A Multi-Agent System for Simulating the Spread of a Contagious Disease

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Abstract

Recent events concerning global health risks have made truly evident the importance of advanced strategies and tools to monitor and prevent the spread of new and unpredictable diseases. COVID-19 showed the world that there are many factors that come into play when facing a viral threat, such as politics, social and economic aspects. Taking those into account when trying to deal with such events can make a huge difference in the efficacy and efficiency of the responses to the viruses. In this paper, we propose the use of a Multi-Agent system that extends the previous multi-agent-based approaches by adding a whole new set of features to control the outbreak during the simulation in order to dynamically verify how the government strategies can impact the disease spread.

Keywords

Simulation, Multi-agent systems, Agent-based modeling

1. Introduction

The simulation of an infectious disease spread is complex, there are multiple factors to take into account and it is quite difficult to model all the interactions that occur between them. Some examples of approach to this problem are the mean-field type models [1], the differential equation models [2] and the cellular automata theory [3, 4]. But those do not consider important aspects such as the spatial and temporal variables that describe the setting of the outbreak [5].

Agent-based modeling (ABM) is able to cover effectively all these topics since, for instance, an agent can be easily used to model different categories of individuals constituting the social structure of the population considered, each one with his own behavior, and his movements in a map during time [6]. The model proposed by [5] took into account all those aspects but lacks of features (depending on the government action and on social factors) for managing the disease spread dynamically.

For this reason we developed [1] an ABM simulation, based on the work of [5], enriched with some social, economical and political factors which happened to be highly relevant during the COVID-19 outbreak.

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[1]The simulation was developed during the lockdown in the midst of the COVID-19 outbreak as a project work for the course on Multi-Agent Systems held by Prof. Berardina De Carolis

The human population, modelled as agents, behaves and interacts in a randomly generated urban setting, where the places with higher risk of contagion are considered. We included households, hospitals, public places, the transportation system, businesses and mass gatherings.

In our simulation humans and businesses dynamically change their behaviour depending on the measures and the restrictions enacted by the local government aimed at slowing down the spread of the disease. In order to simulate a more human behaviour, we also admitted the possibility of reckless actions.

The effectiveness of the government strategies can also be evaluated by monitoring the response of the healthcare system, which can get overwhelmed with tragic consequences on the population.

1.1. Related works

Starting from the early 20th century, even if the first contributions in mathematical modelling of spread of disease were developed by Daniel Bernoulli in 1760 [7], different approaches have been proposed to tackle the complex problem of simulation and prediction of outbreaks such as: the ordinary differential equation model, the discrete differential equation model, the impulsive differential equation model, the differential equation model with time delay, the finite equation theory, the matrix theory, the bifurcation theory, the K-order monotone system theory, the central manifold theory, the Lasalle invariant principle, etc… [8] The models proposed through time can be organized as follows [9]:

Deterministic

In a deterministic mathematical model every individual belongs to a different category, associated with a specific stage of the disease. The model is thus simulated through differential equations because the transition between disease stages can mathematically be represented as derivatives and it's differentiable with respect to time. So, the whole outbreak process can be considered as deterministic, meaning that every step in the simulation can be calculated considering exclusively the previous simulation's step [9].

Stochastic

Stochastic models simulate the possible outcomes of the outbreak considering probability distributions depending on different random variation of variables with respect to time. Those models rely on the probabilistic variations of the disease model variables such as risk of exposure, disease and other illness related events [9].

Some of the most used mathematical model for the simulation of an outbreak are the so called Compartment (or State) Models; those are model in which there's a division in categories between every individual [6].

A clear and simple example of this class of models is the Susceptible-Infected-Recovered (SIR) one [10] in which the whole population can be organized in those three different states. Every individual who gets infected moves from the state Susceptible to the Infected one, and during a fixed amount of time he can infect other Susceptible individuals. After this period, he moves to the Recovered state and, if the immune hypothesis is valid, he can not be infected again [6].

This kind of model has evolved through time getting more complex in relation to the disease considered and the setting in which the simulation holds; for instance, some models take in account the possibility of vaccination and pharmaceutical treatment of the population or, eventually, the measures of quarantine and isolation [6].

