Covid-19 Disease Simulation using GAMA platform

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Abstract— **In less than three months after its emergence in China, the Covid-19 pandemic has spread to at least 180 countries. In the absence of previous experience with this new disease, public health authorities have implemented many experiments in a short period and, in a mostly uninformed way, various combinations of interventions at different scales. These include a ban on large gatherings, closure of borders—individual and collective containment, monitoring of population movements, social tracing, social distancing, etc.**

However, as the pandemic is progressing, data are collected from various sources. On the one hand, authorities allow to make informed adjustments to the current and planned interventions and reveal them. On the other hand, an urgent need for tools and methodologies that enable fast analysis, understanding, comparison, and forecasting of the effectiveness of the responses against COVID-19 across different communities and contexts. In this perspective, computational modeling appears as invaluable leverage as it allows us to explore in silico a range of intervention strategies before the potential phase of field implementation.

Keywords— GAMA Platform, Covid-19 Simulation, Agent-based Modeling (ABM).

I. INTRODUCTION

We cannot precisely know what happens when a big pandemic appears in the world. British and United States did not pay attention to the Covid-19 [1] epidemic at the beginning of the progress. Their government may not want to care about the pandemic because they prefer economic increase. However, the result is worse, yet after several months only with nearly ten thousand people died in the UK, more than thirty thousand people died in the US.

The necessity of simulation is essential for people who do not know the actual result of the pandemic. Simulation can show a detailed picture for the audience and help them to make the best decision.

We decided to develop a simulation by programming based on agent-based frameworks. There are a lot of agent-based structures that provided functionalities such as MATSim, SUMO, AgentPolis, GAMA[2]…We choose GAMA[3], a simulation platform based on Java programming language to develop the simulation. The GAMA platform contains well different features that can be used by modelers to create an epidemic model. GAMA provided loading GIS data (shape files, OSM data,…).

II. RELATED WORKS

There are a lot of simulations that used an agent-based model to implement. Patrick [4] simulated traffic using an open-source tool (GPL), integrated into the GAMA modeling. He provided a modeling approach that is particularly well-fitted for microsimulation. Patrick et al. [6] also applied Raster and Vector's model to simulate the control of urban growth in Can Tho, Vietnam. Becu et al. [7] used a participatory simulation model to develop a simulation to foster social learning about coastal risk prevention measures with local authorities and managers. D. Philippon et al. [5] explored trade and health policies' influence on Dengue spread with an agent-based model. The research contributed to the domain by presenting a sophisticated model to deal with the shortage of data. Alexis et al. [8] designed a social simulation to support decision-making (COMOKIT) based on agent-based modeling. It is a generic model that allows gathering the maximum number of modelers and researches in epidemiology and social sciences. Hoertel et al. [9] has developed a stochastic agent-based micro-simulation model of the COVID-19 epidemic in New York City and evaluated the potential impact of quarantine duration (from 4 to 16 weeks). Rockett et al. [10] present a genome survey of SARS-CoV-2 from during the first weeks of COVID-19 activity in New South Wales (Australia). Kai et al. [11] present two models for the COVID-19 pandemic. It predicts the impact of universal face mask-wearing upon the spread of the SARS-CoV2 virus, one employing a stochastic dynamic network-based compartmental SEIR (susceptible-exposed-infectious-recovered) approach, and the other using individual ABM Monte Carlo. Gomez et al. [12] provided a general agent-based model, called INFEKTA, that combines the transmission dynamics of an infectious disease with agents (individual) that can move on a complex network of accessible places defined over a Euclidean space representing a real town or city.

III. COVID-19 SIMULATION

The scenarios for the simulation are as follows.

A. The spread of the disease

The model will be designed at the individual scale.

We use a classical 4-steps SEIR model to represent the epidemiological states of individuals. Each individual is thus in one of the following states:

- S: Susceptible, meaning that individuals can be infected.
- E: Exposed, meaning that the individual has been affected, but cannot infect other individuals.
- I: Infectious, meaning that the individual has been infected and can infect other individuals.
- R: Recovered, it means that the individual has recovered from the disease. We consider it cannot be infected anymore.

An S individual is affected by an I (with a given probability) when they are close enough (in a transmission distance) and becomes in the state E. An E will become I after a given duration of time (incubation period). I will become R after a given among of time (infectious period).

