

Social Simulations for Intelligently Beating COVID-19

Christian Kammler¹, Annet Onnes², Loïs Vanhée³, Harko Verhagen⁴, Bart de Bruin⁷, Paul Davidsson⁵, Frank Dignum¹, Virginia Dignum¹, Amineh Ghorbani⁷, Mijke van den Hurk⁶, Maarten Jensen¹, Kurt Kreulen⁷, Fabian Lorig⁵, Luis Gustavo Ludescher¹, Alexander Melchior⁶, René Mellema¹, Cezara Pastrav¹, Tomas Sjöström¹

¹Umeå University, Sweden, ²The University of Edinburgh, UK, ³The University of Caen, France, ⁴Stockholm University, Sweden, ⁵Malmö University, Sweden, ⁶Utrecht University, Netherlands, ⁷TU Delft, Netherlands
Corresponding author: ckammler@cs.umu.se

Abstract

The COVID-19 virus has led to a world-wide crisis that requires governments and stakeholders to take far-reaching decisions with limited knowledge of their consequences. This paper presents the ASSOCC model as a valuable decision-support tool for anticipating the consequences of possible measures by considering many interwoven aspects at the individual, group and societal level. Moreover, this paper illustrates how this model can be applied to study the effects of different testing strategies on the spread of the virus and the healthcare system. We found that excluding age groups from random testing was ineffective, while prioritizing testing healthcare and education workers was effective, in combination with isolating the household of an infected person.

Keywords— COVID-19, Agent-Based Simulation, Decision Support, Values, Needs

1 Introduction

The COVID-19 pandemic has been and is causing a global response [WHO, 2020]. Yet, in spite of applying similar *measures*, the effect of this mobilization can lead to very different outcomes depending on the *area* where measures are applied (e.g. countries, social landscapes). Governments and stakeholders are responsible for making high-stakes life-threatening decisions while having limited understanding of the effects of these decisions. This lack of understanding caused the application of globally detrimental measures due to interwoven aspects not being accounted for (e.g. on-time delivery of masks is sound from an economic standpoint but fails when facing a global crisis). Simulation is a highly relevant tool for acquiring such understanding, as classic methods are ineffective given the time pressure and the many interwoven aspects to be accounted for.

Most existing simulation models only consider the epidemiological dimensions, such as the SIR (Susceptible, Infected, Recovered) model [Kermack and McKendrick, 1927]. More advanced models also include more individual attributes such as age and household composition and public measures such as global quarantine, tracking app, and rates of compliance [Hinch *et al.*, 2020; Burke *et al.*, 2006; Chang *et al.*, 2020]. While relevant, these models can oversimplify critical aspects (e.g. no model of when and why people violate quarantine measures) and fail to account for other dimensions: psychol-

ogy, economy, infrastructure load, resource consumption, etc. They rely on rigid equation-based or hardwired agents. This orientation offers greater statistical accuracy at the expense of missing certain core dimensions and making simplifications that can void the relevance of these models. Thus, these classic models offer little insights beyond already available expert knowledge. The model from [Wilder *et al.*, 2020] focuses on regional differences between Hubai and the Lombardy in addition to taken different age groups into account. However, this model remains a SIR model and fails to account for critical aspects, such as how need deprivation affects human behavior. Other nominal work with respect to COVID-19 can be found in [Ferguson *et al.*, 2020].

As an answer to these limitations, this paper introduces the ASSOCC¹ model and shows how it can be used in practice by detailing one of its applications. The ASSOCC model is a social simulation model that is based 1) on advanced agents and 2) that covers a wide range of aspects [Dignum *et al.*, 2020]. Advanced agents here means adaptive AIs that replicate the core psychological aspects that are at play in such a situation, as backed up by social science theories—contrary to agents based on hardwired rules, which are simpler to design but that fail to (be) adapt(able) to new and richer situations. ASSOCC includes many aspects, such as epidemiology (e.g. disease evolution and contagion models), economy (e.g. personal and business bankruptcy), sociology (e.g. social distributions, infrastructures, culture), and psychology (e.g. needs, beliefs on the world and self-health). These aspects can be combined with considered measures (e.g. closing certain places, using a tracking app, testing). Altogether, the ASSOCC model offers a unique complementary source of information for stakeholders, as it provides concrete evidence of potential interdependencies between the consequences of measures.

The remainder of this paper will first introduce the ASSOCC architecture and then details and studies the behaviour of a specific application: an adaptive testing.