More complex models are, for example, the SEQIJR (Susceptible-Exposed-Quarantine-Infective-Isolation-Recovered) model, the SEIRP (Susceptible-Exposed-Infectious-Recovered-Persevered) model and the SLIRDS (Susceptible-Latent-Infected-Recovered-Dead-Susceptible) model [8].

Once the mathematical model is set, an often considered approach to represent it is the Equation-Based Modeling (EBM) in which the relationships among the variables and the states of the simulation are modelled through equations differentiable with respect to time [11]. The SIR model can be formulated with the following equations [12]:

$$\begin{aligned} \frac{dS}{dt} &= -\alpha SI \\ \frac{dI}{dt} &= \alpha SI - \beta I \\ \frac{dR}{dt} &= \beta I \\ S + I - R &= M \end{aligned}$$

where, α is the global transmission rate, β is the recovery (or death) rate, M is the total number of the whole population, $S = S(t)$, $I = I(t)$ and $R = R(t)$ are, respectively, the number of susceptible individuals, the number of infected individuals and the number of recovered individuals at time t [6].

Usually EBM systems are effective to simulate scenarios in which the outbreak can be observed as a mathematical, self-centered event. When this approach fails, other perspectives must be considered. In the ABM, the outbreak is the result of each individual's behaviour and actions that take place in the simulation. This approach allows a better understanding and representation of system's variables such as heterogeneity across individuals, geographical localization and distribution, different forms of interaction between individuals and so on [6]. But, inevitably, it has higher computational and cognitive costs.

These are some other examples of the recent approaches to epidemic spread modelling [6]:

- *Agent-Based Modeling and Simulation of Influenza*:
  In this simulation of influenza [13], the setting is a common Chinese city with a dynamic contact network where every place belongs to one of four categories: workplace, household, place of entertainment and school. Every individual in the simulation lives in a sub-location called mixing group and interacts with other individuals in the same household and mixing group. The interaction types are defined normal, if it occurs in a mixing group, or random, if it occurs between different mixing groups. Every individuals can travel from his house to his assigned location and viceversa. The model has been tested on a city composed by 30000 citizens, 80% of them have been vaccinated, who live in 10252 households. A simulation package QAST verifies the impact of different restriction strategies on the simulation of infectious diseases. The experiment showed that restriction policies can counterattack the outbreak and that agent-based models can represent better models than the mathematical one in studying large-scale population simulations [6].

- *Agent-Based Simulation on Avian Influenza in Vietnam*:
  Using a SIR compartment model [12], combined a EBM and a ABM approach to evaluate the existing restriction measures through a simulation based on the data of the avian influenza contagion. Such model takes into account a well-mixed and homogeneous poultry population where random contacts between infectious and susceptible individuals occur and where the basic reproduction number R_0 of the disease is a mathematically calculated parameter, based on the daily reported individuals' death. The experiments showed, in order to control the outbreak, a strategic campaign of culling, bio-security restriction and large-scale vaccination must been considered [6].
- *Multiagent-Based Simulation of the HIV/AIDS Spatial and Temporal Transmission among Injection Drug Users*:
  In the work [14] a model to simulate the HIV/AIDS transmission model between injecting drug users (IDUs) has been developed. It relies on the multivalent system and geographic information systems (GIS) in an urban setting during a ten years period using the Repast (REcursive Porous Agent Simulation Toolkit) Simphony 1.2 platform. Every individual interacts with other ones through randomly generated social networks, he is described by parameters like gender, education, age and geographic location, and he belongs to one of five different categories: IDU person, HIV-IDU person, HIV person, AIDS person and healthy person. Every day, an individual interacts with five to eight, out of twenty friends. Every individual can affect his friends by encouraging them, if he is healthy, to stop taking drugs or, if he is an IDU, to keep or begin using drugs. The experiment's setting is Kunming, the capital of Yunnan Province, southwest of China. Results showed that individual social influence, the percentage of needle sharing individuals and the starting number of HIV individuals have a major role in the HIV/AIDS outbreak [6].

2. Simulation

The proposed simulation [2] is written in Java and is based on JADE, a software framework for the development of intelligent agents [3].

