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AGENT-BASED MODEL FOR LARGE (URBAN) SCALE SIMULATION OF PANDEMIC SPREAD

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Abstract

The ongoing worldwide COVID-19 pandemic has changed the world significantly since its outbreak in January 2020. Most governments across the world imposed different containment measures to minimize the spread of the virus.
Moreover, public health experts and administrations highlighted the importance of planning these intervention strategies because they have heavy economic and social consequences.
Agent-based simulations can be useful tools to evaluate the impact of the epidemic under different containment policies.
This thesis project focuses on the development of a urban scale agent-based model parameterized for the city of Turin. Unity DOTS (Data Oriented Technology Stack) has been used to simulate the behaviour of a large number of agents, which move across a 2D tile-map environment following a BDI (Belief, Desire, Intention) routine model.
Different intervention policies have been implemented, both non-pharmaceutical and pharmaceutical, to evaluate various scenarios that trying to keep a low infection rate, such as partial or total lockdown and vaccination policy.

To my family, without whom I would never have made it.
To my girlfriend, who has always supported me in difficult times.
To friends of all time, who have always believed in me.
To everyone who has collaborated in this work.

Contents

Chapter 1

Introduction

Covid-19 is a respiratory disease, caused by the SARS-COV2 virus, which broke out in Wuhan, China at the end of 2019.
Due to highly transmissible nature of SARS-CoV-2 virus, it spreads rapidly to almost every country of the world. Till March 2022, the disease affected more than 400 millions of people and over 6 millions of deaths. Since 11 March 2020, the World Health Organization (WHO) declared it a pandemic.
Covid-19 has directly changed human life under different aspects, such as social relationships, education and economy.
In the initial absence of drugs or vaccines, health systems struggled with an unknown adversary and proved unprepared for such a battle. So, the Covid-19 pandemic has become one of the most important challenges for humanity to overcome at the moment.
Moreover, since the initial months, scientists, doctor and researchers start to analyze the virus in order to trying to understand in deep its structure, and therefore create treatments and vaccines.
At the same time, national, regional and local governments across the world have resorted to non-pharmaceutical interventions (NPIs), such as orders to keep "physical distance" in public spaces (especially closed ones), obligation to wear face-masks, and above all partial or total closure of public spaces like schools, offices, restaurants, gyms and discos, and so on. While such measures may be useful to contain the spread of the disease, they cannot be applied for long due to their harmful effects on society and economy. Thus, governments and policymakers have to make a trade-off between public health and economics while implementing policies on NPIs.
Historically, measures assessment is a significant help for policymakers and public health experts and can be achieved using simulation models of the dynamics of the pandemic, which give the possibility to predict its epidemiological evolution, resulting in valuable tools. Models for examining COVID-19 transmission and control measures can be divided into two main types: *equation-based models (EBMs)* or *agent-based models (ABMs).* The former relies mainly on mathematical solutions, and usually operates at very course scales by considering gross statistics, but cannot take into account spatial aspects of the virus spreading process. The latter, instead gives the possibility to approximate reality as closely as possible, simulating the daily lifestyles and social contacts of individuals and

the associated spatial structures. So, an agent-based model can be used to populate real city scenarios with reasonable population number, observing the resultant impacts under the influence of the pandemic and the NPIs.
During the Covid-19 pandemic, several research groups all over the world have been developing agent-based models for larger regions or specific cities. These models have different levels of detail based on characteristics of agents and geographical region of interest, and may include any subset of features such as demographic factors, family patterns, spatial layout, residential areas and public spaces, daily schedule of people and so on.
This thesis presents a multi-layer agent-based model for simulating the pandemic in cities. One layer is the urban environment, which allows the user to directly visualize the spread of the virus in a map environment in real time, giving the possibility to evaluate the areas of the city of greatest contagion. This is possible because the implementation of the model relies on the popular game engine Unity 3D. In particular Unity DOTS (Data Oriented Technology Stack), which enhances code performance, has been used to simulate the behaviour of a large number of agents, which move across a 2D tile-map environment following a BDI (Belief, Desire, Intention) routine model. The second layer is made up by the ABM, so agents and their behaviour. Agents are characterised by different factors, such as age and the social responsibility, i.e. a measure of how well an individual complies with the imposed policies.
Each entity replicates the human behaviour, characterized by some primary basic needs such as going to work, at home to rest, to the grocery store to buy food but also social needs like need for a run in a park or visiting friends.
Transmission of the virus among individuals is inspired by famous contact tracing apps and its dynamics follows the SEIRS (Susceptible - Exposed - Infected - Recovered - Susceptible) model, where each agent passes from a status to another once infection occurs. The intention is to show how a potential viral infection can spread among the population of entities according both to configurable viral parameters, different entities behaviour and current policy application.
In fact, different interventions, both pharmaceutical and not, such as vaccines, total or partial lockdown, have been implemented to analyse different scenarios.
The model was parameterized for the city of Turin and was used to conduct different experiments under different conditions. In detail, the comparisons show the importance of vaccines to reduce the spread of the pandemic and save thousands of lives.

The thesis content is structured as follows:
Chapter 2 presents a literature review of some related works that already have been done concerning control of epidemiological dynamics of Covid-19 and also other disease.
Chapter 3 contains a short historic background of past pandemics and how they were faced by humanity until the ongoing one of Covid-19.
Chapter 4 describes in details the model design, going to deepen the implementation of the various modules that compose it.
Chapter 5 shows the conducted experiments through the model, analysing the different results.
Chapther 6 concludes and advices future developments on the model.

Chapter 2

Literature Review

In this section, the relevant literature on agent-based epidemic models is presented together with the main applications to cities' modelling and pandemic spreading. Moreover, recent models' developments and their adaptation to the Covid-19 pandemic evolution are described.
Most of the models that aim at quantifying the effectiveness of different public health intervention strategies for critical diseases can be classified into two main categories: *equation-based models (EBMs)* or *agent-based models (ABMs)*, with the former generally being simpler and faster in terms of model's resolution, while the latter are generally more complex, detailed, and computationally expensive.

Epidemic equation-based spread models (EBMs)

Epidemiology models represent epidemics of communicable disease using a population-based, non-spatial *top-down* approach. Traditionally, epidemic dynamics have been studied with differential equation-based sets of distinct compartments. These so-called compartmental models divide the population into compartments that represent the different stages of a disease. The most general approach is the SIR model[1], which was described by Kermack [21], considering three compartments: susceptible (S), infected (I), and recovered (R). This model typifies the disease progression as follows:

- S represents the individuals of the population that may be infected for the first time;
- I represents the individuals of the population that are currently infected or infectious;
- R represents the individuals of the population that have recovered from the disease and no longer take an active part in the disease spread.

[1]Susceptible-infected-removed models are generalized behavioural models that are applied both for EBMs and ABMs.

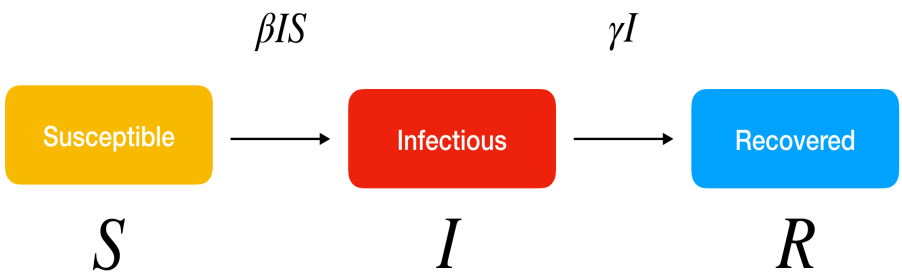


Figure 2.1: Transfer diagram for the basic SIR model

Compartmental SIR-models are composed by a set of nonlinear ordinary differential equations (ODEs) that associate a transition rate to the switch of agents between compartments.

$$\begin{aligned}\frac{dS}{dt} &= -\beta IS \\ \frac{dI}{dt} &= \beta IS - \gamma I \\ \frac{dR}{dt} &= \gamma I\end{aligned} \tag{2.1}$$

where:

- β is an average number representing sufficient contact to get infected
- γ is the transfer rate from the infectious state to the recovered one

The ratio between these two values is called **reproduction number** and represents the number of secondary infections in the total population caused by the initial infection.

$$R_0 = \frac{\beta}{\gamma} \tag{2.2}$$

Moreover, the population is given by:

$$S(t) + I(t) + R(t) = N \tag{2.3}$$

The advantage of these models is that they are easily extendable, have a small number of parameters and can be solved numerically or even have analytical solutions [38].
Based on this general model, different variations of the disease-spreading model can be derived, such as the Susceptible-Exposed-Infected-Recovered (SEIR) model. The latter adds an intermediate stage E that represents a latent state in which individuals have been exposed to the disease but are not yet infective [13].
Within these models, different parameters ,such as transmission rate or contact rate, can be manipulated to simulate the effectiveness of different control strategies [24][36].
Moreover, adding parameters that reflect the implementation of epidemic intervention strategies increases the complexity of an equation-based model without necessarily reaching an higher level of validity and accuracy that may enhance the decision making process

[37].
Numerous compartmental models have been developed or re-adapted for the COVID-19 pandemic. Walker et al. [48] used an age-structured stochastic "SEIR" model to determine the global impact of COVID-19 and the effects of various social distancing interventions. Read et al.[34] developed a SEIR model to estimate the basic reproduction number of cases in Wuhan. Keeling et al.[20] developed a model that looks at the efficacy of contact tracing as containment measure. Finally, Dehning et al.[8] built a SIR model to quantify the impact of intervention measures in Germany. In models such as those by Giordano et al.[15] and Zhao and Chen[50], population's compartments present deeper granularity in order to provide more accuracy in simulating the disease progression through different states, and have been deployed to study the effects of various population-wide interventions - i.e. social distancing - and to test the COVID-19 transmission.
However, such models are based on pandemic's statistics(I.E. ...), and do not take into account a realistic and dynamic representation of how the infection may spread between individuals depending on their locations, interactions and personal behaviour. These elements have, in the context of an infectious disease, a fundamental role in influencing the epidemic dynamics [39].

Agent-based simulation models

In contrast with EBMs, agent-based models (ABMs) apply a "bottom-up" structure. This technique was used in the field of computational social science [10], economics [43], ecology [16], etc. ABMs' ability to model urban systems was used by David O'Sullivan et al.[27] to capture the interactions between different stakeholders and urban components. In fact, more recent urban ABMs focus on specific aspects of cities in greater details. For instance, MATSIM [3] and UrbanSim [31] are ABM-based software packages that simulate city-specific long-term trends related to traffic management, electricity or water usage and gas emissions. The results are used in multi-dimensional policy planning, such as the work by [47] on developing models to support land use and transportation planning and growth management; or the work by [41] to analyse the impact of electric vehicles on Croatia's energy system.
Furthermore, given the increasing performance of computer's computational capacity, agent-based simulation has become a practical method to study epidemics [7]. Therefore, modern epidemiology research is turning towards ABMs, as they focus on the disease progression dynamics by tracking individual's behaviours and contacts within the relevant social networks and geographical areas. [32].
Many agent-based models were proposed to simulate epidemic outbreaks.
Eubank et al. [11] developed a simulation tool called EpiSims. This is an agent-based simulation tool that combines realistic estimates on population mobility - based on census and land-use data - with parametric models in order to simulate the progress of a disease within a host and the transmission between hosts.
Perez-Dragicevic [32] developed a multi-agent model that simulates the spread of a com-

municable disease in an urban environment using measles outbreak as a case study. The model follows the SEIR approach and makes use of census data of Canada.
The work of Rodrigues et al. [4] studies the spread and control of tuberculosis in the city of Rio de Janeiro (Brazil) using an agent-based and SEIR disease dynamic model. They conclude that the models are very helpful to identify the positive impact of the control measures in the interruption of disease spread.
The model presented by Hackl and Dubernet [17] is used to study seasonal influenza outbreaks in the metropolitan area of Zurich (Switzerland) where different activities take place during a daily citizens' routine. Despite of the simplicity of the implemented epidemic spread model, which only account for susceptible, infected, and recovered individuals, the results show how this simulation can help raise awareness on the disease spread dynamics and improve the decision-making process in the context of prevention and control of an epidemic.
During the COVID-19 pandemic, agent-based models have acquired special attention worldwide, as policymakers are interested to assess the impacts of various non-pharmaceutical interventions (NPIs) such as lock-downs and social distancing. Many ABMs have been developed to study this type of countermeasures in United Kingdom[12], Australia [35], Singapore [22] and Rio de Janeiro (in slums context) [46]. An well-performing model was built for the city of Kolkata (India) [14] where different NPIs were implemented (i.e. lockdown (long and short), contact tracing, public transport usage, physical distancing and compliance rates). However, this model does not include vaccination campaigns and economic impact of the pandemic.
Nevertheless, all the works related to epidemic spreading leverage on a general computer software [47] [41] without exploiting the power of a game engine, except for the study conducted by the University of California (San Diego) [49] which implemented its infectious model on "Unity 3D". Thanks to the latter, users can visually monitor a simulated community epidemic situation as it unfolds, make decisions about what strategies to choose and observe simulated outcomes.

The last mentioned work differs from this thesis project because it exploits Unity's DOTS (Data Oriented Technology Stack) and ECS (Entity Component System) that allow for the development of optimized real-time simulations with numbers of agents in the order of the hundreds of thousands. Furthermore, new implementations are developed such as: vaccination policy, conditional lockdown, population breakdown by age and family groups.

Chapter 3

Background

The coronavirus (COVID-19) pandemic is often outlined as an "unprecedented" event. However, from a scientific and historical perspective, the novel coronavirus disease was entirely predictable [25].
Throughout history, communicable diseases have impacted humanity, however these illnesses became more dangerous when human society switched to agrarian life around 10,000 years ago. The birth of closely connected communities has given infectious diseases the chance to turn into epidemics. Illnesses such as tuberculosis, leprosy, smallpox, malaria, and influenza were among those who prospered after this social change.

The first recorded infectious disease occurred during the Peloponnesian War in Greece in 430 B.C.
Subsequently, the "Antonine Plague" has appeared in 163 A.D. and is now deemed to be an first version of smallpox.
Then, in 541 A.D., the "Justinian Plague" spread across Egypt.
During the 11th century, leprosy destroyed Europe and it was followed by the notorious "Black Death" of the 14th century.
In the more recent history, when the world moved into the 20th century, influenza pandemics began their process, such as the "Russian flu" in 1890 and "Spanish flu" in 1918 with more the 50 millions of deaths.
The "human immunodeficiency virus" (HIV) was first identified in 1981. The spread of "acquired immunodeficiency syndrome" (AIDS) is still considered to be a pandemic, due to the fact that more than 32 million humans' lives have been lost.
The most recent pandemics have been the 2002-2004 "SARS" (severe acute respiratory syndrome) and the current COVID-19 pandemic, both caused by coronaviruses.
Despite some strategies implemented against the SARS were used to control the Zika, the Ebola and the H1N1 outbreaks, the world remains unprepared for the COVID-19 disease. In fact, it was definitely declared a global pandemic by the World Health Organization (WHO) on March 11, 2020 [9].

COVID-19 is an ongoing global pandemic caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2).
SARS was relatively less dangerous as it infected ten thousands people with a fatality rate of 11% compared to 24% of the COVID-19. Both syndromes share similar symptoms such as fever, headaches, and respiratory problems like dry cough.
Coronaviruses are a family of viruses that commonly attack birds and mammals, but over time evolved to infect humans too. This peculiar name derives from the particular aspect that the virus presents,indeed spiky and short protrusions cover the surface of the virus. Therefore, the outer surface recalls the shape of a crown (translated to *corona* in Latin). In general, coronaviruses are spread by respiratory droplets caused by infected individuals sneezing, breathing and coughing. This type of viruses can be diagnosed by performing analysis on respiratory or blood samples. As with colds, there are no treatments that can completely cure the "special" flu. Therefore, people usually recover on their own or with home-based care, except for individuals with serious respiratory problems who need to go to intensive care. Vaccines give protection and reduce the spread of these diseases. For Covid-19, the first vaccines started to be administered in December 2020 and will continue throughout 2021 and 2022.