2 ASSOCC Simulation Model

As a central premise, in ASSOCC humans are represented by *agents* that perform *activities* at different places, where they can gather with other people. We call these *gathering points* and *contagion* is assumed to occur there. Gathering is caused by the necessary activities people need to perform to satisfy their *needs* (e.g. working, getting food). Furthermore, agents have *social networks* they want to meet and conform with. Finally, the *economic model*, not further detailed in this paper, represents the basic transfer of money between people

¹Agent-based Social Simulation of the Coronavirus Crisis, online available at [sim, 2020]

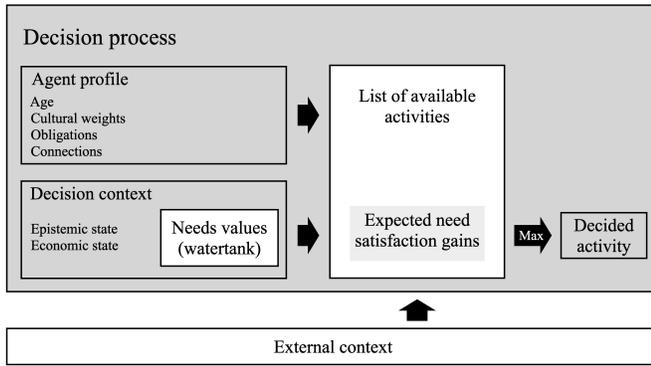


Figure 1: Abstract decision diagram of ASSOCC agent.

and businesses. Even in its simplest form, this model is able to replicate behaviours such as a global recession caused by the lockdown and the growing anxiety of people due to personal and workplace bankruptcy, and thus a threat to the need for safety.

2.1 Concept

Agent Decision Process

The internals of the agents represent the core psychological processes at play when making decisions in various situations, as depicted in Figure 1. The *needs model*, modeled as a homeostatic process, is used as the main driver for decision making. This is supported by an *epistemic model* for tracking agent’s beliefs.

Agent Profile: All agents have a set of static characteristics, including e.g. age and obligations. The agent population is divided into four functional age groups: young, student, worker, retired. Working agents can work at different places: workplaces, schools, universities, essential shops, non-essential shops, and hospitals. The agents have a health status, which they can only partly see. Agents can also be connected to other agents, e.g. living together as well as larger social networks. Young agents go to school and students to university.

Needs Model: This model represents needs based on Maslow’s hierarchy: survival, safety, belonging and esteem [Maslow, 1943]. The needs model is represented using the water tank model [Heidari *et al.*, 2020], which ensures that agents will look at the satisfaction level of all needs, even those with lower priorities. Weights are added to model the relative importance between needs, influenced by other agent characteristics, such as age and culture.

Culture Model: Each agent is related to a culture, modeled by using Hofstede’s cultural dimensions [Hofstede *et al.*, 2010; Hofstede, 2001]. In essence, culture influences agent values, represented by Schwartz values [Schwartz, 2012], which in turn influence the priorities between different needs. The culture model allows applying the simulation to various countries and their specific culture as in [Vanhée and Dignum, 2018].

Epistemic Model: The evaluation of the satisfaction of each need is based on the epistemic model. This model allows deriving how much the various needs are satisfied (e.g. if the agent believes to be infected, then the satisfaction of its health need is relatively lower if the agent decides to work rather than rest at home).

Decision Making: The main decision that agents make, is which activity to perform next given an external contextual set of possibilities (e.g. can work at workplace if it is a work-hour and the workplace is opened). The process consists of selecting the activity that maximizes the satisfaction of the agent’s needs. Formally, this model can be sketched as: $\operatorname{argmax}_d \sum_n w_n \times \operatorname{sat}_n(d)$ where

d is a decision, n is a need, w_n is the relative weight of n and sat evaluates the relative satisfaction of the decision offered to n .

Locations & Places for Actions

Agents have the option of executing actions at places where they might gather with other agents: homes, workplaces, essential shops, non-essential shops, schools, universities, leisure places (public and private), transport, and a hospital. Homes are the places where the agents live. Workplaces represent gathering points where agents work and produce goods for the shops. Essential shops represent supermarkets and pharmacies. Non-essential shops represent stores where people can buy items which satisfy their needs for esteem and luxury. Leisure places represent e.g. parks, bars, and restaurants.

Disease & Contagion

The ASSOCC epidemiology model is based on the disease model from [Hinch *et al.*, 2020], the most up-to-date dedicated COVID-19 model.

Disease model: When infected, the agent has a probability of becoming 1) an asymptomatic carrier, 2) a mild symptomatic carrier, or 3) a severe symptomatic carrier. This probability depends on the age of the agent. Then, if asymptomatic or mild symptomatic, the agent will recover after a few days without needed hospitalization. If severe symptomatic, the agent will go to the hospital and then either recover or die, based on a probability test dependent on agent age. For mild symptomatic and severe symptomatic, the agent will spend an average of six days as pre-symptomatic, i.e. not being aware of being infected (based on a gamma distribution of a mean of 6 days and a variance of 2.5 days). Our needs model makes that agents, when aware of being infected, likely only rest at home for satisfying personal health needs, unless a greater need arises (e.g. no more food at home). When being aware of being severely infected, the agent will likely go to the hospital as soon as possible.

Contagion model: When infected, the agent has a probability of infecting others it meets, depending on the number of days since infected, the severity of the symptoms, and the type of activity it is conducting. This risk applies to each contact it has with others, making large gathering points particularly risky (e.g. concerts).

Public Measures

The model incorporates many parameters that can be set in different ways to simulate different policies and measures. To do so, users can define comprehensible input e.g. decide whether children go to school or not. No complex or abstract parameters or probabilities within the model have to be changed by the user.