During the simulation, it is possible to monitor the contagion curves in real-time (figure 1) and to affect the outcome of the simulation by imposing rules and restrictions such as the social distancing (figure 2).

2.1. Agent Based Model

Every individual of the simulated population is modelled through an agent. Every Individual, during daytime, simulate the human behaviour with a list of tasks, which can occur at a certain location of the map, such as staying at home or at work, or can involve a path in the map, such as moving from the supermarket location to home [5].

Thus, each agent periodically performs several possible actions based on his needs:

- going to the supermarket

[2]Simulation repository: https://github.com/h3r0n/sysag_cds
[3]JADE website: https://jade.tilab.com/

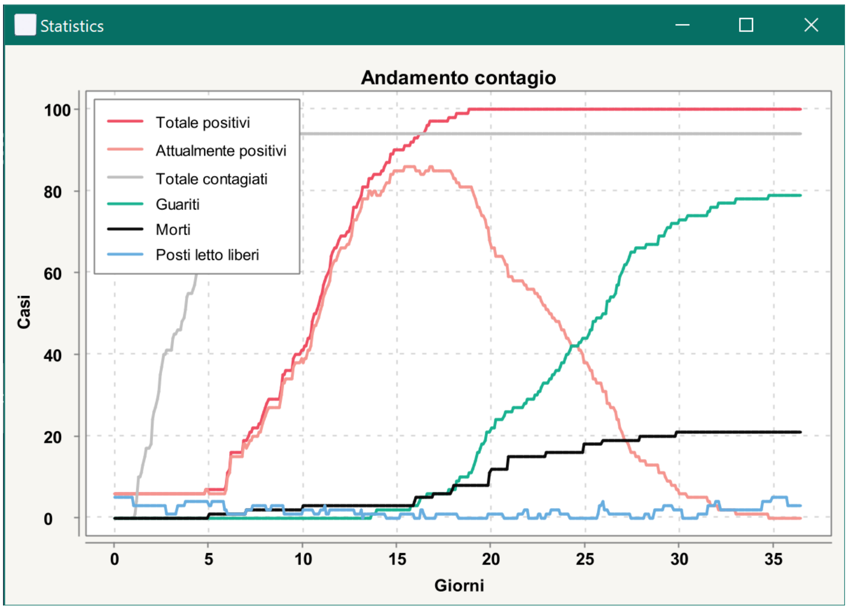

Figure 1: Real-time animated visualization of contagion curves

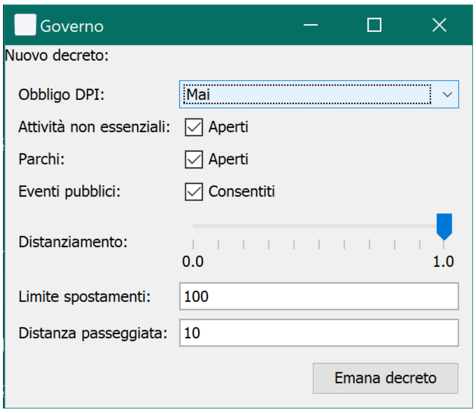

Figure 2: Government GUI

- going to the park
- going to a public event
- going to the hospital if ill
- going outside for a walk

After each action the simulated individual will return to his own house. Since the household transmissibility of diseases like COVID-19 is epidemiologically relevant and it cannot be ignored [15], residences (randomly assigned at the beginning of the simulation) can be shared by agents.

Every agent has some needs to satisfy during its daytime and through its movements it may get in contact with other groups of people who can infect it or that can be infected by it [5]. Some agents simulate workers: in addition to the already specified actions, they will also periodically go to their randomly assigned workplace.

A worldwide study conducted on April 2020 [16] analysed the erroneous conspiracy theory developed by many people during the COVID-19 pandemic: "Those who were more conspiratorial were more likely to report that the government's response was too strong, illogical and that the government hid information to people" [16]. "Some of these beliefs were potentially harmful and some could have led to public rejection of public health measures to suppress the spread of the virus" [16].

For those reasons a number of people who completely ignore the restrictions imposed by the government have been included in the simulation.