In the absence of effective treatment or vaccines for COVID-19, non-pharmacological interventions (NPIs) become the main response to control the pandemic.
The first encounter with the virus took place in December 2019 in Wuhan, China. Since then, specialist started to develop models to study and analyze the dynamics and progression of the virus and the spread-prevention strategies.
NPIs are recommended by the World Health Organization (WHO) to be used during pandemics at any level of severity. They include: personal protective measures (i.e. hand hygiene and face masks); environmental measures (i.e. ventilation and disinfection); social distancing measures (i.e. workplace and school closures or general lockdown); and travel restrictions measures.
Italy was the first country to be severely hit by the virus SARS-Cov2 in Europe. A briefly description of the first containment measures adopted, is reported in the figure below.

Date	*Public health measure implemented*	*Place*	*Authority*
25/01	**Health checkpoints for passengers** coming from China or from areas where one sustained autochthonous transmission of the new Coronavirus has occurred.	Airports, Italy	Ministry of Health
30/01	**Air traffic from China is banned**	Airports, Italy	Government
21/02	**Mandatory supervised quarantine for 14 days** for all individuals who have come into close contact with confirmed cases of disease; **Mandatory communication** to the Health Department from anyone who has entered Italy from high-risk of COVID-19 areas, followed by **quarantine and active surveillance.**	Public Health department in identified areas	Ministry of Health
23/02	**Red zones:** adoption of an adequate and proportionate containment and management measures in areas with >1 person positive to COVID-19 with unknown source of transmission.	11 municipalities in Lombardy Region	Government
23/02	**Suspension of all public events** or open to the public, of any nature; Schools (all levels), public places, gyms, and other places of aggregation	5 Regions in Northern Italy	Ministry of Health
02/03	**Proposal to extend the "red zone"** to three additional municipalities in the provinces of Bergamo and Brescia from local authorities	Three municipalities in Lombardy Region	(not adopted)
08/03	**The "national" Red Zone:** avoid any movement of people except for motivated by proven work needs or situations of necessity (health, food and assistance); public and private employers should encourage to use days of ordinary leave and holidays and smart working; closing of ski facilities; limit travel and activities and sanitization measures and reduce close contacts	Lombardy Region (and other affected areas in 5 additional regions)	Government
11/03	Suspension of all business activities; **Suspension of all commercial activities non-indispensable for production.** Maximum use by companies of smart-working methods for activities that can be performed at home or remotely. Sanitation of workplace areas.	Italy	Government
23/03	**Extension of the ban on non-indispensable activities.** A list of 80 authorized activities is published. The ban extends limitations on individual freedom and on other business activities that were not explicitly closed by the previous measures.	Italy	Government

Figure 3.1: First containment measures in Italy. Source: Timelli [23]

The results of an Italian study (Timelli [23]) on the impact of the NPIs on epidemic dynamics show the effectiveness of these strategies.
For each Italian region, two main measures were computed:

- Cumulative incidence (CI). CI represents the number of cumulative cases of COVID-19 per 100,000 inhabitants within each specific date;

- Number of days between the date on which each region reached the lowest regional CI and the date of national lockdown declaration. This measure captures the delay of this specific NPI.

As shown in Fig 3.2, the incidence of cases was rapidly increasing in all regions. It started with a linear trend until the National lockdown and then flattened in all regions after 21 days, on average, after the lockdown, highlighting a marginal decreasing incidence over time.

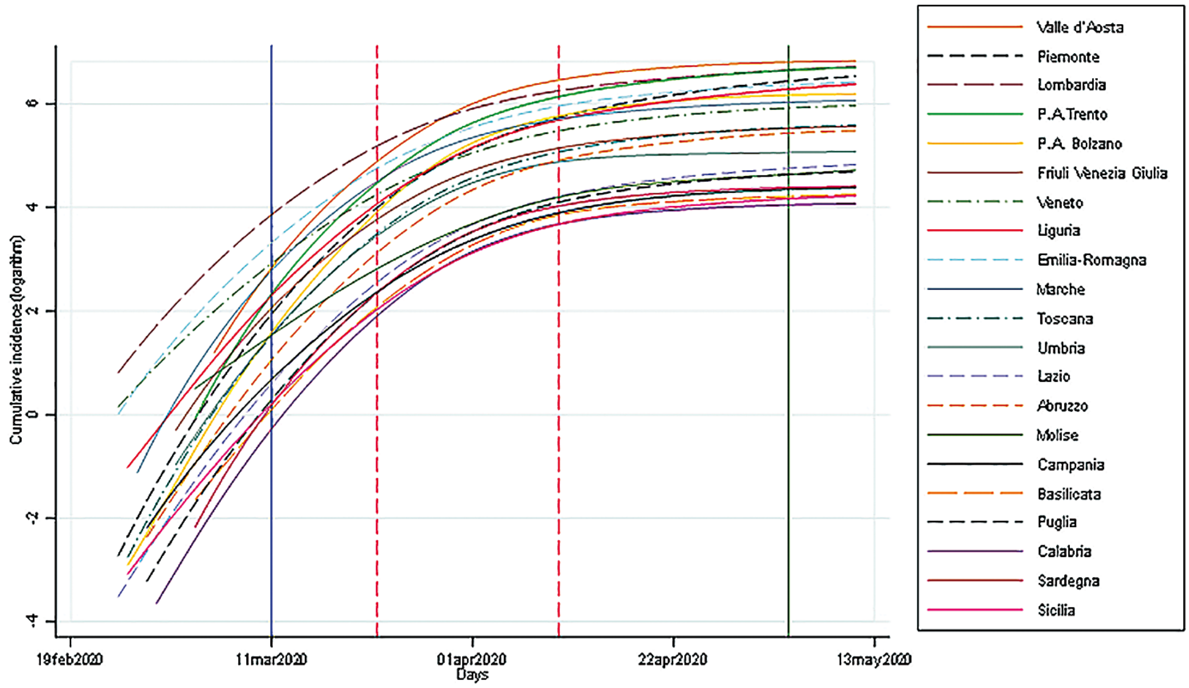


Figure 3.2: Cumulative incidence of COVID-19 by Italian regions.The vertical blue line represents the national lockdown declaration; the green line is the end of the observation period; the red dash lines show the time range in which the number of new cases started to decrease Source: Timelli.

Thus, this study highlights that early timing of NPIs implementation may have had a relevant impact by reducing the outbreak magnitude and lightening pressure on ICU (Intensive Care Unit).

My thesis project aims at developing an ABM-based simulation that exploits the computational capacity of Unity DOTS and ECS technologies and models NPIs implementations and vaccination policies for the city of Turin by exploring various intervention methods and their resulting effects, in order to help prevent adverse scenarios and act in a timely manner.

Chapter 4

Methods and Implementation

4.1 Approach

The aim of this project is to simulate different pandemic scenarios using the popular game engine "Unity3D" in order to collect insightful data on intervention policies' efficacy in containing the COVID-19 pandemic.
The simulation analysis is based on an application initially developed by a team of students of Polytechnic of Turin [30]. For this project, the application was further enhanced with new features that ensure to run smoother and more accurate simulations.
One of the main advantages of the usage of a game engine to develop infectious models is that the user can visualize in real time what is happening in the simulated world. This type of engines are built for the rendering of more sophisticated environments, however, in this case, it has been selected a 2D environment in order to focus most of the resources on the computations.
The environment of the model is a grid-based map, where, for each cell, there could be a home, a office, a supermarket, a pub, a hospital and free spaces. When a simulation in launched, the selected number of agents is generated and they start to mime real-life actions based on their current needs. The infection between humans happens when they are less than two meters away. The contagion logic has several rules as the human needs one.
Different NPIs can be applied, such as the total lockdown or the partial lockdown of pubs and gyms. Moreover, the user can decide if the vaccination policy should be implemented during the simulation.
Different statistics (i.e. counters) are computed and updated in real-time as the simulation unfolds. Descriptive statistics can be used by the user to evaluate the efficacy of the measures implemented in order to contain the spread of the disease.

As mentioned, this tool leverages on "**Unity 3D**" that is written using **C#** as a programming language. Recently, the Unity's developer team has introduced "Data-Oriented Technology Stack (DOTS)", a completely new way of approaching virtual environment simulations. This new data oriented approach is optimized to take full advantage of

today's multi-core processors, allowing to develop highly multi-threaded and optimized **C#** codes which can facilitate the execution in real-time of extremely complex systems. Using this new technology, it is possible to run simulations with numbers of agents in the order of the hundreds of thousands, in order to emulate the daily activities of individuals in a city context.
The core of Unity DOTS is to adapt the simulation logic to the "**Entity Component System (ECS)**" pattern [42], that is

- **Entity**: the entities, or things, that populate your game or program, they are just indices and do not contain any other information;
- **Component**: the data associated with each entity. The data layout is easy to access by the processor;
- **System**: the codes that modifies the data.

ECS makes multi-threading easier and provide huge benefits in terms of performance. The core of the whole simulation is represented by the different systems which are called in parallel by the entities, and run on the CPU's cores modifying the component data.

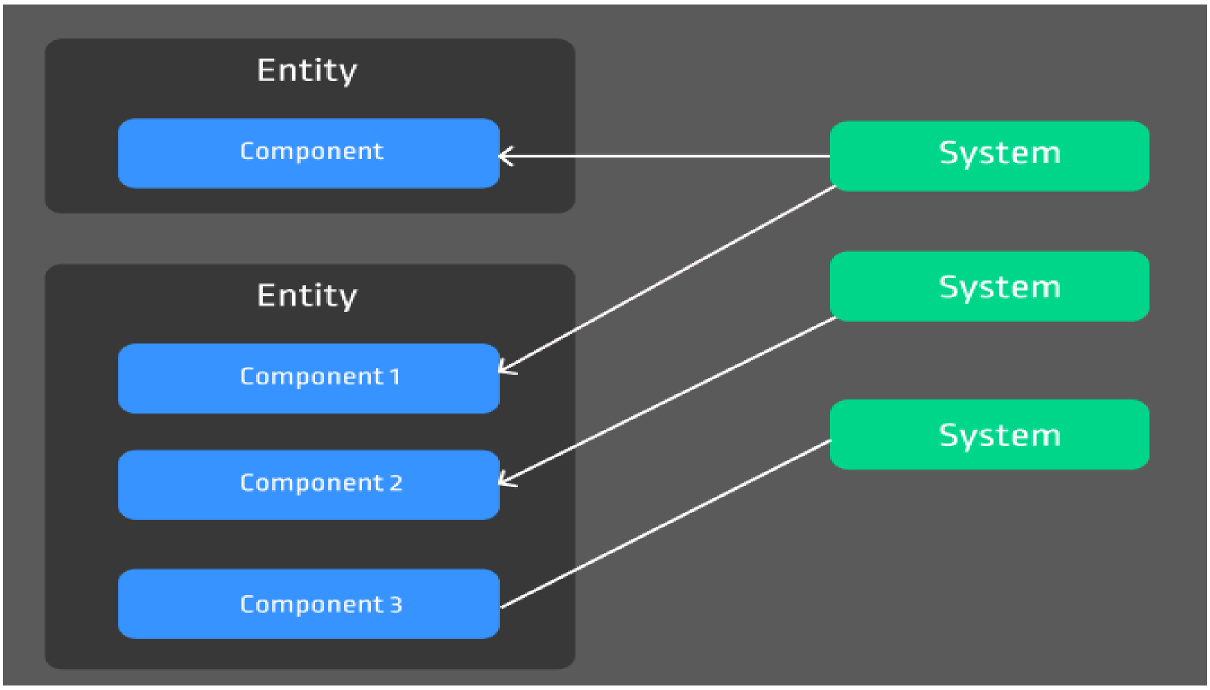


Figure 4.1: Unity ECS structure

4.2 Model design

This section presents, in details, the key concepts of the model. With respect to the initial project, some modules are intensively adjusted, instead others are completely new.

4.2.1 Agents

In an agent-based model, the **characteristics** and the **behaviours** of the agents are fundamental aspects of the tool's accuracy.
At the start of each simulation, a population of agents is created. For each entity, a set of parameters is computed and stored in structures called "components" following the *Unity ECS* theory [42].
Agents are characterised by two groups of parameters: the human component and the infection component.

Human Component

The human component is composed by a first set of parameters that identifies the main characteristics of each agent, such as *age*, *family pattern* and *social responsibility*, that influence the agent's network and individual transmission dynamics. Those are summarized in 4.1.
Another set of parameters, reported in 4.2, specifies the basic needs, such as **hunger**, **fatigue**, **work**, which mainly influence agent's behaviours and movement during the day.

Table 4.1: Human Component Characteristics

Age	Human age based on occupation, it could be student, worker or retired
Family key	Humans family pattern they belong to
Social Responsibility	How much (in percentage) human is social responsible to the pandemic, for instance wearing masks and respect the social distancing
Home Position	The home position in the grid environment expressed in x,y,z coordinates (z stands for different floors)
Office Position	The office or school position in the grid environment expressed in x,y,z coordinates
Job Essentiality	How much (in percentage) a job can't be done remotely
ProVax	If a human intends to get vaccinated
First Dose Time	How much time must pass to get vaccinated for the first time
Vaccinations	How many vaccine doses a person has got
Immunity Time	How much time last from the last vaccination or recovering from the disease

Age and **Family key** are strictly correlated and they are some of the new features of this thesis project.
Each family key identifies one of the five different family templates:

1. 2 students and 2 workers, like a couple of parents with 2 children
2. 1 student , 2 workers , 2 retired, like a couple of parents with 1 child and 2 grandparents
3. 3 students, like university students who share the same apartment
4. 2 workers
5. 2 retired

The population is divided in family patterns according to the statistics provided by [44] which is exploited to compute, for each family key, the percentage of population that is grouped in that specific template. These percentages must be specified by the user at the beginning of the simulation.
Thanks to these values, the number of individuals for each group age is consequently determined. The main difference among the three groups is the occupation, in fact students have *schools* as workplace, workers have *offices*, while retired people have no workplace. That is, the age influences the contact networks of each agent. For instance, retired people stay at home most of the time because they do not go to work. On the contrary, students go to school for 5 hours per day and dedicate to other activities during the rest of the day therefore enlarging their daily contact network.
Every family lives in the same house, so the members of the same family share the same **Home position**, which is randomly chosen across the map environment. Retired people can live also in *retirement home*. Then, for workers and students is selected a **Office position** near their home.
Social responsibility determines the level of alertness to the virus and influences the transmission dynamics Section 4.2.3. This specific parameter is drawn, for each agent, from a Gaussian distribution with a mean of 0.5 and a standard deviation of 0.45. In more detail, the Box-Muller transformation is used. This transformation is generally used as a random sampling system in order to generate pairs of independent and standard normally distributed random numbers. The latter are a transformation of two uniformly distributed random numbers in the interval (0,1]. In the simulation, this method is applied to generate only one of the two numbers belonged to the pair and it is done through the set of equations 4.1 and 4.2. Suppose that *R1* and *R2* are the two random numbers uniformly distributed in the interval (0,1].

$$Z = \sqrt{-2 \ln R1} \cos(2\pi R2); \tag{4.1}$$

The value Z in equation 4.1 is normally distributed with mean 0 and standard deviation 1. It is then linearly transformed in order to generate the final social responsibility parameter.

$$SocialResponsibility = \mu + \sigma * Z; \tag{4.2}$$

where $\mu = 0.5$ and $\sigma = 0.45$. Obtained results are winsorized between 0 and 1.
The final value of this parameter is used to compute another important human characteristic, that is **ProVax** intention. In fact, if the single agent is more than 30% social responsible, he will also agree with the vaccination policy.
This threshold was calibrated in order to reach, within the simulation horizon, the actual trend of the vaccination campaign in Italy where 70% of the population had at least the first dose [19].
Some parameters like **First dose time** is computed for **ProVax** agents and is based on the age, that is, retired humans will be vaccinated earlier respect to workers and students.

