An Agent based model for the transmission and control of the COVID-19 in Dijon

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1 Introduction

The coronavirus disease (COVID-19) is a global threat with a profound impact on health and economy in the world. Realistic mathematical models are needed in order to evaluate the effects produced by the containment policies such as total or partial closure of facilities (universities, companies, shops). This goal can be reached using compartmental models with various degrees of sophistication [1, 2]. Classical mean-field models assume an homogeneous population where all the individuals are identical. Metapopulation models go one step further by introducing a spatial dimension. The entire population is split into a finite number of sub-populations with their own local epidemic model and individuals commuting patterns. More recent models integrate individuals spatial and social structure as well as the awareness evolution of the population during the epidemic [3–5]. While these models allow to understand the macroscopic behavior of an epidemic in a large population, they are not well suited to analyze the transmission dynamics in small populations with complex behavior. On the contrary, agent-based modeling allows to observe the emergence of global behavioral patterns through a set of simple rules describing the interaction among individuals with distinct characteristics [6]. In this work, an agent-based model to evaluate the spatiotemporal transmission process of the COVID-19 in Dijon is presented. Simulated agents make decisions depending on spatial patterns and infection conditions. Each agent is characterized by an individual profile defining its main social characteristics and health conditions. The proposed framework allows to perform simulations on the progress of the COVID-19 virus. It relies on collected data required for simulating the epidemic spreading (before containment, after containment, containment measure, etc.), and the geospatial data associated with its semantics and reliable information. Based on the SEIR epidemiological model, it allows to carry out simulations according to different types of scenarios, such as a more or less virulent virus, more or less strict confinement rules, and the number of Intensive care units available. Initially, the study is restricted to Dijon city center in order to reduce the size of the geospatial data and the number of agents for simulations.

2 Epidemiological model

Any individual can potentially be in one of the following states of the SEIR (Susceptible-Exposed-Infectious-Recovered) compartmental model.

- S: ”Susceptible”: The agent is healthy;
- E: ”Exposed”: The agent is incubating the virus. This state is characterized by the incubation period;
- I: ”Infectious”: The agent is contagious. We are talking about a period of infection;
- R: ”Recovered”: The agent has recovered or is removed (dead).

The infectious state period is divided into three different parts. The case ”Us” is the classic period, the patient presents the symptoms of the virus and is contagious. Case ”A” is the asymptomatic case, the patient is contagious but has no symptoms of the virus. It is, therefore, a very difficult case to identify and which can infect a large number of people. The last case, the “Ua” case, is a rarer case in the epidemiological models of other viruses. This is an intermediate case, sometimes preceding the ”Us” case. The patient begins to be contagious before the end of their incubation period. It does not then present any symptom but will develop after a noted duration $|\gamma|$ variable depending on the patient, when it passes in the ”Us” case. It is also a very dangerous condition because it can infect a large number of people before being detected. The transition rates between the various states can be defined at the individual level. Therefore, individual conditions such as age, gender, and co-morbidity can be easily integrated into the model. In the present version, global data have been used. These data can be replaced by those calculated by a laboratory wishing to use this simulation. In our case the statistics used are from [6] and [7].

3 Spatio-temporal Dynamics

Gama platform

The software used for agent simulation is the GAMA platform [8]. GAMA allows ”complete modeling and simulation” of large-scale simulations. It combines explicit multi-agent simulations with GIS data management, multi-level modeling, and the capability to implement Belief-Desire-Intention (BDI) and reactive agents. Thus, it is powerful for prototyping and the automatic simulation generator through its agent-oriented language GAML.

Geospatial data

In order to gather data from the city center, different files were collected. A Shapefile containing all of the buildings throughout Burgundy, and another file containing all of the roads were extracted from OpenStreetMap. It is from these two files that it is possible to extract data from Dijon city center.

Mobility

When the simulation starts, the agents go to work between 6 and 8 am. In the evening, they stop between 4 and 8 pm and can then go to a place of leisure. The principle is the same for those under 18, but they go to school rather than work. All these parameters can be modified by the user.