2.2. World Model

There are a multitude of factors that can hugely affect the outcome of an outbreak. Different social networks and geographical settings determine a different spreading dynamics and different types of epidemiology [5].

For this reason, in the simulation, agents' activities and tasks take place in geographical locations inside a simplified model of an urban setting in which individuals may interact with each other, this includes engaging in activities related to the daily commuting through the urban transportation network [5]. When an individual leaves a group, he travels through space and time to another destinations to accomplish a different task, which often implies interacting and joining another group of individuals [5]. This approach allows a more realistic simulation of the daily routine of each individual, and, therefore, a more accurate simulation of the population dynamics [5].

The world in which the agents act is modelled as a graph in which the nodes are buildings and the edges are the roads. The graph is randomly generated at the beginning of the simulation. Each component of the geographical world is characterized by a set of coordinates in the graph and by a density factor which describes the average distance allowed in that place, which affects the probability of the contagion.

Roads are used to model a simplified version of the urban transportation network. Therefore, in order to move from a location to another, an individual has to calculate the shortest path to his destination, which is composed by a list of roads the individual must pass through [5].

During the COVID-19 outbreak, the lockdown status imposed the suspension of a great percentage of the commercial and productive activities, which caused a dramatic crisis worldwide [17].

The presence of activities, companies, institutions can affect the spread of the disease and have been used [17] to predict the risk of contagion. Because of their importance on the spread dynamics, businesses were included in the simulation in order to support the local administrations in formulating the best approaches to reduce or restart the local activities during lockdown restrictions [17].

Each business is associated with a specific building, it can be the workplace of one or several workers and can be closed or reopened by the Government. We distinguish different kinds of business:

- supermarket
- park, which represents recreation and entertainment places
- hospital
- non strictly necessary business
- necessary business

The last two categories are needed to differentiate the businesses which are absolutely necessary for the well-being of the population, such as food factories, from those that can eventually be closed to control the outbreak.

Events of large-scale group infection [18] have been considered, they occur in circumstances in which a huge number of individuals are located in the same place, leading to a massive increase in chances to be exposed to the infection,in a short period of time. It has been estimated that 71.7% of the confirmed COVID-19 cases in Korea [18] are related to such events, which usually occur in places like factories, dormitories, schools, companies or places in which individuals are constrained in a limited physical space.

Parks represent all recreation and entertainment places and can also be casually selected as the setting of public events, attended by a large percentage of the population and may be the source of large-scale group infections.

During a pandemic the healthcare system has an higher risk to collapse because of difficulties in triaging, allocation, and a shortage of high-level care beds [19].
Thus, hospitals in the simulation have a limited number of beds, which implies that if the outbreak gets out of control and all the beds get occupied, those disease-ill individual with strong symptoms are much more likely to die due to the lack of proper care.
This allows to further evaluate the success of the Government's strategies to control the spread of the disease.

2.3. Government Model

Social distancing can be defined as "a deliberate effort instituted to stop or slow down the spread of a highly infectious or contagious diseases" [20]. In order control an outbreak, every individual must then reduce the interactions with the rest of the population,which leads in closing partially or wholly social activities specially business and transport because they may enhance social interaction and disease spread [20].

In order to control the epidemic of COVID-19, more than 10 million people in Wuhan were restricted to their home by the Chinese government. By reducing the contact rate of latent individuals, interventions such as quarantine and isolation have effectively reduced the potential peak number of COVID-19 infections and delayed the time of peak infection [21, 22].

At any time during the simulation, the user can pose as the local government and can issue and lift restrictions and social distancing measures with a simple GUI (figure 2). Several ways to try to control and eventually stop the outbreak are provided:

- close the non strictly necessary businesses
- close the parks

- forbid public events
- make the use of PPE mandatory (never, everywhere or just indoors)
- close the buildings with a low average distance between individuals
- reduce the maximum movement range to go for a walk
- reduce the maximum travel distance of every individual

The government can enact those restrictions by issuing a “decree”. After this event, all the agents simulating individuals and businesses get notified and eventually modify their behaviour.