As it was mentioned above, the other set of parameters of the **Human Component** is composed by the agent's basic needs, which outline entity's behaviour. It is modelled through a belief–desire–intention *system* called **Need System**.
Every need is determined by a counter, for each counter a specific time threshold t_1 defines the onset of the need that lasts for a specific time period t_2. When the counter reaches t_1, it stops, and the agent goes to the destination where he can satisfy the need in the needed amount of time t_2. Human needs and their thresholds are described in Table 4.2

Table 4.2: Human Component needs

Need	Description	t_1	t_2
Hunger	Human eat 1 hour three times each day	6h	1h
Rest	Human rest for 8 hours, need restored after 16 hours from fulfillment	16h	8h
Sportsmanship	Human does 1.5 hours of sport every two days	44h	1.5h
Sociability	Human does 2 hours of sociability each day	21h	2h
Grocery	Human goes to the supermarket for one hour once every 3 days	72h	1h
Work	Human goes to work for 8 hours every day	16h	8h
Vaccine	If ProVax, Human goes to the hospital to vaccinate himself every 4 months	4M	30m

For some needs, thresholds can differ by age. For instance, students go to school for 5 hours while retired people do not increase their *work* need. The **Need System** can be divided in three sub behaviours that in ECS theory are called "**Jobs**":

- Job 1: it increases the counters by a delta time parameter[1] up to t_1. Moreover, it defines specific rules - that affect the increment of a counter - that depend on the type of NPI applied and on the status and characteristics of the entity. For instance, if the lockdown policy is activated, the *grocery* need increases more slowly than during normal time, while the sociability and sportsmanship counters are increased by a factor of (1 - Social responsibility), so it means that people more responsible develop these needs later respect to the less responsible ones. Another

[1] The delta time parameter represents the time between two consecutive frames.

rule determines the only need to consider in case of specific circumstances such as during the quarantine of a social responsible agent[2]. In this occasion, just the *rest* need is increased to constraint the entity to stay at home. Finally, there is a specific rule that, on the basis of agent's characteristics (age) specifies which are the relevant needs. The *work* need is not increased for retired people.

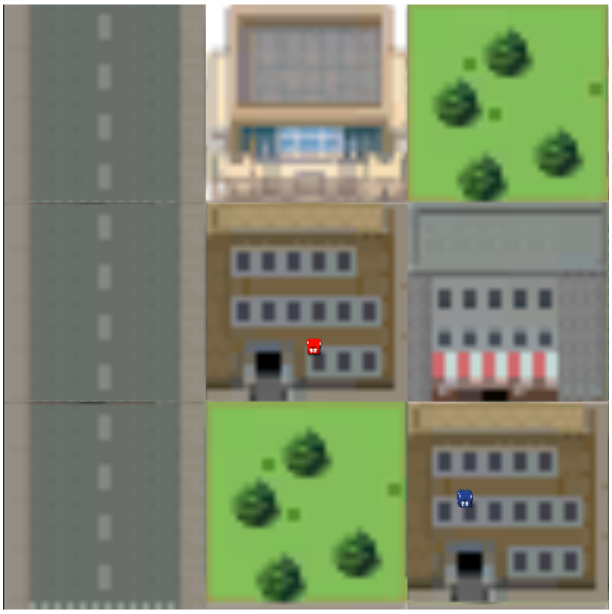


Figure 4.2: Example of human quarantined at home

- Job2: it is the need assignment: whenever a counter (updated from previous *Job*) exceeds its threshold t_1, the entity sets the corresponding need as its current one, stores it in the **Need Component** (see figure 4.3 for a visual example in Unity's inspector) and takes action to satisfy it.

Figure 4.3: Example of Need Component in Unity entity inspector

- Job 3: it decreases the need counters once the entity reaches the destination where the need could be satisfied. The decrease speed is determined by the duration of the need t_2 and depends on t_1. For instance, the *grocery* need reaches its threshold every 3 days (that are expressed in seconds as $3days * 24hours * 60minutes$). Considering that an human goes to the supermarket for 1 hour, the counter will be decreased by a quantity of 3 * 24 every real second (that corresponds to a minute

[2]In this case, an agent is considered social responsible if the specific parameters is at 50%

in the simulation). In this way, after 60 real seconds, the entity will have satisfied its need and the counter will be able to start again from 0.

Infection Component

The infection component contains information related to the COVID-19 pandemic. Those are displayed in table 4.3.

Table 4.3: Infection Component

Status	One of the status included in the SEIRS model
Contagion counter	How long contact with an infected person lasted
Exposed counter	How long an entity is in exposed status
Infectious counter	How long an entity is in infectious status
Recovered counter	How long an entity is in recovered status
Exposed threshold	Maximum time threshold that determines when to go to the infectious state
Infectious threshold	Maximum time threshold that determines when to go to the recovered state
Recovered threshold	Maximum time threshold that determines when to go to the susceptible state
Symptoms probability	Probability to develop Covid-19 symptoms
Death probability	Probability to death after critical infection, it has been considered the **IFR** (Infection Fatality Rate) that it the proportion of deaths among all infected individuals
Current immunity level	How much (in percentage) an human is protected from the disease, it depends on vaccinations or recovered status

During the simulation, each human passes from a **Status** to another, following the **SEIRS** model. To mark this transition in the model, agents are represented by a 2D sprite symbol which can take different colours based on the current infection state, which could be:

- **S**: Susceptible
- **E**: Exposed
- **I**: Infected, further divider into Symptomatic and Asymptomatic
- **R**: Recovered or Removed, the last simulate the human death
- **S**: Susceptible, some time after recovery, an entity may be infected again, restarting the cycle

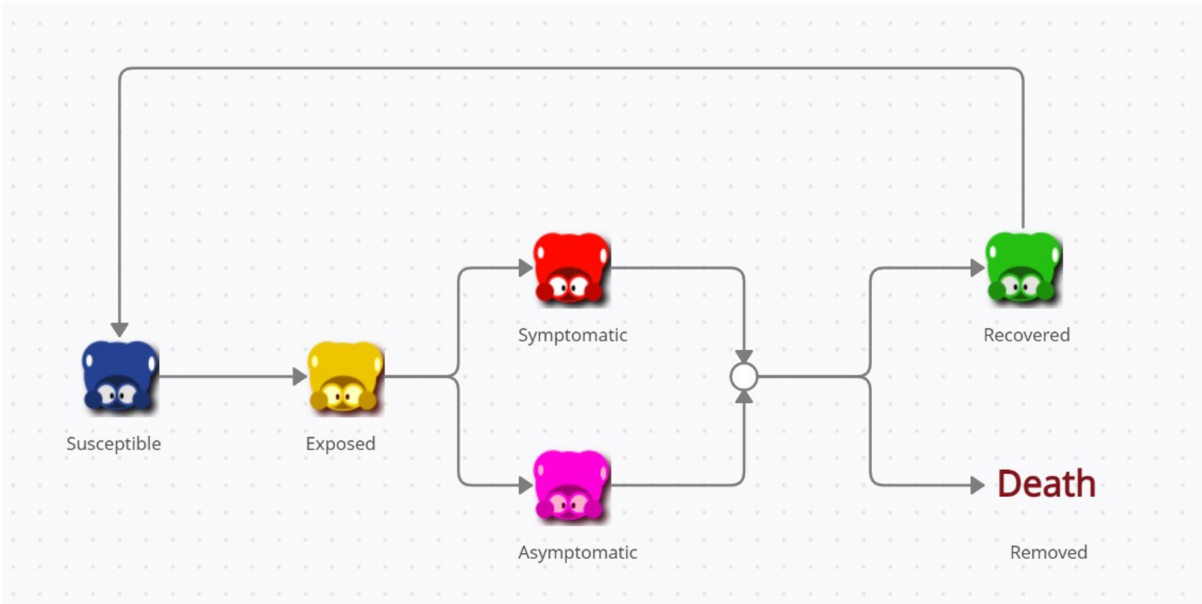


Figure 4.4: SEIRS model diagram

When a counter reaches its specific threshold (that is agent dependent), the agent passes to the next status. The dynamics of status' changes are explained in the section related to the Transmission dynamics 4.2.3.
The following parameters are computed via the Box-Muller transformation as explained in equations 4.1 and 4.2:

- **Exposed threshold**(with a minimum and maximum level of 2 and 14 days, respectively)
- **Infectious threshold** (with a minimum and maximum level of 4 and 15 days, respectively)
- **Recovered threshold** (with a minimum and maximum level of 6 and 10 days, respectively)
- **Symptoms probability**
- **Death probability**

Minimum and maximum levels for the thresholds are selected according to the *World Health Organization*'s research [29].
Symptoms probability and death probability are transformed according equation 4.2 using mean and standard deviation values that approximate the probabilities reported by age groups by Poletti [33].
In detail, the following percentages are selected as mean μ for the different groups:

- Student: *symptoms probability* 20% & *death probability* 1%
- Worker: *symptoms probability* 30% & *death probability* 3%

- Retired: *symptoms probability* 50% & *death probability*10%

The **current immunity level** changes value according to specific events like receiving a vaccine dose or recovering from Covid-19 disease. In the first case, it will guarantee a protection of 90%, then once "immunity time" reaches 4 months (see table 4.1), its value will drop to 40%. These percentages are taken from an Italian article by the "ISS" (Istituto Superiore Sanità) [18]. While, in case of a person recovering from the disease, this value will rise to 80% according to Hansen [5].

4.2.2 Contact Networks

Once an agent decides its intention, based on the current need, he moves towards a destination in the map creating its personal **contact networks**.
Given the available destinations, the model outlines three different type of contact: **household**, **workplace** and **community**.
Figure 4.5 shows the different lines within the contact network which a single agent can build during the day.

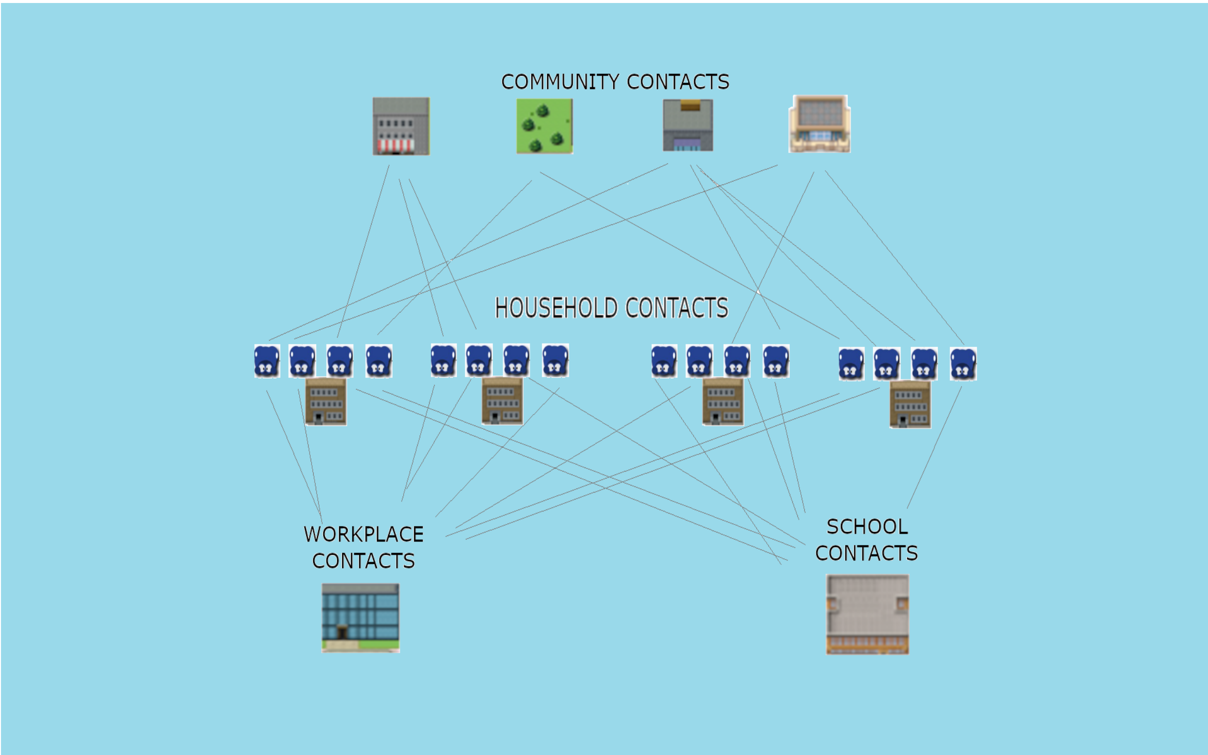


Figure 4.5: Contact Networks

Every network line is generated in real-time starting from agent's current need, this means that it can change every day. In fact, contacts happen with random patterns due to the changing personal needs and characteristics of each human.
For instance, it may happen that agents of the same household do not meet during the day due to different time schedules driven by personal needs.
Also the *intervention policy* has a large impact on contact networks' generation because it can limit access to some destinations like *school, gym and pub*.
Another parameter that influences contact network generation is the *age*, because, for example, retired people do not go to work and stay at home most of the time, increasing their household contacts.
As it was described above, when an agent sets his current need, he moves across the environment, building a contact network line.
A new important feature implemented in this model that heavily influence the networks of each agent is the possibility to have different layers of tiles in a specific cell of the grid environment. It allows, for instance to have building with different apartments/household

or offices like in reality. Consequently, transmission dynamics are also influenced because infection cannot happen among different floors.

The **Get Path Need System** takes care of assigning to each entity the right destination to satisfy his current need. Table 4.4 describes which tile destination is suitable for each specific need.

	Home	Office/School	Park	Pub	Supermarket	Hospital	Gym
Hunger	X			X			
Rest	X						
Sportsmanship			X				X
Sociability	X		X	X			
Grocery					X		
Work	X	X					
Vaccine						X	

Table 4.4: Map destination for specific need

Some needs could be satisfied by more than one destination. Therefore, the code outlines conditions that determine the contact network line that the entity would chose at that specific time.
Those conditions can be summarized as follows:

- **Hunger**: if *lockdown* (total or partial on pubs) policies are not activated, 30% of times humans eat outside instead of eating at home.

```
if (random.NextDouble() < 0.30 && !lockdown && !lockPubs)
```

  If they decide to eat at home, as home position is already saved inside the *Human component* (see table 4.1) they will immediately start to search a path towards it. If not, they will search a pub around their current area of the map.

- **Sportmanship**: if *lockdown* AND *lockdown gym* policies are not activated, humans will search around their current position a gym where to satisfy their sport need. If they do not find it, their research will focus on the nearest park. Obviously, if the above mentioned policies are turned on, the humans will go to park 100% of times.

- **Sociability**: Agents decide to visit a friend at home 20% of times if lockdown is not activated. Instead, if lockdown policy is in place and **Social Responsibility** is close to zero, agents visit friends at home with a probability of around 50%.

```
if ((random.NextDouble() < 0.20 && !lockdown) ||
(random.NextDouble() < 0.5 * (1 - humanComponent.socialResposibility) && lockdown))
```

If both conditions are false, agents set a pub or a park as their current destination. Obviously, it is not possible to select the pub if it is closed due to restrictions.

- **Work**: selection of destination in case of work need depends mainly on the age of the involved agent. In particular, if he is a worker and he has a *job essentiality* parameter (described in 4.1) greater than 50%, he will be able to work on site despite the lockdown policy activated. Otherwise, he will work remotely from his home.
  If he is a student and *lockdown* AND *lockdown schools* policies are not activated, the student will be able to study at school. On the contrary, he will study remotely. In these situations, the positions of the destinations are saved directly in the entity's component as this type of places are unique for each human.

However, when the human's destination is not set at home or office, but it is one of the already mentioned locations, the entity will search the destination tile near its position. This research is done by sub-diving the entire map in "*Quadrants*" - that can represent the neighborhoods - and the agent will start to analyze the quadrant he occupies and that must contain almost one of each type of destination.
The "Quadrant" approach is also used to help the *Contagion system* in order to simplify the research of contagious people around the current entity. Obviously, these two methodologies differ in quadrant size because they have different purposes. Specifically, destination search has a wider search range compared to the search of infected people near an agent's location, that it performed within a very small quadrant.

