.264801	50	policies.DayStartPolicy1 = 7
1	1	0.454176	5	0.277309	5	policies.DayStartPolicy1 = 7
2	1	0.28926	2	0.369462	30	policies.DayStartPolicy1 = 7

3	1	0.3433	2	0.203908	15	policies.DayStartPolicy1 = 7
4	1	0.221311	3	0.27797	5	policies.DayStartPolicy1 = 7
5	1	0.449786	2	0.373799	5	policies.DayStartPolicy1 = 7
6	1	0.440273	5	0.286875	50	policies.DayStartPolicy1 = 7
7	1	0.391976	3	0.245838	5	policies.DayStartPolicy1 = 7
8	1	0.356554	6	0.227344	30	policies.DayStartPolicy1 = 7
9	1	0.43227	6	0.254846	5	policies.DayStartPolicy1 = 7

0	2	0.364644	2	0.264801	50	policies.DayStartPolicy1 = 15
1	2	0.454176	5	0.277309	5	policies.DayStartPolicy1 = 15
2	2	0.28926	2	0.369462	30	policies.DayStartPolicy1 = 15
3	2	0.3433	2	0.203908	15	policies.DayStartPolicy1 = 15
4	2	0.221311	3	0.27797	5	policies.DayStartPolicy1 = 15
5	2	0.449786	2	0.373799	5	policies.DayStartPolicy1 = 15
6	2	0.440273	5	0.286875	50	policies.DayStartPolicy1 = 15

7	2	0.391976	3	0.245838	5	policies.DayStartPolicy1 = 15
8	2	0.356554	6	0.227344	30	policies.DayStartPolicy1 = 15
9	2	0.43227	6	0.254846	5	policies.DayStartPolicy1 = 15
0	3	0.364644	2	0.264801	50	policies.DayStartPolicy2 = 1
1	3	0.454176	5	0.277309	5	policies.DayStartPolicy2 = 1
2	3	0.28926	2	0.369462	30	policies.DayStartPolicy2 = 1
3	3	0.3433	2	0.203908	15	policies.DayStartPolicy2 = 1

4	3	0.221311	3	0.27797	5	policies.DayStartPolicy2 = 1
5	3	0.449786	2	0.373799	5	policies.DayStartPolicy2 = 1
6	3	0.440273	5	0.286875	50	policies.DayStartPolicy2 = 1
7	3	0.391976	3	0.245838	5	policies.DayStartPolicy2 = 1
8	3	0.356554	6	0.227344	30	policies.DayStartPolicy2 = 1
9	3	0.43227	6	0.254846	5	policies.DayStartPolicy2 = 1
0	4	0.364644	2	0.264801	50	policies.DayStartPolicy2 = 7

1	4	0.454176	5	0.277309	5	policies.DayStartPolicy2 = 7
2	4	0.28926	2	0.369462	30	policies.DayStartPolicy2 = 7
3	4	0.3433	2	0.203908	15	policies.DayStartPolicy2 = 7
4	4	0.221311	3	0.27797	5	policies.DayStartPolicy2 = 7
5	4	0.449786	2	0.373799	5	policies.DayStartPolicy2 = 7
6	4	0.440273	5	0.286875	50	policies.DayStartPolicy2 = 7
7	4	0.391976	3	0.245838	5	policies.DayStartPolicy2 = 7

8	4	0.356554	6	0.227344	30	policies.DayStartPolicy2 = 7
9	4	0.43227	6	0.254846	5	policies.DayStartPolicy2 = 7
0	5	0.364644	2	0.264801	50	policies.DayStartPolicy2 = 15
1	5	0.454176	5	0.277309	5	policies.DayStartPolicy2 = 15
2	5	0.28926	2	0.369462	30	policies.DayStartPolicy2 = 15
3	5	0.3433	2	0.203908	15	policies.DayStartPolicy2 = 15
4	5	0.221311	3	0.27797	5	policies.DayStartPolicy2 = 15

5	5	0.449786	2	0.373799	5	policies.DayStartPolicy2 = 15
6	5	0.440273	5	0.286875	50	policies.DayStartPolicy2 = 15
7	5	0.391976	3	0.245838	5	policies.DayStartPolicy2 = 15
8	5	0.356554	6	0.227344	30	policies.DayStartPolicy2 = 15
9	5	0.43227	6	0.254846	5	policies.DayStartPolicy2 = 15
0	6	0.364644	2	0.264801	50	Baseline
1	6	0.454176	5	0.277309	5	Baseline

2	6	0.28926	2	0.369462	30	Baseline
3	6	0.3433	2	0.203908	15	Baseline
4	6	0.221311	3	0.27797	5	Baseline
5	6	0.449786	2	0.373799	5	Baseline
6	6	0.440273	5	0.286875	50	Baseline
7	6	0.391976	3	0.245838	5	Baseline
8	6	0.356554	6	0.227344	30	Baseline

9	6	0.43227	6	0.254846	5	Baseline

Table 19. Experimental setup for Helsinki.