2.4. Infection Model

Our model, based on [5], will consider a SEIR epidemic spread model where every individual (agent) of the simulation can be in one of four different states:

Susceptible
individuals who can contract the disease

Exposed
individuals who have contracted the disease and are not contagious

Infected
individuals who have contracted the disease and are contagious

Recovered
individuals who are healed from the disease and that cannot contract it anymore

The progress of the infection in an individual is then represented through the unidirectional translation between those states, starting from the Susceptible one and ending in the Recovered one, assuming that once an individual is Recovered he becomes immune to the disease.

Once the individual becomes Exposed, there is a latency period before he becomes Infected. This can be represented with a simple formula [5]:

$$I_{pi} = t_i + x_{LP}$$

Where t_i represents the moment in time where the contagion occurs and x_{LP} is the number of days necessary to become infected.

After reaching the Infected state, there is another latency period before the individual heals completely, becoming Recovered:

$$R_{pi} = I_{pi} + x_{IP}$$

Where I_{pi} represents the moment in time where the individual becomes Infected and x_{IP} is the number of days necessary to become Recovered. The translation between Susceptible to Exposed occurs when an Infected individual infects a Susceptible one. The way this happens depends on two conditions:

- The two individual must meet in the same place
- The contagion must occur

The meeting represents a violation of social distancing and is modeled as a probabilistic event. It occurs when the following formula is true:

$$randomvalue < max(infectiousDist, susceptibleDist)$$

where $infectiousDist$ and $susceptibleDist$ are the probabilities (respectively associated to the infectious individual and the susceptible one) of getting close with anyone. Those values are randomly generated every time an individual reaches any geographical location. The values cannot be lower than the density value associated to the location and cannot be higher than the maximum density allowed by the Government (unless the individual is ignoring the decrees issued by the Government).

Similarly, the Contagion event follows a probabilistic distribution and occurs if the following formula is true:

$$randomvalue < P(infectiousPPE, susceptiblePPE)$$

where P is a function depending on whether or not the infectious individual and the susceptible one are wearing personal protection equipment (PPE) like a mask, as according to the World Health Organization Writing Group, wearing a mask can prevent respiratory infectious diseases [23], [24].

This claim has been proven by several studies [24]:

- "In a large systematic review of physical interventions to control spread of infectious diseases, Jefferson et al. concluded from 67 studies that wearing masks is effective as one of the important barriers to transmission of respiratory viruses, and evidences indicate N95 respirators were non-inferior to surgical masks" [25], [24].
- "Other studies also found evidence that wearing masks can significantly reduce the risk of SARS and influenza-related diseases" [26, 27, 28], [24].
- "Aldila et al. constructed MERS determinant mathematical model and found that compared with auxiliary nursing and government publicity, wearing masks is the optimal choice for reducing the number of infections" [29], [24].
- "Barasheed et al. systematically analyzed the utilization and effectiveness of masks by integrating 12,710 samples from more than 50 countries in the world, and found that wearing masks in crowded places could reduce the risk of respiratory infections by 20%" [30], [24].
- "A study in Hong Kong found that the odds ratio (OR) value of wearing masks in public places was only 0.36, which was lower than that of living room disinfection (OR = 0.41) and frequent hand washing (OR = 0.58), indicating that wearing masks effectively restricted the community spread of SARS-CoV in Hong Kong" [31], [24].

Each individual only wears a mask if compulsory as long as he doesn't ignore the Government's dispositions.