4.2.3 Transmission dynamics

The transmission dynamics are based on two main elements: the **Quadrant System** and the **Contagion System**.

The **Quadrant System**, that plays an important role in the spread of the disease, builds an important structure to keep track of infected humans that may have contact with each susceptible agent. For each infected agent (both symptomatic and asymptomatic) that is not in intensive care, some specific information (**Current position**, **Current floor**, **Current status**, **Family key**, **Symptomatic flag**) are stored in a structure. Then, the **Quadrant System** groups each infected agent's structure by labels that correspond to the quadrant where each agent has been infected. The overall structure is continuously updated at each frame to account for changes in infected agents' position[3].
In this way, the *Contagion system* can easily access this structure, in order to analyze the current infected people in the same quadrant of the current entity. Obviously, there is no need to check for infected agents in other quadrants (labels) as the contagion can happen just within that specific quadrant. This feature helps the entire engine save resources.

The transmission dynamics are inspired by the contact tracing app Immuni [40] and are based on a formula that keeps into account several parameters.
As it was described above, an infected entity enrolls himself in the "quadrant structure", obtaining a quadrant label. So, in the **Contagion System**, susceptible humans will check, after their label computation, if there are contagious people in the same quadrant. If the **distance** between a susceptible and an infected human is less than two meters, then a risky contact occurs.
Nevertheless, transmission events happen with certain probabilities based on the location they take place. Approximately, they happen 30% at household, 20% at workplace or school and 30% at the community [6]. When the risky contact happens, the *contagion counter* (described in table 4.3) will be increased in time. If this value - that measures the exposure time - exceeds 20 minutes (that are 20 real seconds), the susceptible entity will be infected and enters in the **Exposed** phase. However, infection may take longer due to some specific aspects of the contact, such us the *social responsibility* of the involved agents and the *current immunity level* of the susceptible agent. The code below helps better understand this dynamic.

```
ic.contagionCounter += (ContactTypePercentage) * deltaTime
* (1 - humanComponent.socialResposibility) * (1f - ic.currentImmunityLevel);
```

First, it is important to clarify that the '+=' syntax implements the cumulative sum of the parameter on the left, which in this case is "**contagion counter**". The first member in the right-end-side (RHS) of the equation increases the "**Contagion counter**" as the time passes given transmission rate of the virus based on the type of contact

[3]For instance, an agent can be infected at school and then move home in order to quarantine. In this case, the agent's structure label will change if school and home are in a different quadrant.

(**ContactTypePercentage**). These rates are taken from a study conducted in Luxembourg [26]. However, the more the susceptible agent is social responsible and the higher his immunity level, the lower the counter will be increased over time.

The **Contagion system** manages different scenarios based on the contact typology between the two involved entities and their location. It distinguishes:

- **Household transmission**: the susceptible human checks if there are contagious people in his home and if they are at the same floor. If this is the case, an household transmission occurs with a *ContactTypePercentage* of 18% if the infected human is symptomatic, otherwise 5%

Figure 4.6: Example of household transmission

- **Workplaces transmission**: the susceptible human checks if there are contagious people in his office and if they are at the same floor. If this is the case, a workplace transmission occurs with a *ContactTypePercentage* of 15% if the infected human is symptomatic, otherwise 2%

Figure 4.7: Example of workplace transmission

- **Community transmission**: the susceptible human checks if there are contagious people around him while he is outside (and if they are at the same floor if location is, for instance, gym or pub). If this is the case, an outside transmission occurs with a *ContactTypePercentage* of 10% if the infected human is symptomatic, otherwise 1,2%

Figure 4.8: Example of household transmission

The **Contagion system** is the core of the the **SEIRS** infectious model because it continuously checks the human status and establishes when an entity must pass to another status of the model.
When the entity reaches the **Exposed** phase, the system increases the *Exposed counter* by delta time (see table 4.3), as it is shown in figure below, which also represents how the **Infection Component** is outlined within the Unity's inspector.

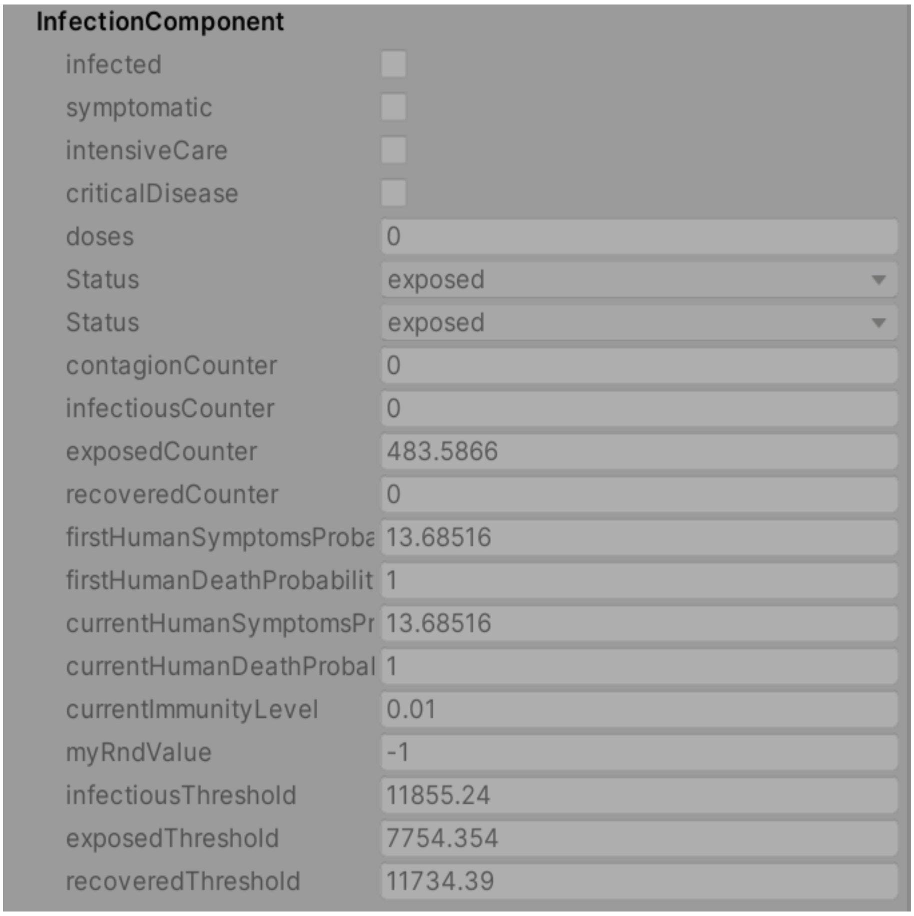


Figure 4.9: Example of Infection Component in Unity entity inspector

When the Exposed counter reaches the *Exposed threshold*, which is agent specific, the human passes to the **Infected** state. This phase is very crucial for the single entity, in fact, it determines if the human will be symptomatic or not and if he will require to go in intensive care.
This depends on the **Symptoms probability** which is affected by the **current immunity level**.
People with high protection will have less probability to develop the symptoms.
Once a human is symptomatic, the system checks if the entity is in a critical situation and therefore needs to go in intensive care. Poletti [33] highlights that the probability of developing a critical illness is close to the probability of dying. Therefore, death probabilities, reduced by human current protection, are used for probabilities of developing a critical illness. If the agent develops the critical illness, the **Intensive Care** parameter is set to *true* only if there are available Intensive Care Units (ICU), otherwise the agent will be in "*critical disease*" mode. Obviously, if the human does not develop any critical condition, he will be a normal symptomatic who should be in quarantine (if he is social responsible enough).
When the entity's intensive care flag is turned on, the **Need system** selects the special *need to heal* as the current one and blocks that entity at the hospital.

Figure 4.10: Example of human in intensive care

There is another important aspect that happens during this phase: if a human is in intensive care, his probability of dying will be slowly decreased because he is at the hospital supported by the doctors. On the contrary, if he is in *critical disease* mode, as there are no available units at the hospitals, the probability of dying is slowly increased during simulation time.

When the **infectious counter** becomes greater than the **infectious threshold** (see table 4.3), the system decides if the human will die or not. This decision, obviously, considers the **Death probability**.
If the entity dies, he is removed from the simulation. If not, he enters the **Recovery** stage. In this phase, the *current immunity level* is set to 80% and the agent waits until he becomes **Susceptible** again, that is when the **recovery counter** reaches the **recovery threshold**.

4.2.4 Interventions

This model allows to simulate the spread of the pandemic and to understand how the contagions react to the activation of different policy interventions by governments. The policies that can be activated are mainly divided into two categories:

1. Non-Pharmaceutical Interventions (NPIs). NPIs include all measures or actions, different from the use of medicines or vaccines, that can be implemented to slow the spread of the pandemic. During the first stage of the pandemic, NPIs are often the most accessible interventions, given the time needed to develop specific vaccines. Therefore, they may play an important role in reducing the transmission mechanisms in community settings (WHO, 2019 [28]). Two NPIs can be implemented during the simulation:

    - **Total lockdown**: it was implemented in the original project, but it was further enriched with detailed information that changes the **behavior** and the **contact networks** of the entities in order to mimic the effect of the regulations implemented by many countries during the most recent pandemic diseases. This general policy includes also the partial lockdowns. One of the main aspects affected by this policy is *work*: only in case of lockdown, the **Job Essentiality** parameter (described in 4.1) is Normal distributed with an expected value around 20% (otherwise it is constant at 100%). If lockdown applies, workers can do "smart working" if *Job Essentiality* is lower than 50%, while students can do distant learning.

      During the lockdown, some counters in the **Need System** are slowed down, such as *grocery*, *sportmanship* and *sociability* where the last two are inversely proportional to the *social responsibility* parameter.
      Furthermore, the probability of visiting a friend house to satisfy need for *sociability* is drastically reduced. However, it is not set to zero in order to represent those people that could misbehave.
      The lockdown policy reduces also the probability of going to pubs to satisfy *sociability* or *hunger* needs.

    - **Partial Lockdown**: this is a new feature implemented respect to the initial project. Partial lockdown allows to close some destinations to humans. In particular, as the total lockdown, also this feature heavily influence the **behaviour** and **contact networks** of the agents.
      The user can select the following partial lockdowns:
        - Lockdown at pubs/restaurants/bars
        - Lockdown at schools
        - Lockdown at gyms

      ‘

2. Pharmaceutical Interventions (PIs): they are one of the most important features implemented in the model.

- **Vaccination policy**: vaccines have a substantial impact on the transmission dynamics, by modifying the susceptibility to infection and the probability of developing symptoms of each agent.
  In order to properly capture the dynamics of this policy, it is important to remember and analyze two fundamental parameters described in the **Human Component** (see table 4.1): **ProVax**, which establishes if a person intends to get vaccinated or not, and **First dose time**, that is computed only if the *vaccination policy* is activated and if the entity is pro vaccine. The willingness to get vaccinated depends on the *social responsibility* parameter. In particular, the agent agrees to get vaccinated only if he is more than 30%[4] social responsible.
  If **ProVax** is set to *true*, the *first dose time* value is randomly computed depending on the agent's age:

  - **Retired** will do the first dose of vaccine in the first 30 days of simulation

  - **Workers** will do the first dose of vaccine between 20 days and 30 days since the start of the simulation

  - **Students** will do the first dose of vaccine between 30 days and 90 days since the start of the simulation

  These threshold values give precedence to the elderly as it has actually been the case.

  A pro vaccine agent will increase his **vaccine** need until it exceeds the **first dose time**. Then, he will go to nearest hospital to get the first dose, activating the immunity time. When the **immunity time** reaches 4 months (see table 4.3), he will receive the next doses and so on. There is a special case that could happen during the simulation: if a human who intends to get vaccinated gets infected before receiving the first dose, his **first dose time** is delayed considering the recover from the disease.

[4] This percentage could be changed, however 30% is used in the context of this project in order to reach the threshold of 70% of the population being vaccinated, following statistics for Italy [19]

Figure 4.11: Example of humans get vaccinated

- **Healthcare system**: agents who have critical and severe symptoms are assumed to require the support of the *healthcare* system and of intensive care unit (ICU). The number of ICU is computed at the start of the simulation proportionally to the initial population and considering that 14 units should be available every 100,000 inhabitants, according to estimations for Piedmont region [1].
  The intensive care logic is manly described and implemented in the **Contagion system** that it is already explained in Section 4.2.3. If a human can find a ICU available, he is potentially "blocked" at the hospital and he cannot go anywhere.

4.2.5 Additional Features

Data Input

The **Configuration** file is an important element of the simulation settings as it contains all the parameters that the user must input in order to run the simulation. Parameters can be boolean, integers (or floats) or strings. The main parameters are:

- **appendLog**[true/false] allows the user to start the new simulation from the status quo reached in the previously launched simulation. Practically, new counters are appended to the log already saved;
- **numberOfHumans**[int]: the number of the humans at the beginning of the simulation;
- **numberOfInfects**[int]: the number of *Symptomatic* people at the beginning;
- **timeScale**[int]: the speed of the simulation;
- **map**[str]: the name of the file of the map;
- **minDaysInfectious**[int]: lower threshold of days of Covid-19 infectiousness;
- **maxDaysInfectious**[int]: upper threshold of days of Covid-19 infectiousness;
- **minDaysRecovered**[int]: lower threshold of days of recovering from the virus;
- **maxDaysRecovered**[int]: upper threshold of days of recovering from the virus;
- **minDaysExposed**[int]: lower threshold of days of incubation period;
- **maxDaysExposed**[int]: upper threshold of days of incubation period;
- **lockdown**[true/false]: general lockdown, full details soon after;
- **vaccinationPolicy**[true,false]: it activates the vaccination policy;
- **lockGym**[true,false]: it activates lockdown at gyms;
- **lockSchool**[true,false]: it activates lockdown at schools;
- **lockPubs**[true,false]: it activates lockdown at pubs;

The **map** is a 2D grid environment where the agents exist. It heavily influences simulations for its structure. The map is built with the software "**Tiled Map Editor**" [2], which allows the user to create tile-maps of any size starting from a tile-set. Once the map is completed, there is the possibility to generate an XML file with all the information about the grid environment.
The tile-set used is composed by 13 different kinds of tile (see figure 4.12). Each tile represents a place in which the agents can satisfy their current needs.
Four more tiles have been added in this thesis project, in particular they are: **Gym**,

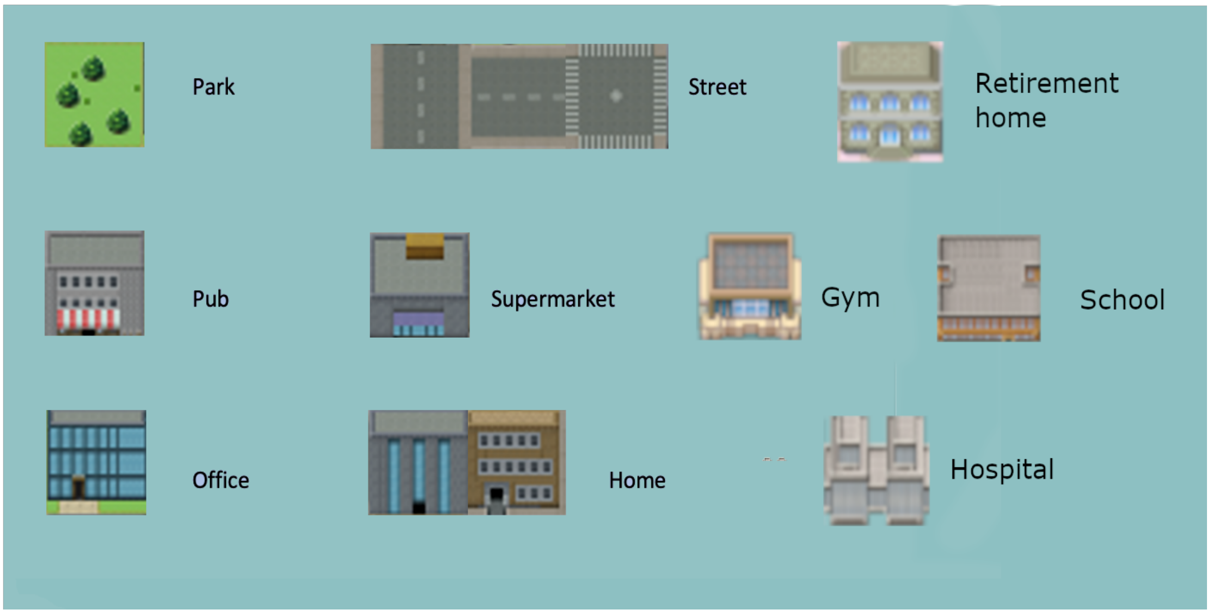


Figure 4.12: City buildings legend

School, **Hospital** and **Retirement home**. These additions are crucial for the implementation of some features which will be explained later in details.
For the purpose of this thesis, the map of Turin has been used. To build a scale tile-map representation of the real city, real coordinates of roads, buildings, parks, etc., have been used. Moreover, the geo-localization information was converted to a matrix of tiles.
It is worth mentioning that not only 2D data are taken into account. In fact, every map's cell could potentially develops vertically, in order to represent, for instance, a building composed by different floors.
Below, the final tile-map representation of the city of Turin is reported, which covers a space of 9.5x9.42 km, that is 950x942 grid blocks.