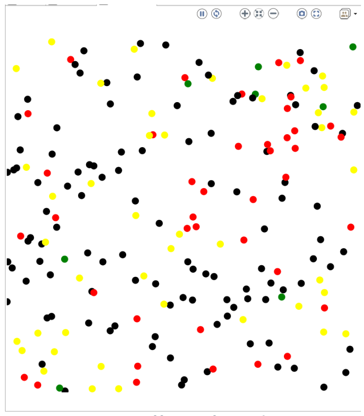


Figure 2: Effect of randomness

2. Impact of the number of individuals

We define a GUI experiment, creating 11 experiments, with the same seed value but with several individuals from 200 to 2000 (with a step of 200) and plot the evolution of the number of I individuals. (Figure 3).

3. Impact of the indicators

We define two indicators:

- The cycle of the maximum number of infected peoples.

- The duration of the epidemic (when the number of Exposed and Infected is 0).

```
//evolution of the number of I (1.2 and 1.1)
monitor "number of S" value: susceptible count(each.state = 0);
monitor "number of E" value: susceptible count (each.state = 1);
monitor "number of I" value: (susceptible count (each.state = 2 or each.state = 4) + infectious count (each.state = 2));
monitor "number of R" value: (susceptible count (each.state = 3) + infectious count (each.state = 3));
```

Figure 1: SEIR model sample code

a. Model M1.1

Implement a population of agents of species "Individuals" with an attribute for its epidemic state. They move randomly in a continuous space (cf.moving skills, wander action). At each step, an individual infects one of the S individual agents in its transmission distance (with a given probability). Individuals also execute their disease dynamics. When they are E, they become I after some steps and from I to R after another duration. This duration is different for each individual. Agents are displayed with a circle, with a color depending on their epidemic state. At the initialization phase, we create 500 individuals, and one infected in the population. Display the agents and plot the number of agents in each of the states

1. Effect of randomness

We define a GUI experiment and then create ten tests (with different seed values) and plot the evolution of the number of I individuals for each simulation. Figure 2 illustrates a sample of the mechanism.

And then, we define a batch experiment plotting the evolution of these indicators in the function of the number of peoples. Save these values in a CSV file.

b. Model M1.2. R_0

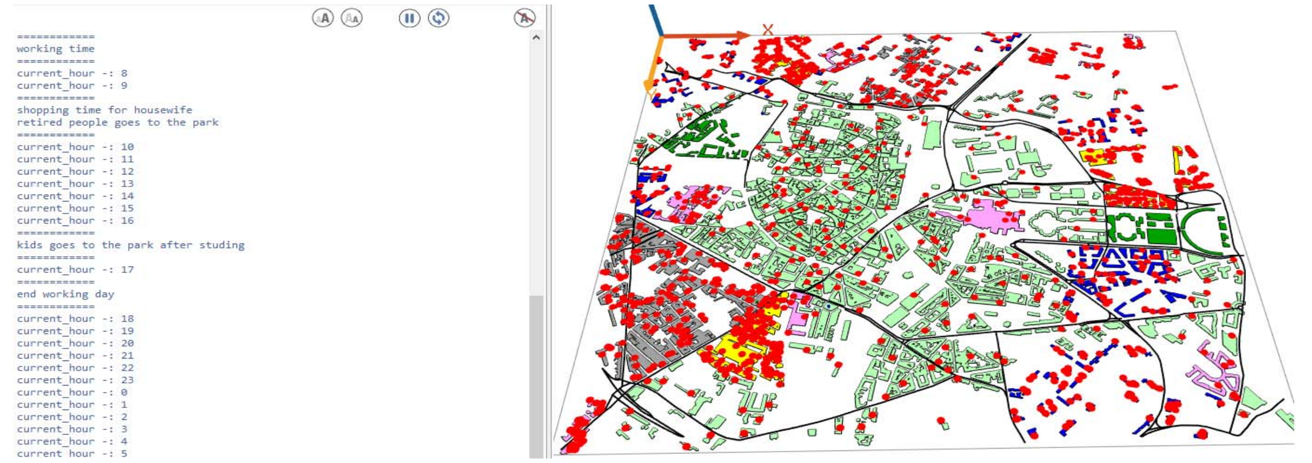


Figure 6: Realistic population sample

The R_0 value represents the number of susceptible individuals, an infected individual infects. Modify the model so that each individual computes the number of individuals it has affected.