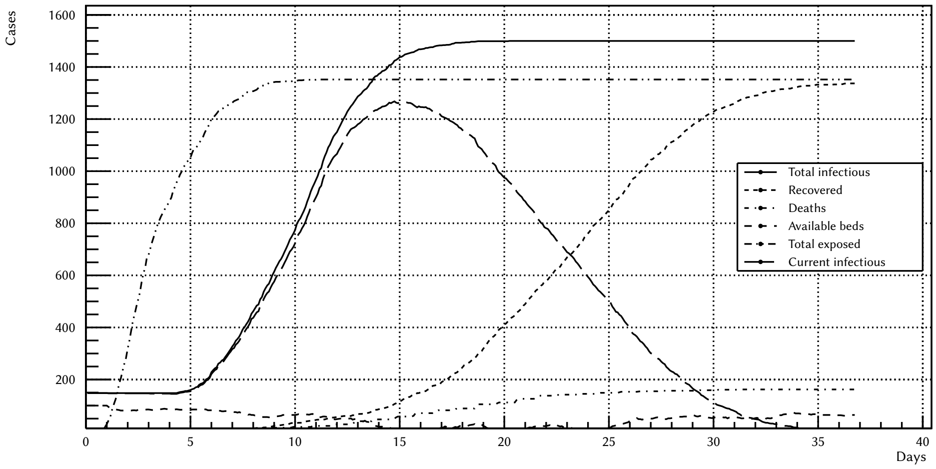

Figure 3: Scenario 1: No precautions - High number of infectious

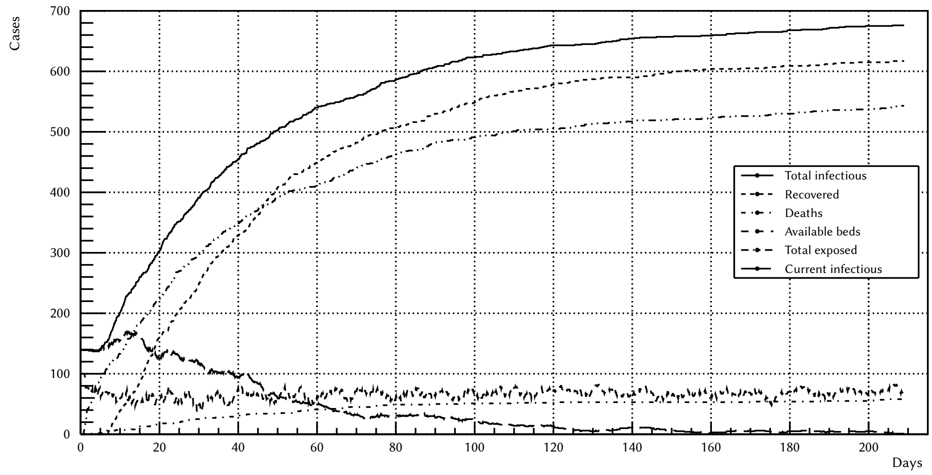

Figure 4: Scenario 2: Precautions - High number of infectious

3. Simulated Scenarios

We chose to simulate 6 different scenarios in order to verify the capabilities of the created model. In each one 1500 people are simulated, of which 20% ignore the Government's restriction and 50% are workers. The map consists of 3600 buildings with 500 businesses. Hospitals have a combined capacity of 100 beds.