Furthermore, there are also other default maps of different sizes:

- tiny with 10x5 cells
- small with 30x20 cells
- medium with 90x70 cells

In particular, the "extralarge" map, which is shown in figure 4.14, was used for a first set of simulations which are described in detail in the following chapter.

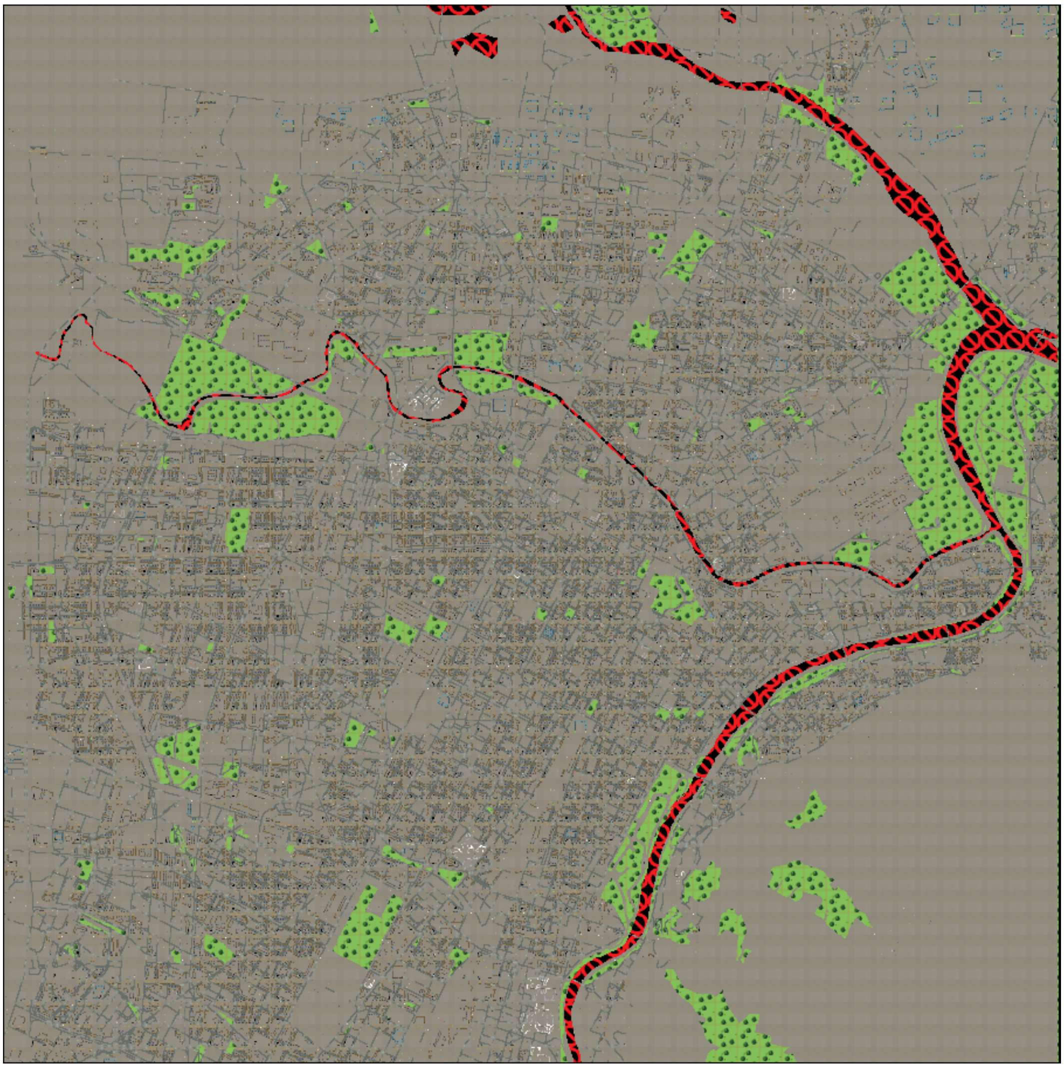


Figure 4.13: Turin tile-map based

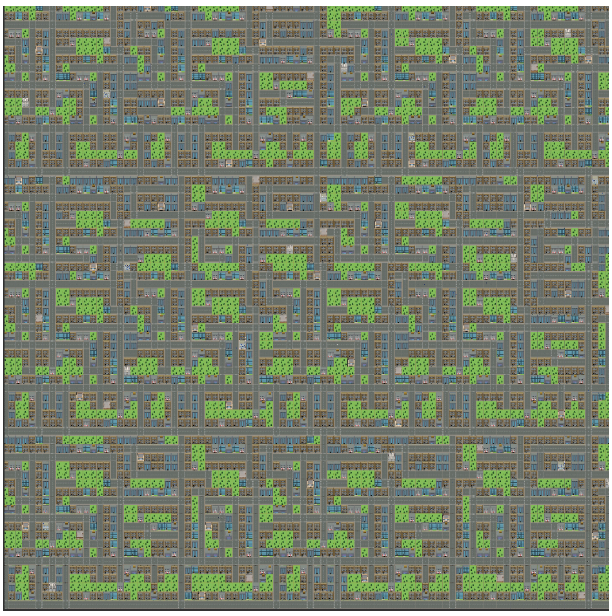


Figure 4.14: Extralarge tile-map 90x70

Another input that is required is the **family pattern** percentages on total population. As it is described in the related paragraph, the values used for the experiments are taken from demographic statistics for the city of Turin [44].
The structure of the families outlines also the group ages across the population, so they are important parameters because influence the **behaviour** and the **contact networks** of agents.

Data Output

This subsections aims at clarifying what is rendered on screen. The simulation takes place on a customized 2D top-view tile map of a city, where numerous entities circulate. The user can visualize on screen in real-time how the infection disease is spreading. Several counters are displayed on the screen during the execution of the application. The values of these counters change in real-time based on the current status of each entity.
Moreover, those values are saved and updated in the statistics file (log file), therefore, at the end of the simulation, the user can use them as inputs to show how the current scenario behaves over time.
As it is shown in the example in figure 4.15, the displayed counters are:

- **Time passed**: the time passed dived in days, minutes and seconds
- **Population**: the current number of entities displayed on the screen
- **Intensive care available**: the current number of intensive care units available
- **Exposed**: the current number of humans who have just been infected, but they are in a virus incubation phase
- **Symptomatic**: the current number people who showed symptoms of the disease after the exposition time
- **Asymptomatic**: the current number of agents who are infected but have no symptoms
- **Recovered**: the current number of humans who are recovered from the disease and cannot be infected at this stage
- **Deaths**: the number of deaths since the beginning of simulation
- **Intensive care**: the current humans who are hospitalized in intensive therapy

In the example, the last six counters (reported above) are reported both for people who are not vaccinated yet and for people with at least one vaccine dose. For vaccinated people, there are four more counters which indicate how many first, second, third and fourth doses were made since the start of the simulation. Obviously, the user will visualize these last mentioned counters only if the vaccination policy is activated at the beginning.

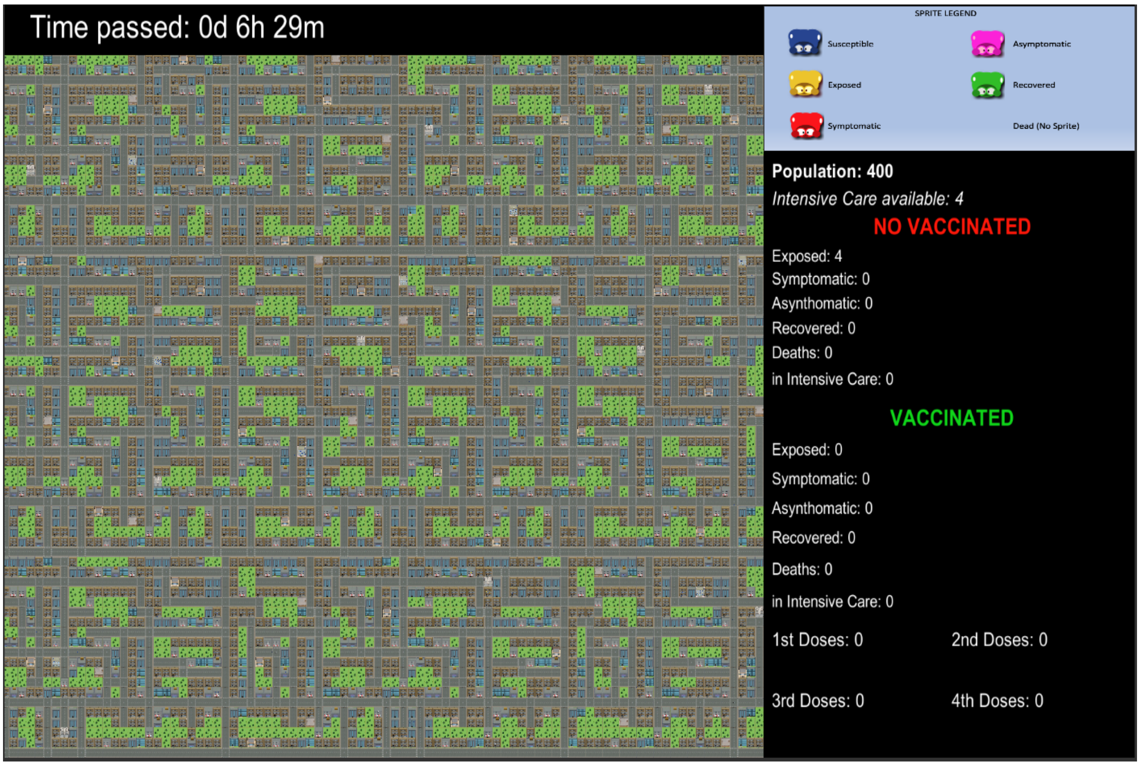


Figure 4.15: Example of simulation view on screen

During run-time, all the counters are constantly saved into a log.txt file, which describes the evolution of the virus during the simulation.

Save System

Compared to the initial project, this one has got a new important feature about the statistics management. In fact, there is the possibility to save the counters of the current simulation and load them in order to continue the simulation with different settings (policies) taking therefore into account the status quo of the current simulation.
With this opportunity, the user can combine interesting experiments approximating the different scenarios of the reality of these years.
When the user wants to save the current "world", he has to press the "K" button and every entity and related information are cached in a file in memory. Then, to load what it was saved before, first the user has to modify the **Configuration** by setting to true the flag **appendLog**.
When the Configuration file is ready and a new simulation can start, the user has to press the "L button" and all the previous entities and statistics are loaded in the new "world".

Optimization for larger map

Larger maps could be a problem in terms of computation time, CPU and memory usage, therefore, an optimization was implemented.
When the grid map exceeds 200x200 cells, the original way of implementation of the

agent's path-finding is inappropriate. Therefore, a new way of reading the entire map was outlined.
In detail, the grid environment is subdivided in sections of an arbitrary size (50x50 tiles for the experiments), and the agents are constrained to move within the assigned section. In this way, to satisfy all the human's basic needs, a new rule has been imposed: all the possible destinations must exists within each section.
To achieve this result, a Python script called "Map corrector" was coded to place missing destinations across the sections.
Thanks to this optimization, it was possible to perform the tests on the map of Turin, which is very large.

Chapter 5

Tests and Results

This chapter presents the results of the tests performed using the developed ABM. Two sets of experiments that differ by the environment's dimensions and structure are conducted. The first one is based on a default reduced environment (medium tile map of 90x70 cells as it is described in chapter 4, in 4.2.5), the second one is simulated in the larger map of Turin (950x942 cells).
For each set, six simulations are ran and compared on the basis of total duration and type of policy:

1. No policy for 15 days, then total lockdown is introduced for 45 days
2. No policy for 30 days, then total lockdown is introduced for 30 days
3. No policy for 30 days, then partial lockdown on pubs and gyms is introduced for 30 days
4. No policy for 30 days, then total lockdown is introduced for 120 days
5. No policy for 30 days, then vaccination policy is introduced for 120 days
6. No policy for 30 days, then total lockdown and vaccination policy are introduced for 120 days

At the beginning of each simulation, an arbitrary number of symptomatic people is introduced in the map, in order to let the virus spread.
In the reduced environment set, the map is populated by 40,000 individuals, with only 5 symptomatics. In the Turin set, instead, 800,000 individuals populate the environment, with 100 symptomatic people in order to cover the entire map and to maintain the same proportion. The comparisons between the six simulation (enumerate above) are organised in the following way:

- Simulations n.1 and n.2 last both 60 days and focus on the timing of policy application, in the case of total lockdown
- Simulations n.2 and n.3 last both 60 days and focus on the best policy to apply between total and partial lockdown

- Simulations n.4, n.5 and n.6 last 150 days and focus their analysis on the best policy too, but in the long term and involving the vaccination policy

Illustrative graphs help to better understand the conducted experiments. They show trends of each status (also for vaccinated people) of the **SEIRS** model during the simulation time. Trends are computed on **Number of individuals** in **simulation time** (expressed in days) and they respect the equation $N = S + E + I + R$; so the *Deaths* curve is a cumulative number since the start.
Each chart is the output of a Python script, which uses *pandas* package that is a set of APIs very useful for data analysis. This script receives as input the *log.txt* file that every simulation generates. Furthermore, it computes final values of each represented curve, expressed in percentage on total population. These values are compared with real data coming from daily screenings made for Piedmont region since the beginning of the pandemic [45], and they are slightly increased compared to reality. However, it must be considered that the model analyzes the current state of each person within the simulation, while the real statistics do not evaluate the entire population. In fact, statistics fail to assess the real state of the virus spreading process; for instance just think that not all positive people perform an official SARS-COV2 antigen test, and therefore they could never be tracked by the official system.
The following sections describe the above mentioned scenarios.