We define a GUI experiment that plots the min, max, and average values of the R0 among the population over time. Figure 4 describes the meaning of the R_0.

```
//evolution of the number of I (1.2)
display chart {
    chart "c" type: series {
        data value: min(r0) legend: "Min" color:#red;
        data value: max(r0) legend: "Max" color:#blue;
        data value: sum(r0)/((susceptible count (each.state = 2 or each.state = 4)
            + infectious count (each.state = 2)
        ) = 0 ? 1 : (susceptible count (each.state = 2 or each.state = 4)
            + infectious count (each.state = 2)
        )) legend: "Avarage" color:#orange;
    }
}
```

Figure 4: Min, Max, and the average value of R0 chart

B. *Spread in a city with a heterogeneous population*

The objective of this second part is to implement the disease spread in a realistic city, with a mixed population. The inhabitants will have a daily plan, that will depend on their age. The simulation will be made with a 1-hour simulation step. A consequence is that we will not model the precise mobility of people on the roads: people will move instantaneously from one building to another one.

a. *Realistic city*

We use a shape file of buildings based on the Lambert Conformal Conic map. The building has types, including home, industry, office, school, shops, supermarket, coffee, restaurant, and public park and then, we display the buildings with a color depending on their type.

b. *Population*

People are initialized in a building (their home) and will go to work (in the morning) (and school building) in another structure (of type industry or office) and come back home (in the afternoon). Modify the epidemic dynamic so that an Infected individual can infect all individuals in the same building (and only these). We do the same as E1.1 regarding randomness. Figure 5 shows the detail of the sample.

c. *Realistic Population*

We want to initialize a working population: add to each sex, an age. The building's home will now contain a household (a set of agents). We make the hypothesis that each building contains only one family. We make the hypotheses on the homes (you are free to explore the internet to review these hypotheses to have more precise information): each house contains:

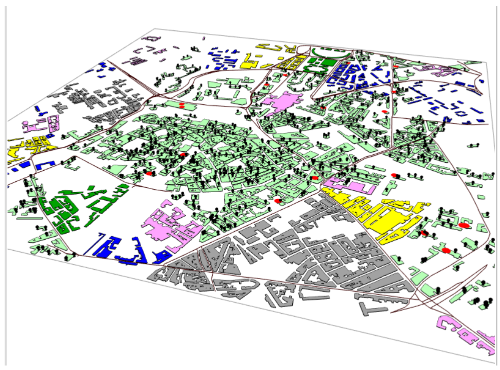


Figure 5: Spread in a city with a heterogeneous population

- One male and one female adult individuals (in an age of working, so between 23 and 55 years old).

- From 0 to 3 kids (age below 22 years olds).

- Possibly grandfather or grandmother (individuals with age higher than 56 years old, who do not work to office or industry).

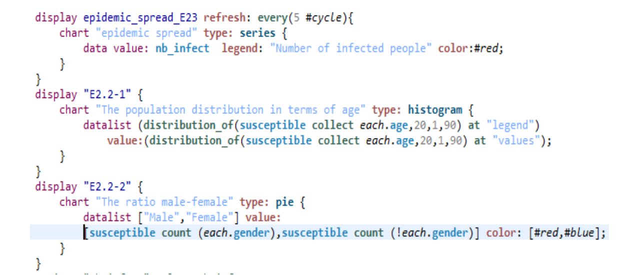
We will define a different schedule (set of activities of the day) for each age category (children, adult, and retired people). A plan can be a map associating to each day hour an activity type (an activity is made in a building). As an example:

- The children go to school at 7 am, at 4 pm they go to the park, and at 5 pm go back home.

For each home building, we create a household at initialization.

1. Population characteristics

We define a GUI experiment, plotting (with histograms, for example) the ratio male-female, the population distribution in terms of age, and conditions on the number of people.



```
display epidemic_spread_E23 refresh: every(5 #cycle){
    chart "epidemic spread" type: series {
        data value: nb_infect  legend: "Number of infected people" color:#red;
    }
}
display "E2.2-1" {
    chart "The population distribution in terms of age" type: histogram {
        datalist (distribution_of(susceptible collect each.age,20,1,90) at "legend")
            value:(distribution_of(susceptible collect each.age,20,1,90) at "values");
    }
}
display "E2.2-2" {
    chart "The ratio male-female" type: pie {
        datalist ["Male","Female"] value:
        [susceptible count (each.gender),susceptible count (!each.gender)] color: [#red,#blue];
    }
}
```

Figure 7: Sample code of histogram

2. Epidemic plotting

We define an experiment to plot epidemic spread (number of individuals in each state)

d. Environmental transmission

The virus of CoVid19 can survive in the environment a few days and infect people even when they are not in contact with infected people. We modify buildings to contain a viral load that is increased when infected people are in the building and decrease over time.