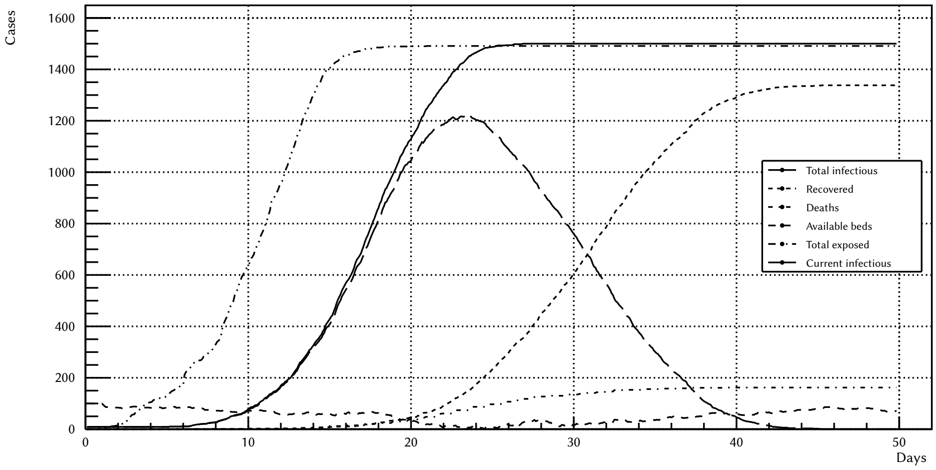

Figure 5: Scenario 3: No precautions - Low number of infectious

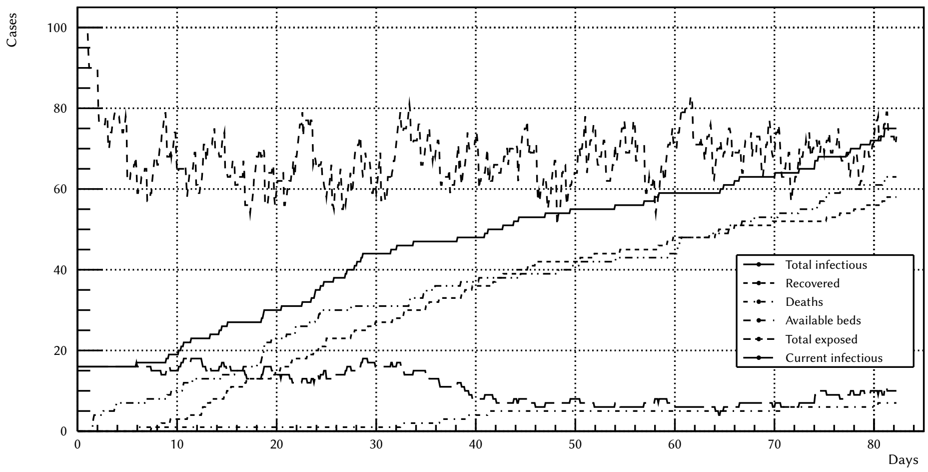

Figure 6: Scenario 4: Precautions - Low number of infectious

- *Scenario 1*: No precautions - High number of infectious
  This scenario simulates a community of 1500 people facing a large wave of contagion (10% of the population is infectious at the beginning, everyone else is susceptible) without adopting any social distancing policy.
  In this scenario, as shown in figure 3, the whole population contracts the disease in a single week and the healthcare system gets overwhelmed a few days later. As a result a