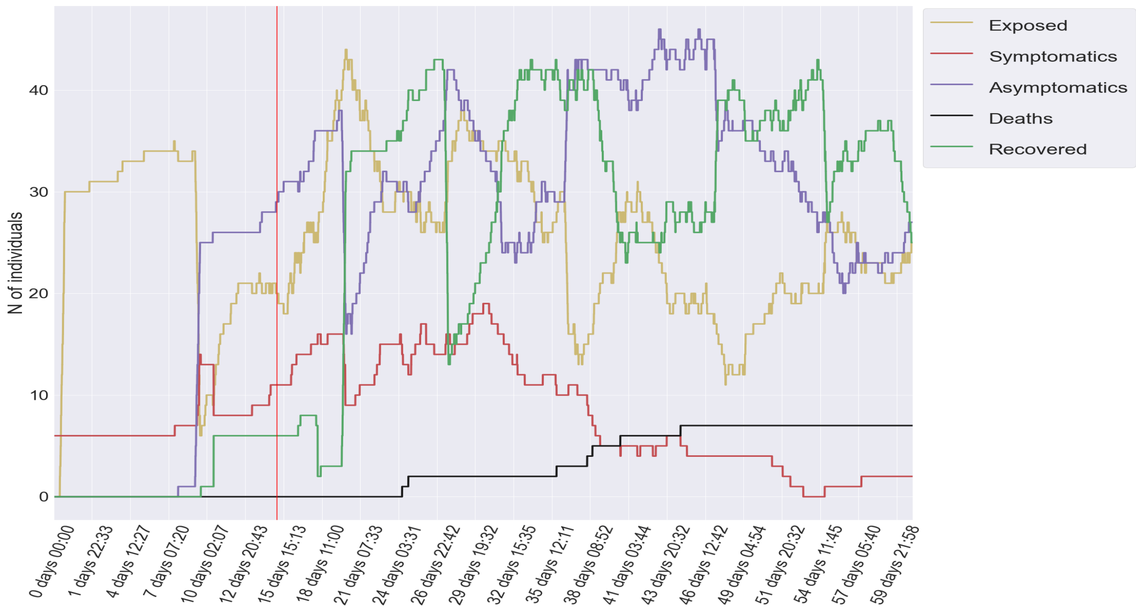
5.1 Reduced Scenario

This section presents the different comparisons between the simulations in a 90x70 grid environment, populated by 40,000 individuals. In such an environment, where there are less free spaces and more closed spaces all close together, is possible to have a better control of the output. This can be due to reduced contact networks and possible destinations for each agent. So, act on them by applying the various policies gives usually reasonable and expected results.

Policy timing on short-term

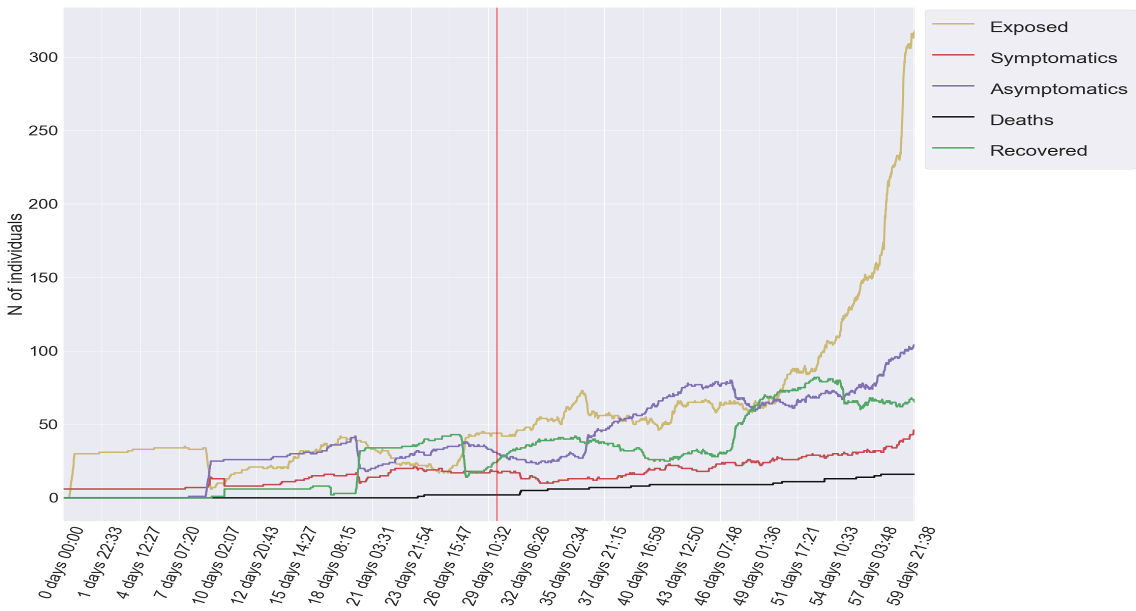
As explained above, this comparison involve two simulations and analyses the trend of curves under different timing of policy application. The policy is the same, and for the purpose, **total lockdown** was used. Figures 5.1 and 5.2 show explanatory charts of the two experiments; in the former the NPI was applied after 15 days, in the latter, instead, after 30 days. Red vertical lines indicate when starts the policy application.

Figure 5.1: No policy for 15 days, then total lockdown is introduced for 45 days



Final percentages on total population: **Exposed** 0.06%, **Symptomatic** 0.01%, **Aymptomatic** 0.06%, **Death** 0.02%, **Recovered** 0.08%

Figure 5.2: No policy for 30 days, then total lockdown is introduced for 30 days



Final percentages on total population: **Exposed** 0.08%, **Symptomatic** 0.12%, **Aymptomatic** 0.26%, **Death** 0.04%, **Recovered** 0.16%

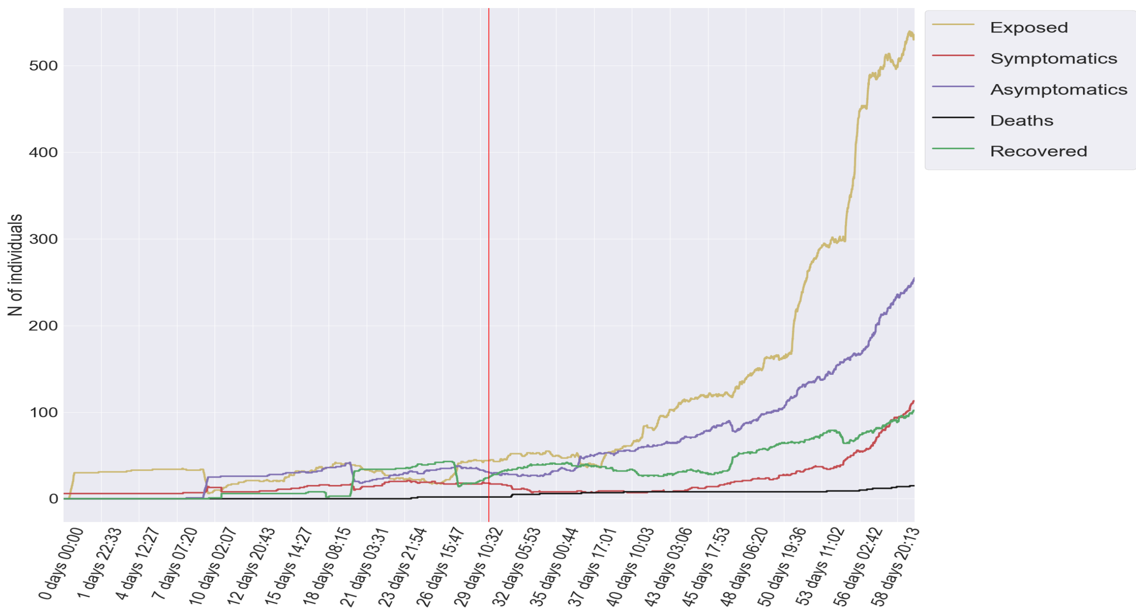
The above graphs represents two different epidemic evolution. Figure 5.1 show that applying such a policy at the right time, is possible to keep the contagion under a certain maximum threshold, in terms of numbers (near 50).
Furthermore, curves tends to have deadlock days which show a slow spreading of the disease, especially for deaths and symptomatics. Symptomatics (red line) are reduced in

time until they reach few units. Deaths remain constant every near 10 days. Also the number of exposed individuals has a slow decrease, resulting in low infection rate and more control of the pandemic.
On the contrary, applying late the total lockdown, as it is illustrated in figure 5.2 can lead to an uncontrolled evolution of the virus. In fact, during the second experiments the number of exposed people increase rapidly, especially at the end when they are around 300 individuals. Thus, it easy to forecast an even greater contagion in the next days with that high number of exposed at the end. Moreover, symptomatic agents never stop to increase and asymptomatics, reaches more than 100 units.
At this point, it is clear that the timing of application of interventions have an impact in the epidemic dynamics.

Better short-term policy

Transmission dynamics not only depends on timing of the policy application, but also on the typology. This paragraph shows the **total lockdown** efficacy respect to the partial one.
Thus, the chart of the last comparison 5.2, representing the total lockdown in 60 days is used. Then, a new experiment of the same duration, but under less binding restrictions, has been made to make possible a compare. In detail, it shows how the pandemic evolves under a **partial lockdown** on **pubs** and **gym** implemented after 30 days of no policies applied, see figure 5.3.

Figure 5.3: No policy for 30 days, then partial lockdown is introduced for 30 days



Final percentages on total population: **Exposed** 1.34%, **Symptomatic** 0.28%, **Aymptomatic** 0.64%, **Death** 0.04%, **Recovered** 0.26%

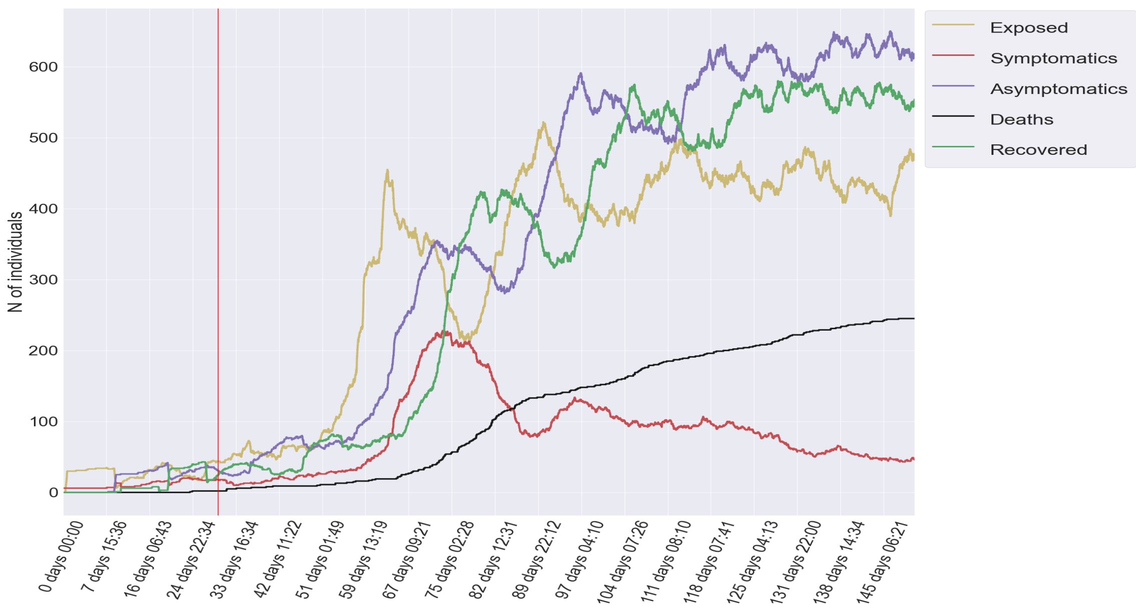
The two different charts help understand that the partial lockdown is a more dangerous policy to apply in terms of spreading the virus. For instance, exposed people exceed 500, almost double respect to the first graph.

Therefore, as it was expected, **total lockdown** influences heavily the epidemic dynamics because it change drastically the way the agent build their personal **contact network** and also their behaviour.
On the contrary, **partial lockdown** on pubs and gyms has a less impact. This may be due to the fact that such a policy still allows contacts in workplaces, which are among the places of greatest transmission of the disease.
However, even if not considered in the model, applying very strict policy for long time can influence the economic system and also the mental health of humans.

Better long-term policy

On the long term of 150 days, is possible to evaluate more interesting scenarios, which involve also pharmaceutical interventions such as the **vaccination policy**. As described in the relevant chapters, vaccines have a huge impact on the dynamics of transmission, without changing the behavior and contact networks of each agent like NPIs do.
Three experiments have been conducted to analyze the best policy on long term (150 days). In case of vaccines, the same experiment is plotted twice, one show numbers for **NO VAX** people, the other for people with at least one dose.
These comparisons highlight the power of pharmaceutical interventions, which greatly reduce the contagion and save thousands of lives.
For the purpose, figure 5.4 was used as worst case scenario to analyze what could be happen without the introduction of vaccines, and surviving only with total lockdown applied.

Figure 5.4: No policy for 30 days, then total lockdown is introduced for 120 days

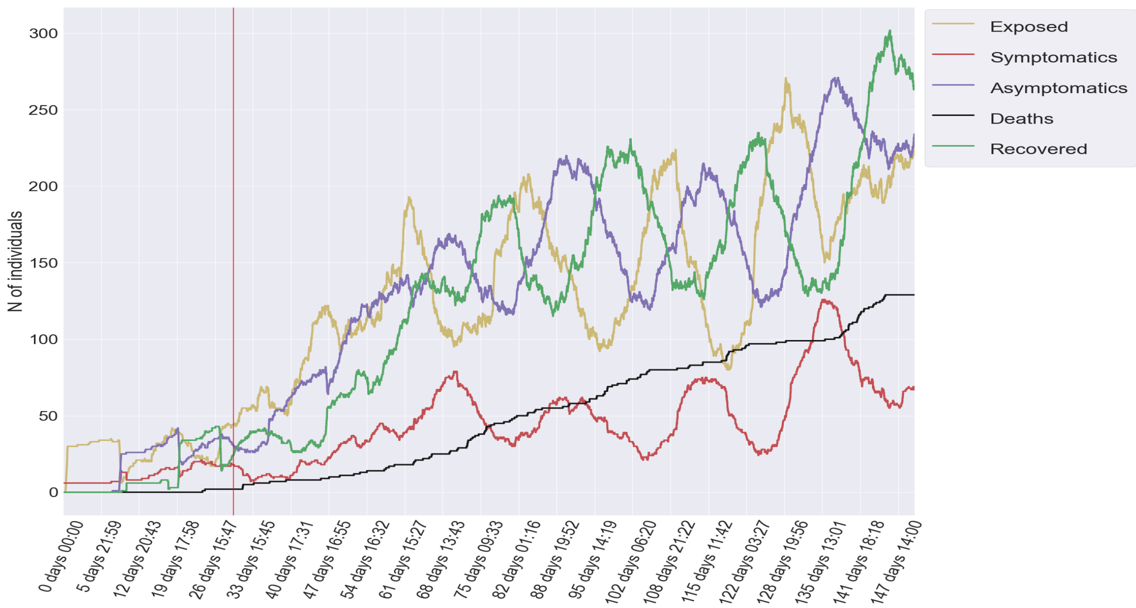


Final percentages on total population: **Exposed** 1.18%, **Symptomatic** 0.12%, **Aymptomatic** 1.55%, **Death** 0.62%, **Recovered** 1.39%

The application of **total lockdown** on long term slow down the increase of the virus spread after near 100 days since its application. Furthermore, it generates an evident

decrease of symptomatic people, who are the ones who risk the most.
However, curves' trends present high values that are reached only in this "what if" scenario, resulting the worst in terms of virus spread. Precisely, to make a valid comparison with total lockdown scenario, charts 5.5 and 5.6 show NO VAX people status during the vaccination policy and during a combo of vaccines and total lockdown (applied at the same moment).