C. Public health policy

a. Authorities and policies

We will now define two new species: the local authority and the Policy. The Local Authority will be in charge of deciding the strategy and deciding when to apply it. The trigger of this decision can be made.

(i) time (a policy is applied at step 0, at stage N).

(ii) when an infected individual appears in the population.

(iii) when tests identify an infected individual.

The authority can also choose to drop a policy in some conditions (e.g., stop containment after 15 days, 30 days). The plans can include:

(i) total move freedom.

(ii) complete lockdown.

(iii) containment by ages.

(iv) close schools.

(v) wear masks.

Define this authority and some policies (you can choose the one that is the more relevant and even to define new ones). Modify the model to make these policies impact individuals' behaviors

b. Impacts of these policies

We implement experiments that can show the effect of the defined procedures, of their applications, and drop conditions. We describe experiments to compare various policy effects.

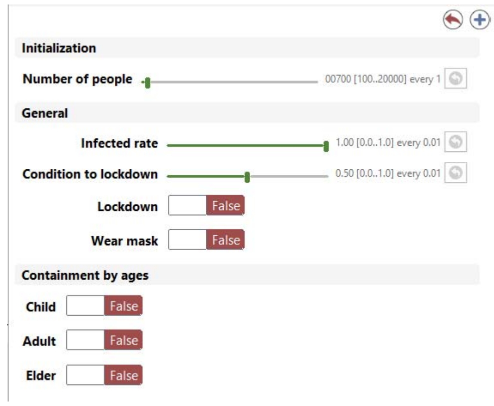


Figure 8: Public health policy

c. Improve the epidemic model

A massive issue with CoVid19 is that many of the infectious peoples are asymptomatic (no symptoms). This problem of these people makes the identification of the infected people much more difficult, and there is a need to use tests to identify them. Modify the epidemic dynamics so that, after being Exposed, the individuals have a probability of becoming symptomatic or asymptomatic. Authorities cannot determine asymptomatic without testing. We try to improve the model to take this fact into account

IV. ANALYSIS AND RESULT

The simulation is divided into three phases. In the first phase, we describe some basic ideas for the simulation; for instance, the effect of randomness, the impact of the number of individuals, and the infection progress. ((Figure 10).

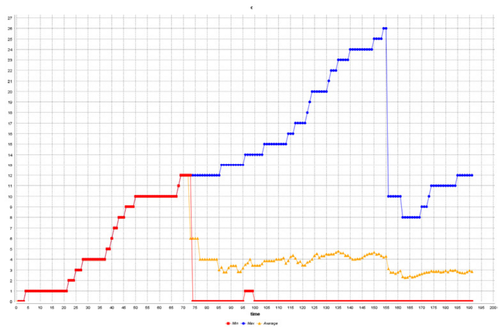


Figure 9: Basic idea for the simulation

The number of infected individuals will increase very fast if the authorities do not control the infected individuals.

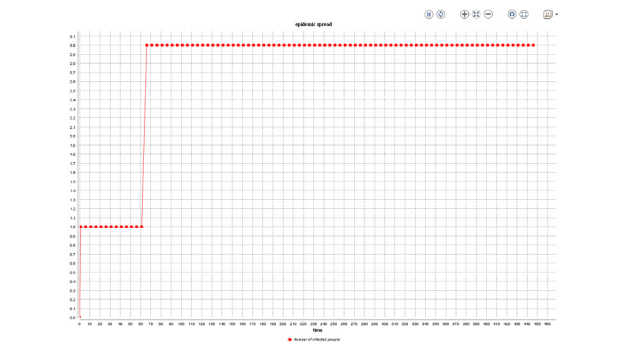


Figure 10: Epidemic spread

In the second phase, we simulate the spread of the disease in a particular city with a heterogeneous population. This phase contains a realistic town, along with the society. We try to simulate the effect of randomness that is mentioned in the first phase with a real community and detailed scenarios. Figure 10 shows the spread of the disease.

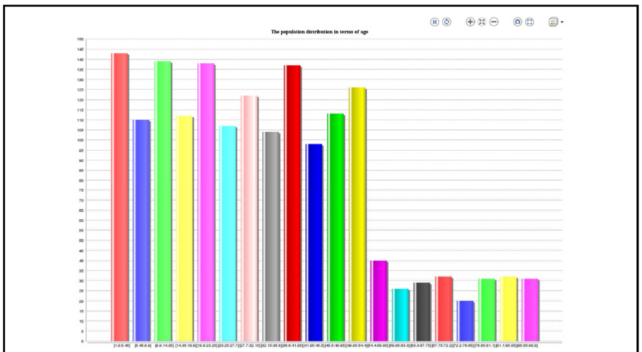


Figure 11: The population distribution in terms of age

The simulation describes the distribution of the population based on their age. (Figure 11).