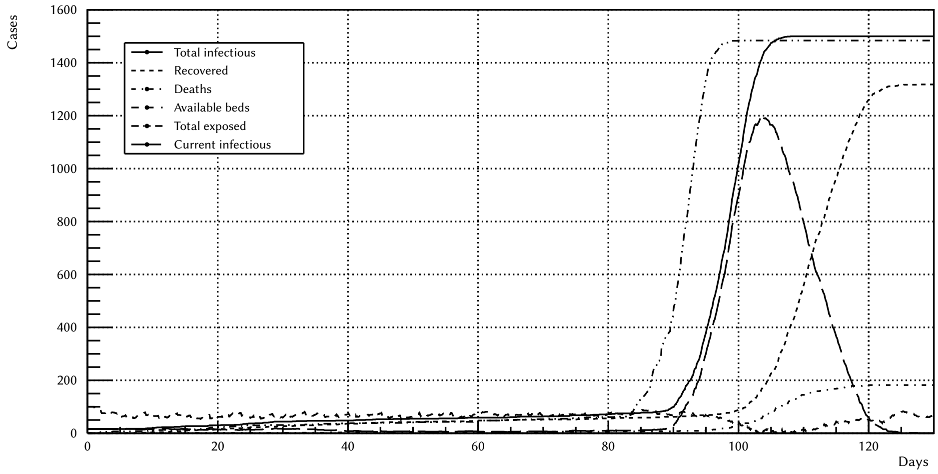

Figure 7: Scenario 5: Premature Reopening

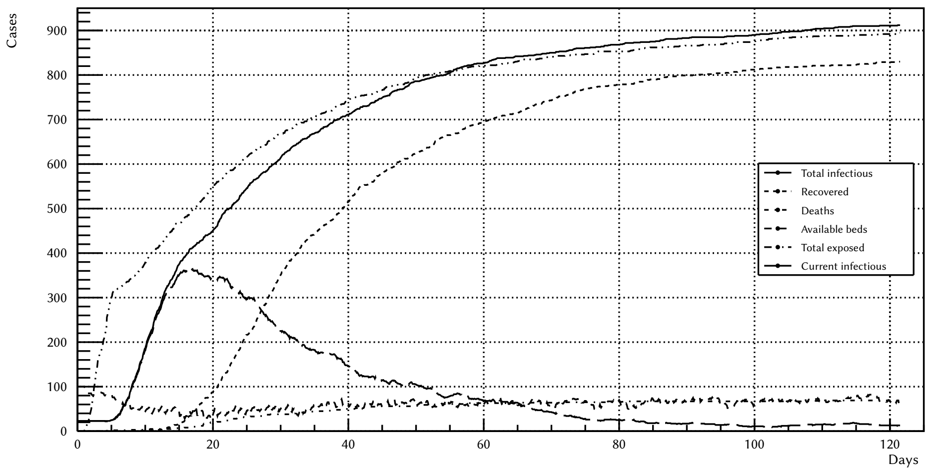

Figure 8: Scenario 6: adopting progressively stricter social distancing measures

relevant number of individuals dies due to the lack of proper care.

- *Scenario 2*: Precautions - High number of infectious
  The starting conditions of this scenario are the same of the previous one, except it simulates the adoption of restrictive social distancing policies.
  The outcome (shown in figure 4) is vastly different as the disease spreads much slower. As a result hospitals don't have to operate at over capacity and less people die.

- *Scenario 3*: No precautions - Low number of infectious
  In this scenario 1% of the population is infectious at the beginning and no social distancing policy is adopted. Despite the different starting conditions, the outcome (shown in figure 5) is close to the *Scenario 1* due to the exponential nature of the infection transmission.
- *Scenario 4*: Precautions - Low number of infectious
  The starting conditions of this scenario are the same of the previous one except it simulates the same social distancing policies adopted in *Scenario 2*.
  As shown in figure 6, the spread of the disease progresses very slowly compared to the previous scenarios, while the number of active cases slowly decreases over time.
- *Scenario 5*: Premature Reopening
  This scenario simulates the non gradual lifting of all restrictions at the end of the previous scenario. The outcome (shown in figure 7) is the same of *Scenario 1* and *3* with the whole population exposed to the disease and a large number of deaths.
- *Scenario 6*: adopting progressively stricter social distancing measures
  This scenario (shown in figure 8) is similar to *Scenario 4*, except the Government doesn't act proactively, but only gradually enacts restrictions after a spike in the number of infectious people.
  The outcome (shown in figure 8) is different because of the large share of the population who contracts the disease, but less people die (compared to *Scenario 1* and *3*) because the healthcare system doesn't get overwhelmed.

4. Conclusions and Future Work

The proposed model is able to simulate a wide range of different situations. It allows to take into account aspects often overlooked by other works, such as the response of local administrations, the capacity of the health system and the presence of local businesses. These factors, as shown in the simulated scenarios, have a not negligible importance on the spread of the disease and its effects on the population.

Even if the proposed approach is general enough to model a generic contagion setting, the examples are shown in the context of the COVID-19 disease. In this context, the contagion curves observed during the COVID-19 pandemic show a strong resemblance to the more realistic scenarios such as Scenarios 4 and 6. Especially in the case of European countries where the adoption of social distancing measures (similar to the simulated ones) allowed the local governments to control the spread of the virus.

The COVID-19 outbreak has given a new perspective on the variables which rule the outbreak response. The economic consequences of the quarantine, isolation and social distancing strategies have been far more worse than expected and every government in such situations has to make very complex choices.

Our goal with this proposed approach is to simulate the effect of such choices on the population and the public health system in order to help making such difficult choices to preserve the interests of the nation and of the population. Even though this simulator relies on a quite simple mathematical formulation, it has been able to properly reproduce the normal distribution of the disease spread curve when no restrictions were imposed while it follows a linear trend when those restrictions come into force. Those results are then matching the expectations and the events that occurred during the COVID-19 outbreak.

However there are many aspects of this tool which can be improved, such as:

- a wider geographical setting where people are able to travel between different communities
- a more heterogeneous social structure with more classes reflecting each individual's age and role
- a more diverse and complex behaviour of each agent allowed by the use of a BDI model

In the future we believe that improving those aspects, with the help of experts in the field, can provide a valid tool that can assist the administrations, before and during an outbreak, in choosing the most optimal strategies to safeguard public health and minimize the consequences of restrictions on the economy at the same time.

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