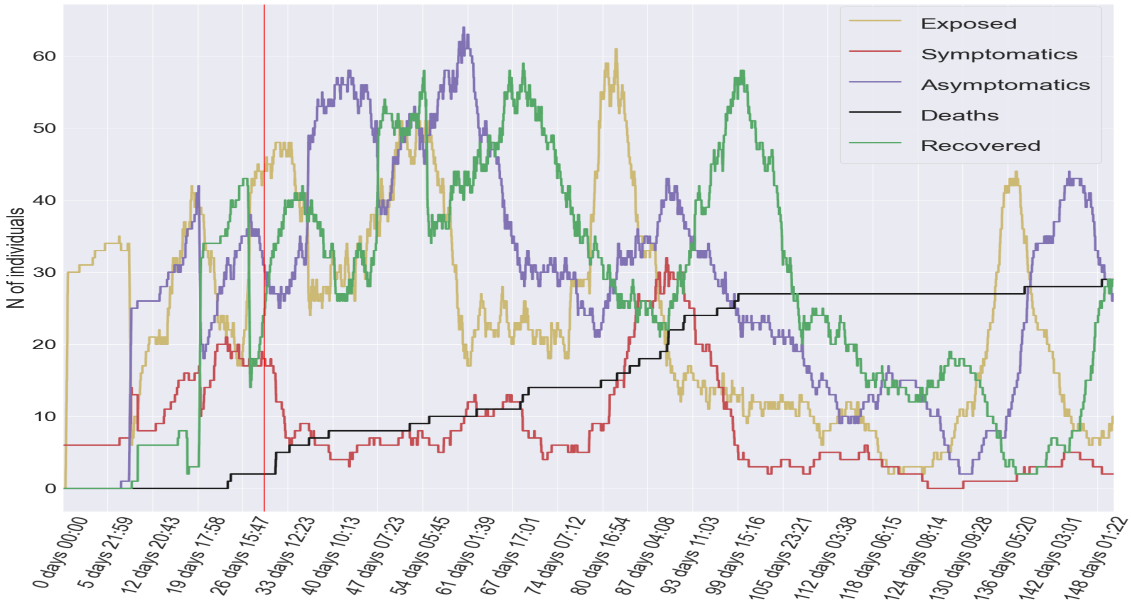
Figure 5.5: No policy for 30 days, then vaccination policy is introduced for 120 days, NO VAX graph



Final percentages on total population: **Exposed** 0.55%, **Symptomatic** 0.17%, **Aymptomatic** 0.59%, **Death** 0.32%, **Recovered** 0.66%

With only the vaccination campaign in progress, the contagion among NO VAXs is roughly halved respect to scenario 5.4. This is due to the effect of new type of agents involved in the simulation, the vaccinated people. They get infected with lower probability and heavily reduce the amount of potentially infected people around ones without protections.
Another peculiar evidence of graph 5.5 is that the contagion increase slowly according to the vaccine efficacy duration, which slow down in time, as it was described in the related chapter.
Figure 5.6 outlines an ideal case in which the contagion is controlled and kept under low values (near 60). After 100 days symptomatic people tends to zero and deaths don't increase for at least 20 days.
This can be due to the fact that agents not vaccinated, which are the less social responsible too, have rules to respect. Additionally, they also suffer the effect of vaccines.
The combo of both lockdown and vaccines, can be also evaluated for vaccinated people, who necessarily are impacted by the introduction of such a strict policy, like the total lockdown. In fact, as it is illustrated in graphs 5.7 and 5.8, there is a big difference in numbers among involved agents.
In particular, considering each maximum value of each status during the entire time, it

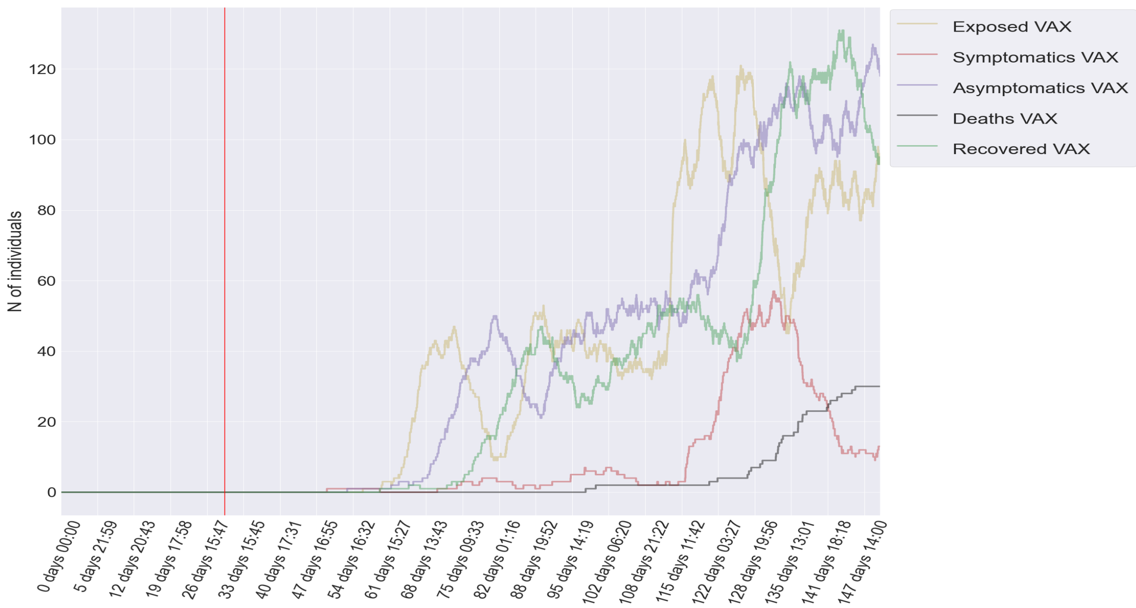
Figure 5.6: No policy for 30 days, then total lockdown and vaccination policy are introduced for 120 days, NO VAX graph



Final percentages on total population: **Exposed** 0.02%, **Symptomatic** 0.01%, **Aymptomatic** 0.07%, **Death** 0.07%, **Recovered** 0.07%

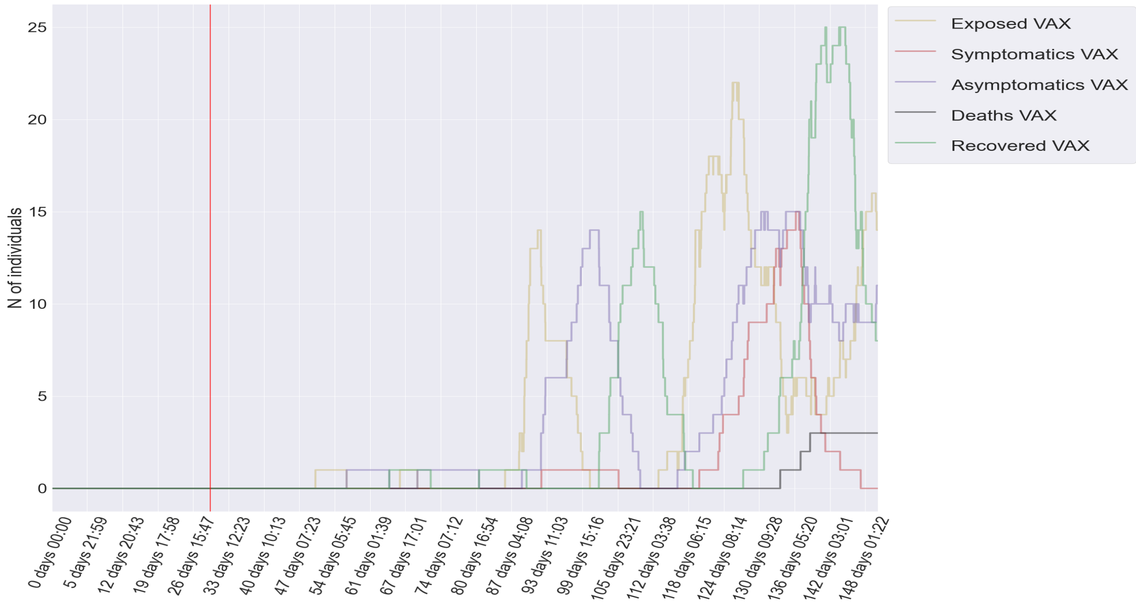
can be seen that in the first scenario there are values four times greater than the second one. Therefore, having low infected and vaccinate people among the total population, benefits also the not vaccinated yet, as it was just explained before.

Figure 5.7: No policy for 30 days, then vaccination policy is introduced for 120 days, VAX graph



Final percentages on total population: **Exposed** 0.24%, **Symptomatic** 0.03%, **Aymptomatic** 0.3%, **Death** 0.08%, **Recovered** 0.24%

Figure 5.8: No policy for 30 days, then total lockdown and vaccination policy are introduced for 120 days, VAX graph



Final percentages on total population: **Exposed** 0.04%, **Symptomatic** 0.001%, **Aymptomatic** 0.03%, **Death** 0.01%, **Recovered** 0.02%

In conclusion, the best policy to apply in terms of contagion control and without considering other human aspects, like economy or social consequences, is the combination of vaccines and total lockdown. This scenario control the virus and keep the pandemic dynamics under low thresholds which are reasonable and acceptable, in respect on what happen in reality.

5.2 Turin Scenario

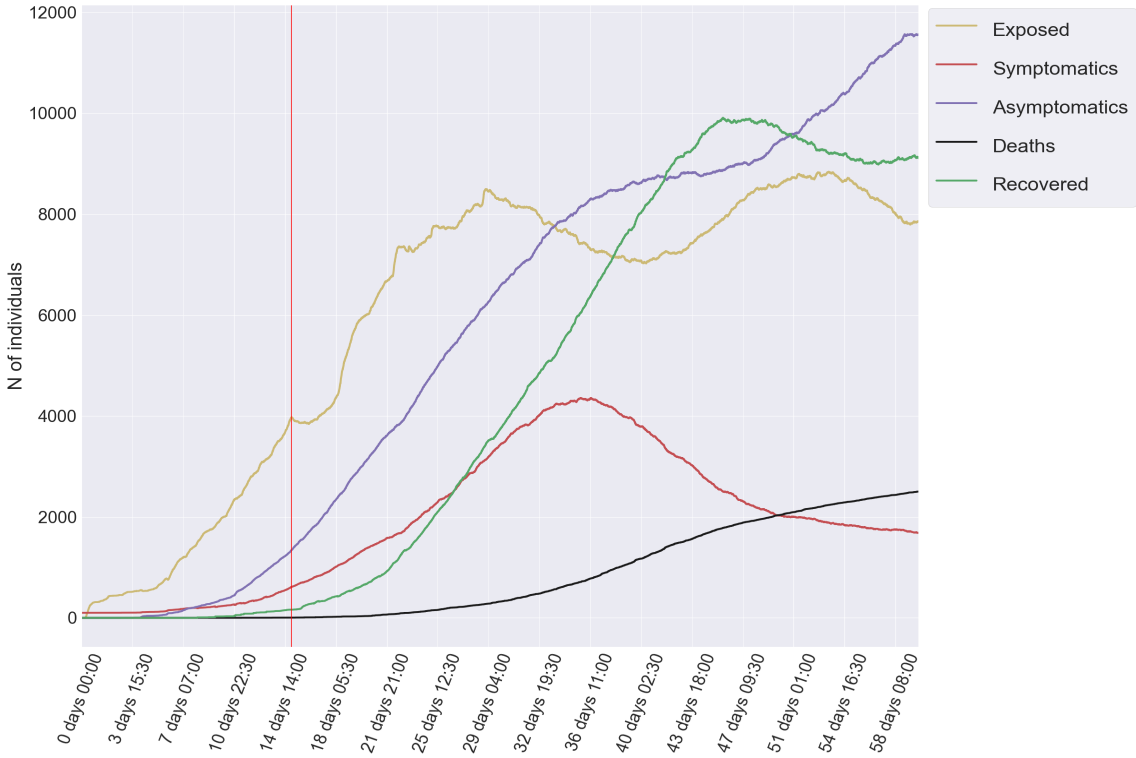
Turin environment is presented in this section. The same type of experiments have been conducted in a very large map populated by 800,000 agents, 20 times grater than the last scenario.
For this use case, the model has been simulated different time because factors such as the size of the map, its structure and above all the number of agents considerably increase the randomness of the simulations. However, in the end, reasonable results were reached and they are similarly comparable with the previous ones and to the official data.

Policy timing on short-term

Timing was also evaluated for this set, graphs 5.9 and 5.10 show small improvements in terms of the number of exposed, which start a decrease before the delayed version of the experiment. It's important to remember that the exposed status is the initial phase of the infection cycle; so, it can be see as a measure of the level of contagion spreading process.

Looking at the final percentages, they also suggest that the timing of policy application could help in contain the pandemic.

Figure 5.9: No policy for 15 days, then total lockdown 45 days



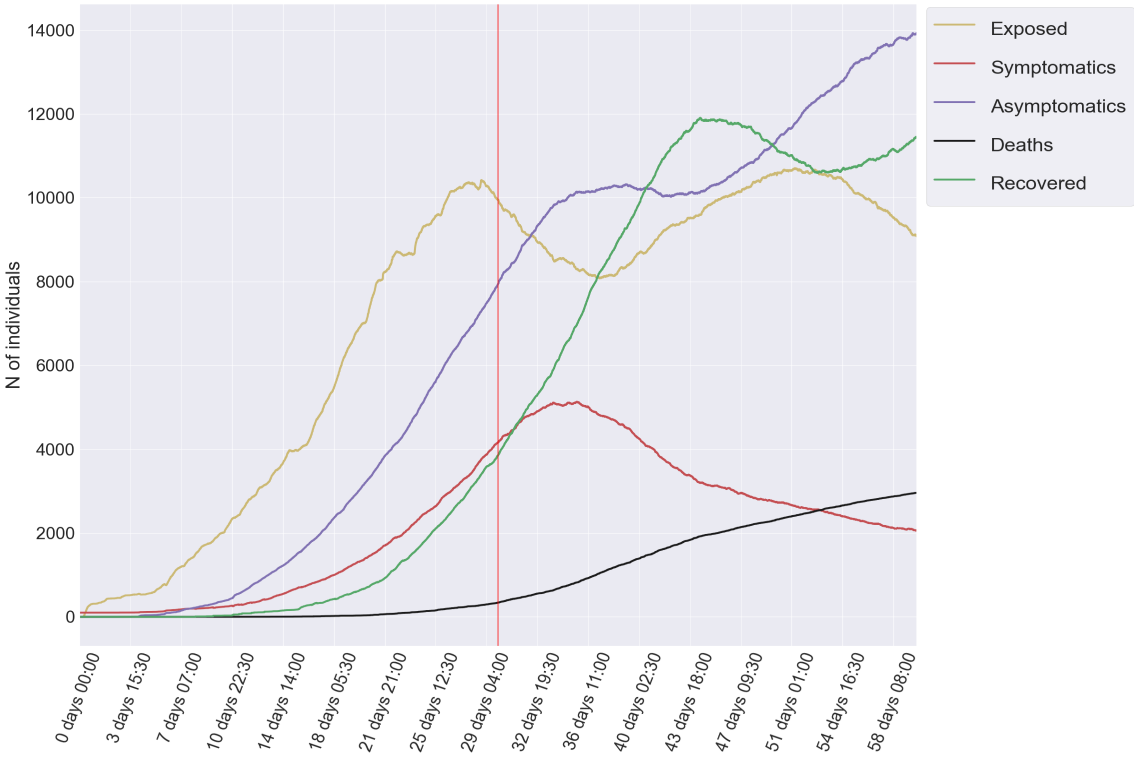
Final percentages on total population: **Exposed** 0.98%, **Symptomatic** 0.19%, **Aymptomatic** 1.45%, **Death** 0.31%, **Recovered** 1.14%

Asymptomatic people are reduced, in fact its trend is kept under "12000" threshold.
The curve of deaths seem apparently the same, but analysing the final cumulative number of deaths, it is clear that intervening at the right time can save many lives. In particular, the first case finishes with 2,486 deaths, while the second one reach 3,067 dead agents after 60 days.
In conclusion, the numbers for exposed, asymptomatic and recovered have the same path for both the charts, but in the first case are slided down by "2000" factor.