Simulation

One of the agents is infected at the beginning. Depending on their state of health, the agents have a different color. The healthy agents are yellow, those in the incubation period are orange, the symptomatic infected are red, the asymptomatic infected are red with purple borders, the hospitalized infected are red with green borders, the agents in

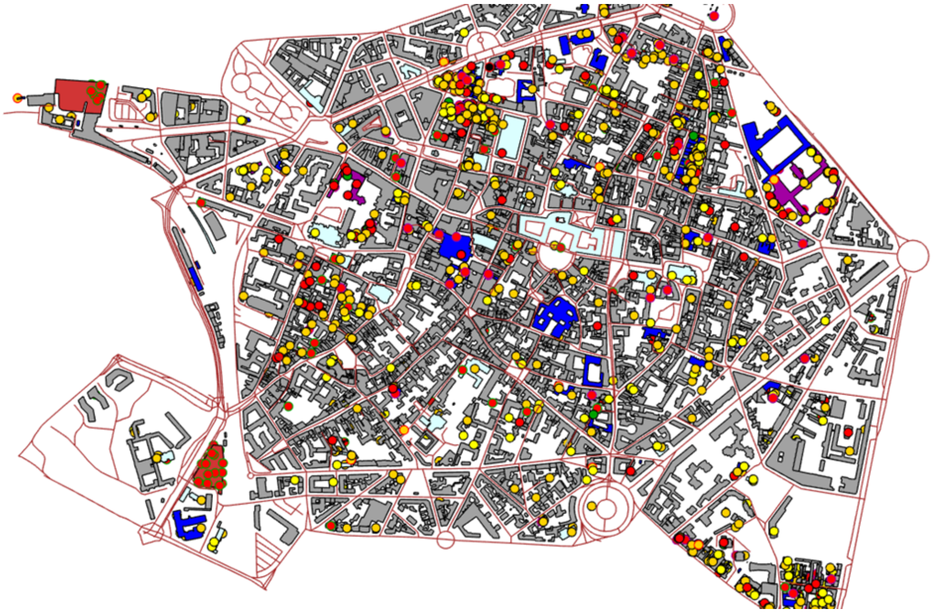
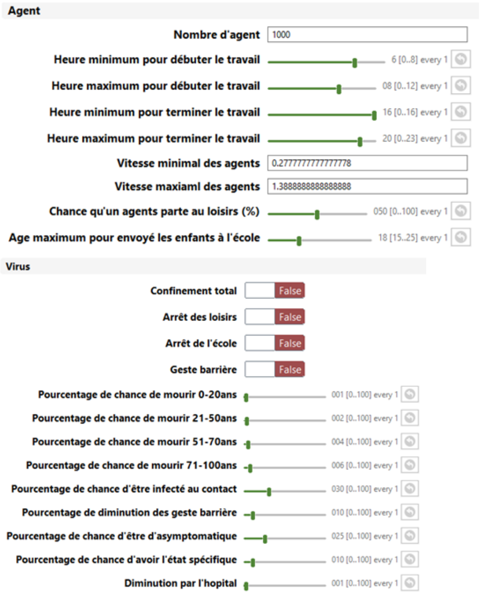


Fig. 1. Map of Dijon with the agents and their state of health



Agent

Nombre d'agent: 1000
Heure minimum pour débuter le travail: 6 [0..8] every 1
Heure maximum pour débuter le travail: 08 [0..12] every 1
Heure minimum pour terminer le travail: 16 [0..16] every 1
Heure maximum pour terminer le travail: 20 [0..23] every 1
Vitesse minimal des agents: 0.2777777777777778
Vitesse maxiaml des agents: 1.3888888888888888
Chance qu'un agents parte au loisirs (%): 050 [0..100] every 1
Age maximum pour envoyé les enfants à l'école: 18 [15..25] every 1

Virus

Confinement total: False
Arrêt des loisirs: False
Arrêt de l'école: False
Geste barrière: False
Pourcentage de chance de mourir 0-20ans: 001 [0..100] every 1
Pourcentage de chance de mourir 21-50ans: 002 [0..100] every 1
Pourcentage de chance de mourir 51-70ans: 004 [0..100] every 1
Pourcentage de chance de mourir 71-100ans: 006 [0..100] every 1
Pourcentage de chance d'être infecté au contact: 030 [0..100] every 1
Pourcentage de diminution des geste barrière: 010 [0..100] every 1
Pourcentage de chance d'être d'asymptomatique: 025 [0..100] every 1
Pourcentage de chance d'avoir l'état spécifique: 010 [0..100] every 1
Diminution par l'hopital: 001 [0..100] every 1

Fig. 2. Parameters of the agents and lockdown parameters

specific states are orange with red borders, the recovered are green and the dead are black with red borders. It is possible to change settings on the virus, as seen below. It is possible to close the schools, which means that young people stay at home. The stop of leisure time has the same effect as does the total containment. In this case, the agents stay at home and do not move. All of these parameters are aimed at reducing the spread of the virus. There is also the possibility of implementing barrier gestures that decrease the percentage of chance that the virus is transmitted.

Hospitalization of infected individuals can be activated to decrease the likelihood of dying from the virus. Parameters linked to the hospital, such as the number of beds, can be modified like the other parameters.

4 Conclusion

Preliminary results indicate that the proposed model can offer a very flexible tool for public health decision-makers to evaluate various control policies in order to minimize the expansion of infectious disease and the impact on the local economy.

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