And the ratio between males and females. (Figure 12).

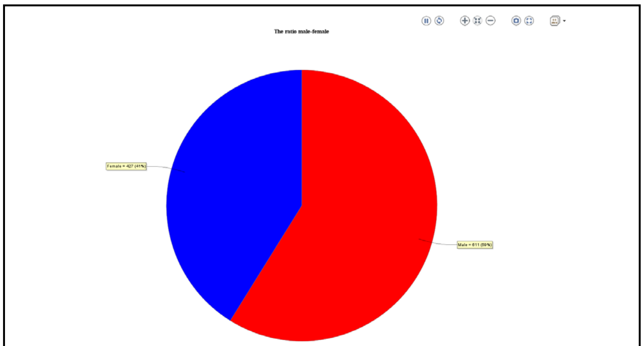


Figure 12: The ratio male-female

In the last phase, we added Policy from authorities for the simulation. The policies affect to the spread of the epidemic. There are two main policies: lockdown and wearing a mask. You can see the result of applying strategies to the detaining of the disease by the figure below (Figure 13).

We can change the parameters in the left menu and observe the effect of the input on the map. The number of infected people is decreasing when the user choose lockdown or wearing a mask

CONCLUSION

In this paper, we presented a detailed simulation for the COVID-19 pandemic using GAMA platform. The simulation helps to understand the dangers of the epidemic.

In comparison to the existing COVID-19 simulation, the advantage of our simulation is that it is very detailed and completed in the scenarios of the outbreak. Users can base on our simulation to apply for other cities or countries only with loading and preparing the shape files.

The limitation of this research is that it has not been developed as a framework of the agent-based model, which can provide a simple way for the user. The user still has to program the application using GAMA platform.

For future work, we plan to enrich the simulation by more functionalities. We also want to compare between GAMA and other simulation frameworks to have a proper perspective of the simulation framework in general.

The code we used to implement our model is available at https://github.com/duongpl/FPT-Gama-Covid-Research..

REFERENCES

[1] https://www.who.int/emergencies/diseases/novel-coronavirus-2019 [Accessed May 2sd, 2020].

[2] Gama website: https://co de.go ogle.com/p/gama-platform. [Accessed May 2sd, 2020]

[3] Taillandier, Patrick & Vo, Duc-An & Amouroux, Edouard & Drogoul, Alexis. (2010). GAMA: A Simulation Platform That Integrates Geographical Information Data, Agent-Based Modeling, and Multi-scale Control. PRIMA 2010. LNCS. 7057. 242-258. 10.1007/978-3-642-25920-3_17.

[4] Taillandier, Patrick. (2014). Traffic simulation with the GAMA platform.

[5] Philippon, Damien & Choisy, Marc & Drogoul, Alexis & Gaudou, Benoit & Marilleau, Nicolas & Taillandier, Patrick & TRUONG Chi, Quang. (2017). Exploring Trade and Health Policies Influence on Dengue Spread with an Agent-Based Model. 111-127. 10.1007/978-3-319-67477-3_6.

[6] Taillandier, Patrick & Banos, Arnaud & Drogoul, Alexis & Gaudou, Benoit & Marilleau, Nicolas & TRUONG Chi, Quang. (2017). Simulating Urban Growth with Raster and Vector Models: A Case Study for the City of Can Tho, Vietnam. 21-38. 10.1007/978-3-319-51957-9_2.

[7] Becu, Nicolas & Amalric, Marion & Anselme, Brice & Beck, Elise & Bertin, X. & Delay, Etienne & Long, Nathalie & Marilleau, Nicolas & Pignon-Mussaud, Cecilia & Rousseaux, Frederic. (2017). Participatory simulation to foster social learning on coastal flooding prevention. Environmental Modelling and Software. 98. 11. 10.1016/j.envsoft.2017.09.003.

[8] Drogoul, Alexis & Taillandier, Patrick & Gaudou, Benoit & Choisy, Marc & Chapuis, Kevin & Nghi, Huỳnh & Doanh, Nguyen & Philippon, Damien & Brugière, Arthur & Larmande, Pierre. (2020). Designing social simulation to (seriously) support decision-making: COMOKIT, an agent-based modeling toolkit to analyze and compare the impacts of public health interventions against COVID-19.