Better short-term policy

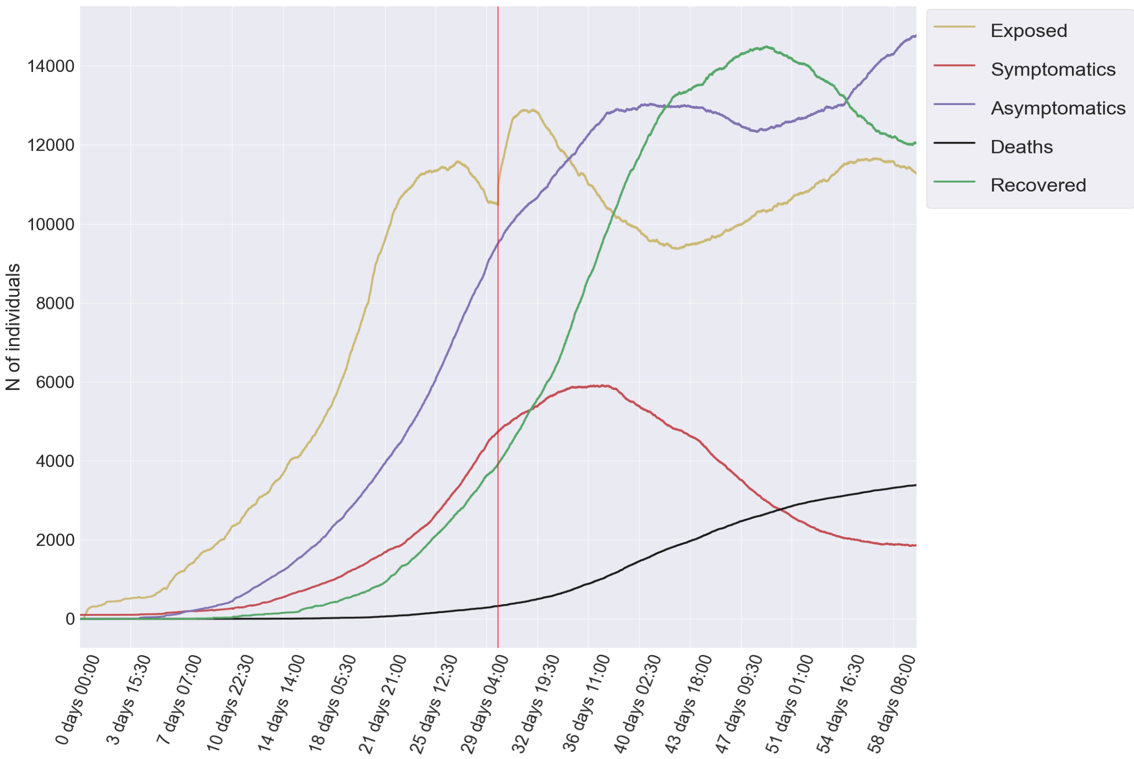
During short-term tests on this large map, it has been noted that the model does not highlight big differences, but it start to show them in long simulation time. Therefore, the difference between **partial** and **total lockdown** in the Turin context can be again evaluated in terms of deaths and number of exposed. Figure 5.11 is ten compared with 5.10 of the previous paragraph.

Figure 5.10: No policy for 30 days, then total lockdown 30 days



Final percentages on total population: **Exposed** 1.20%, **Symptomatic** 0.26%, **Aymptomatic** 1.75%, **Death** 0.42%, **Recovered** 1.44%

Figure 5.11: No policy for 30 days, then partial lockdown 30 days



Final percentages on total population: **Exposed** 1.52%, **Symptomatic** 0.3%, **Aymptomatic** 1.86%, **Death** 0.50%, **Recovered** 1.51%

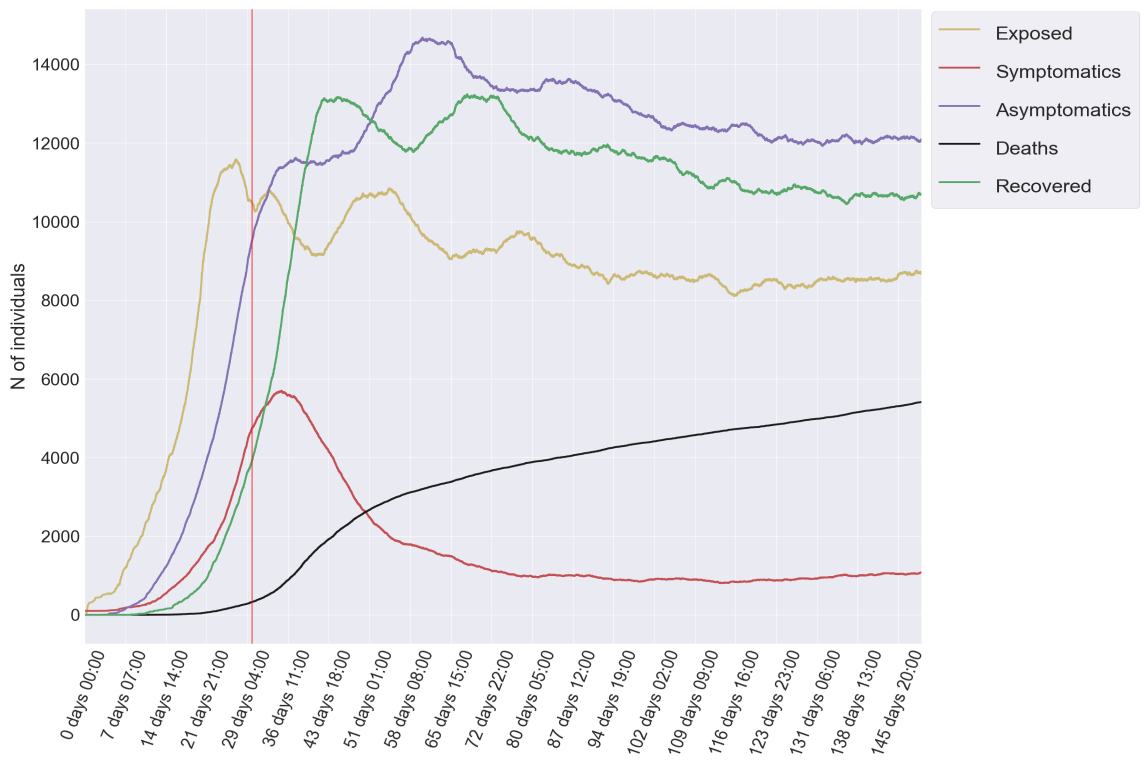
As it is illustrated in the related chart, total lockdown policy keep for long the number of exposed under the 10,000 threshold, while in the partial one, the curve tends often exceed it.

Furthermore, the deaths are three hundred more than the numbers already mentioned for the total lockdown, reaching 3,374.

Better long-term policy

This paragraph analyzes three type of interventions on the total duration of 150 days. Like the previous scenario, also in the Turin context was used the vaccination policy, in order to show its benefits to the society. Charts 5.12, 5.13 and 5.14 present the population status trends under respectively, **total lockdown**, **vaccination policy** and both applied together. One more time the best way to contain the spread is by using the last combination of policies.

Figure 5.12: No policy for 30 days, then total lockdown 120 days



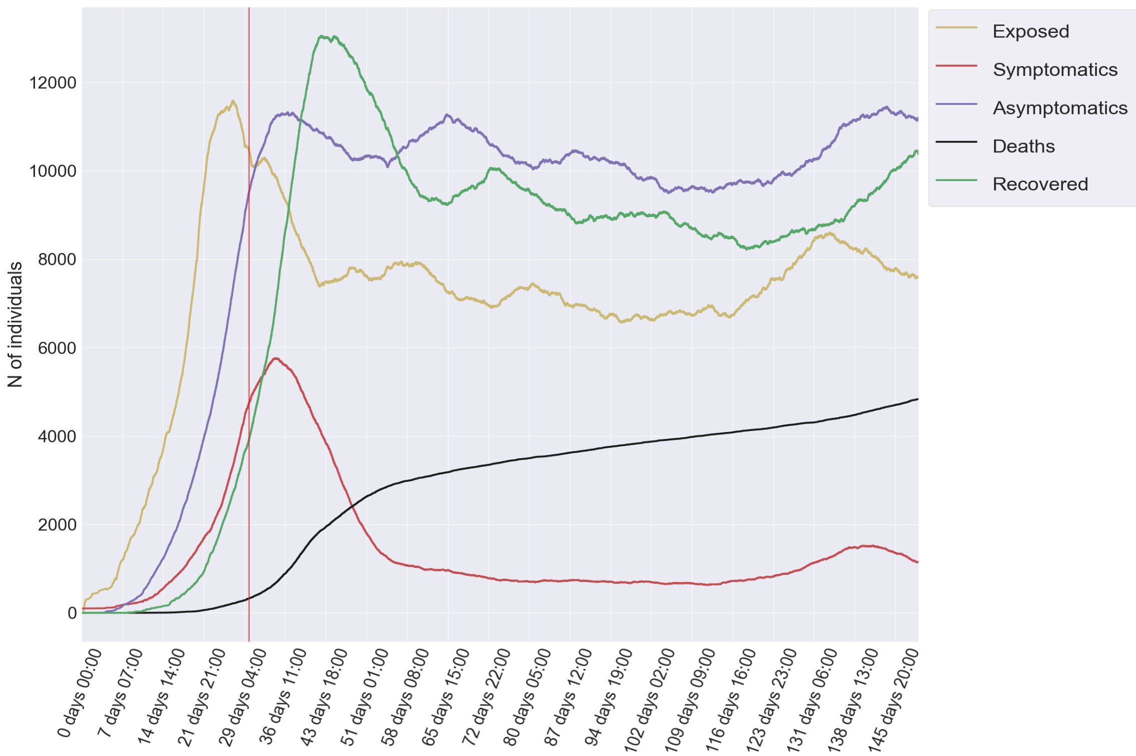
Final percentages on total population: **Exposed** 1.09%, **Symptomatic** 0.14%, **Aymptomatic** 1.52%, **Death** 0.68%, **Recovered** 1.39%

The first graph is used again as worst case, but it show a constant slow decrease of the contagion. Together with exposed, also symptomatic and asymptomatic numbers tends to reduce their values after near 80 days since the beginning.

This scenario can only be placed side by side with the second graph because both have similar values. In the second chart 5.13, representing a scenario with only the vaccination campaign applied, are displayed curves for NO VAX people. These curves have similar trend of the previous one, but they remains under lower threshold. This is due to the fact

that from NOVAX agents side there is no policy applied, and therefore their networks and their behaviors are not compromised.
However the reduced numbers are caused by vaccinated people around them, so what occurred in the reduced scenario also occurs here, but less incisively.

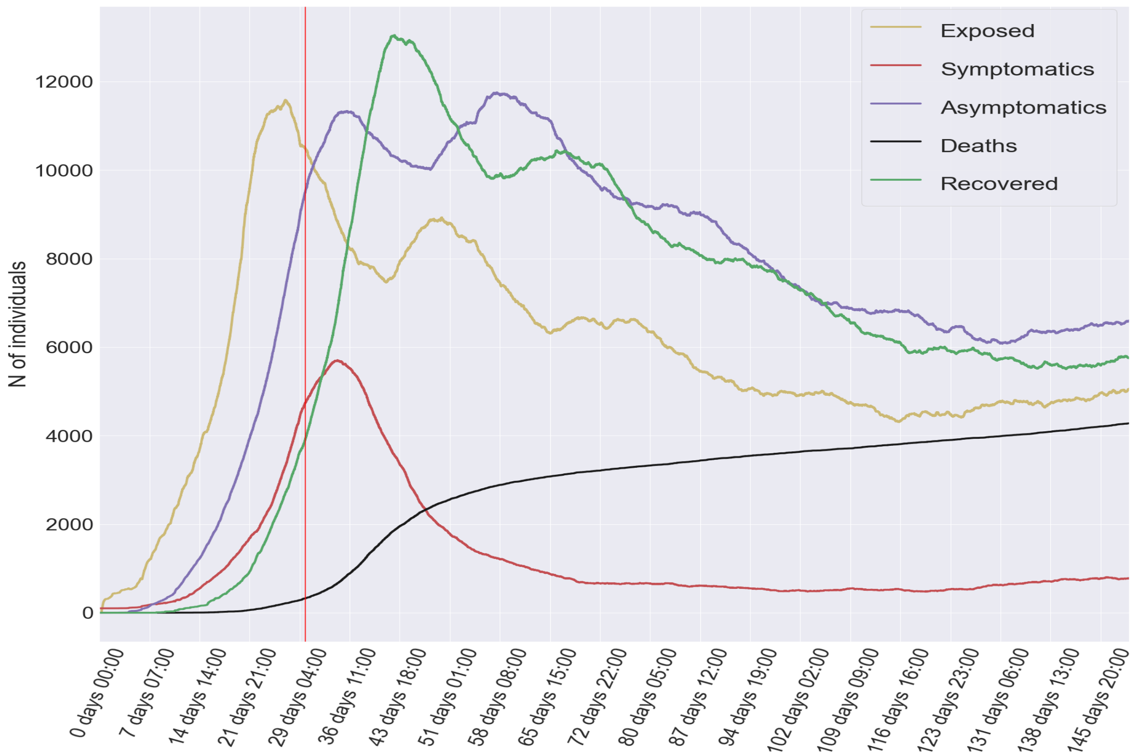
Figure 5.13: No policy for 30 days, then vaccination policy 120 days



Final percentages on total population: **Exposed** 0.89%, **Symptomatic** 0.10%, **Aymptomatic** 1.41%, **Death** 0.6%, **Recovered** 1.31%

The best "what if" scenario is illustrated in figure 5.14, where it is analyzed the status of NOVAX agents under the just mentioned combination of policies. With respect to the other cases, exposed, asymptomatic and recovered trends decrease rapidly after 60 days and reach the "6000" threshold and remain constant for other 50 days.
Consequently also deaths are heavily reduced, comparing them with the other experiments. In fact, the total lockdown scenario ends with 5,513 deaths, the second one with 4,835 while the best one have at the end 4,180 dead agents.

Figure 5.14: No policy for 30 days, then total lockdown and vaccination policy 120 days



Final percentages on total population: **Exposed** 0.51%, **Symptomatic** 0.05%, **Aymptomatic** 0.83%, **Death** 0.45%, **Recovered** 0.72%

In conclusion, first and second graphs have respectively near one thousand and six hundred of deaths more than the third one, and this is enough to understand that vaccines are necessary to win the battle with such a pandemic. Therefore, the mentioned number of lives saved concerns people without a dose of the vaccine and this allows to understand that they are the subjects who are most at risk.

Chapter 6

Conclusions and Further Developments

The Covid-19 pandemic presented humanity with a great challenge to face.
Since its outbreak in Wuhan, China in December 2019, public health experts, policymakers and governments started to apply different NPI (Not-Pharmaceutical Intervention) to contain the virus spread.
During these years, tools like ABM (Agent-based Model) become very important to evaluate the various strategies to apply at a specific time. Thus, they allow to simulate pandemic scenarios with different level of detail.
This study proposes the development of an agent-based model, which let the end user to simulate the outbreak of a communicable disease, such as Covid-19, in an urban area where different activities take place during a daily citizens' routine.
It is an open and extensible multi-layer model, where it is possible to visualize in real time the virus spread among agents that move across the environment.
This model leverages on the popular game engine Unity 3D and exploits one of its new feature: Unity DOTS (Data-Oriented Technology Stack), a new way of enhancing code performance. Thanks to it, it was possible to insert near one million of agents in a simulation, giving the possibility to reproduce real scenario.
In fact, the model was parameterized and tested for the city of Turin, where a scaled representation of the city and real parameters concerning the population were used for the experiments.
These tests are executed under different intervention, such as total or partial lockdown and vaccination policy. After evaluation of the results, it can be said that non-pharmaceutical interventions help in keeping constant the virus spread. Instead, vaccines are crucial in reduce the infected people, and moreover the victims of the disease. The results are satisfactory and can be nearly compared to what happen in reality during these year according to official statistics coming from daily screenings for Piedmont region [45].

Considering the power of Unity engine, it is relatively convenient and easy for developers to extend the simulation's functionality and features, thus increasing the complexity of simulations to make them more realistic.
In fact, possible future work could be making the application more "user-friendly", in

order to better control and understand the state of the simulation; such as run time adjustable simulation speed/time scale, visual controls for saving/loading the state of the simulation.
Additionally, it can be implemented social and economic consequences of a particular policy application according to real data.
Moreover, new type of policy such as the green pass to access to some destination can be developed. Also add new variants of the virus with more or less infectiousness can be introduced.
Furthermore, new mechanics for agent's movement can be added, so the implementation of a transportation system, focusing primarily on public transport
These are some advices that could enhance and making the model more accurate in reproducing real scenario. Fortunately, this model is easy to extend with more features once a mastery of Unity ECS paradigm has been achieved.

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