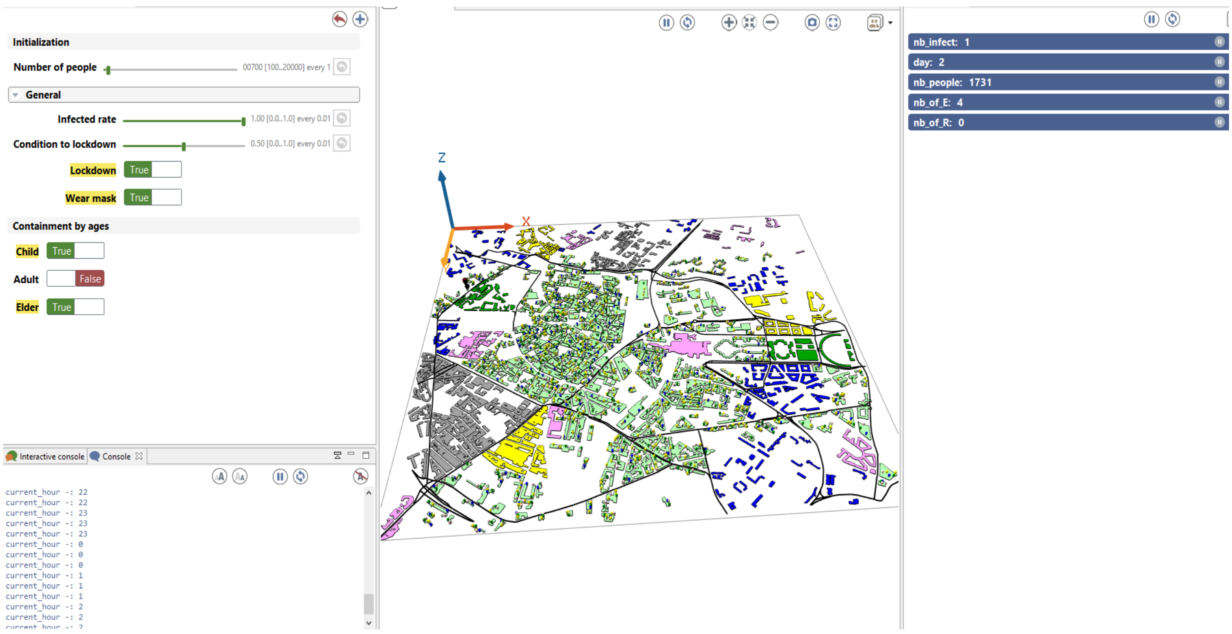


Figure 13: Authorities and policies

[9] Hoertel, Nicolas & Blachier, Martin & Blanco, Carlos & Olfson, Mark & Massetti, Marc & Limosin, Frédéric & Leleu, Henri. (2020). Facing the COVID-19 epidemic in NYC: a stochastic agent-based model of various intervention strategies. 10.1101/2020.04.23.20076885.

[10] Rockett, Rebecca & Arnott, Alicia & Lam, Connie & Sadsad, Rosemarie & Timms, Verlaine & Gray, Karen-Ann & Eden, John-Sebastian & Chang, Sheryl & Gall, Mailie & Draper, Jenny & Sim, Eby & Bachmann, Nathan & Carter, Ian & Basile, Kerri & Byun, Roy & Sullivan, Matthew & Chen, Sharon & Maddocks, Susan & Sorrell, Tania & Sintchenko, Vitali. (2020). REVEALING COVID-19 TRANSMISSION BY SARS-CoV-2 GENOME SEQUENCING AND AGENT BASED MODELLING. 10.1101/2020.04.19.048751.

[11] Kai, De & Goldstein, Guy-Philippe & Morgunov, Alexey & Nangalia, Vishal & Rotkirch, Anna. (2020). Universal Masking is Urgent in the COVID-19 Pandemic: SEIR and Agent Based Models, Empirical Validation, Policy Recommendations. 10.13140/RG.2.2.21662.08001.

[12] Gomez, Jonatan & Prieto, Jeisson & Leon, Elizabeth & Rodriguez, Arles. (2020). INFEKTA: A General Agent-based Model for Transmission of Infectious Diseases: Studying the COVID-19 Propagation in Bogota - Colombia. 10.1101/2020.04.06.20056119.