2.2 Implementation

The ASSOCC platform is developed in NetLogo [Wilensky, 1999], the most widely used programming language for social simulation. This language has been selected for its ease to produce quick prototypes, which was needed for best responding to the crisis. The project is large-scale, holding thousands of lines of code, hundreds of parameters and constitutes one of the largest NetLogo projects ever created and is yet ongoing. This NetLogo model is the simulation machinery. Since, the resulting interface is only usable for proficient NetLogo users, the model has been integrated with a Unity-based GUI to provide governments and decision makers with a clear cut and easy to use interface. Regardless, the NetLogo model can be used as a standalone tool and a connection to the Unity interface is not required.

3 Adaptive Testing Scenario

This section describes how ASSOCC is deployed for studying certain questions brought forward by stakeholders: How to adapt ran-

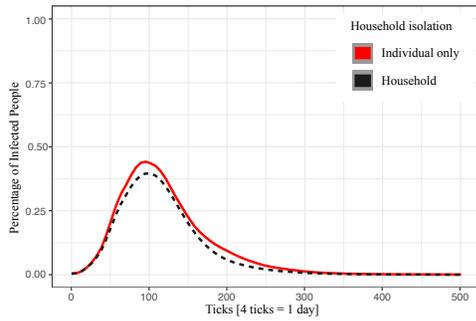


Figure 2: The effects of various isolation policies on infections when no testing is performed

dom testing combined with targeted isolation for optimizing its usefulness? This study is referred to as the *adaptive testing scenario*.

Random testing, in combination with targeted isolation, is a common measure for fighting the spread of COVID-19. However, the implementation of this measure is to be optimized, as only limited tests and testing facilities are available. The adaptive testing scenario investigates the effect of a variety of *testing policies* on the number and temporality of infection, hospitalizations, and casualties.

3.1 Setup

The key parameters defining testing policies are: 1) *testing regimes* (i.e. categories of people to be tested), and 2) *high priority groups* (categories of people to be tested first), and 3) *isolation policies*. The following testing regimes were considered: test everyone, test everyone except youth, test only elderly, and test no one. The following priority groups were considered: education workers, healthcare workers, both education & healthcare workers, and no priority groups. An isolation policy describes how to react when a person has tested positive and has two possible values: isolating the person, and isolating the whole household.

The size of the community is set to 1002 people and the number of daily available tests is set to 50 (i.e. up to 5% of the population can be tested every day, as requested by our stakeholders, the Italian government). Output variables encompass the amount of infections, the amount of hospitalizations, and the mortality rate over time. In the figures values are averages of 30 simulation runs.

3.2 Exploration Results

Whereas an exhaustive description and study is not feasible due to space consideration (96 plots), here we present an analysis following a One Factor At a Time (OFAT) exploration: select the best value for each parameter, show the most sensitive effects on output variables, and repeat with the next until convergence [Czitrom, 1999]. We start from: no testing, no priority, only isolate the infected person.

Isolation Policy: Figure 2 shows that isolating the household of infected members has a marginally positive impact on the number of infections when no testing is performed. We continue this exploration setting the isolation policy to the whole family.

Testing Regimes: Figure 3 compares the effect of the various testing regimes on the number of infected, with no prioritization. This figure shows that the flattest curve is testing everyone, although the differences are minimal. There is no difference between prioritizing the elderly with leftover tests or excluding young people from testing.

Prioritizing Regimes: Based on the results from the previous two figures, the results for the second factor, prioritizing regimes, are shown in Figure 4. Prioritizing different professions while testing everyone has a limited effect, similar to the results of Figure 3. The

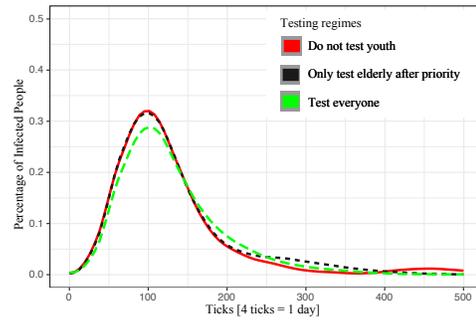


Figure 3: The effects of testing regimes when no priority in testing is applied and infected households are isolated

smallest number of infections can be found when prioritizing both education and healthcare workers.

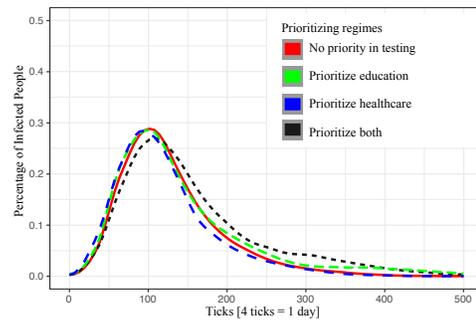


Figure 4: The effects of prioritizing regimes when testing everyone with leftover tests and infected households are isolated

Considering the results we concluded that the most compelling reduction was found when testing everyone with leftover tests, in combination with family isolation and prioritizing both education and healthcare workers. Figure 5 shows the curve for this combination of regimes, and household isolation has a much bigger effect compared to not testing (Figure 2).

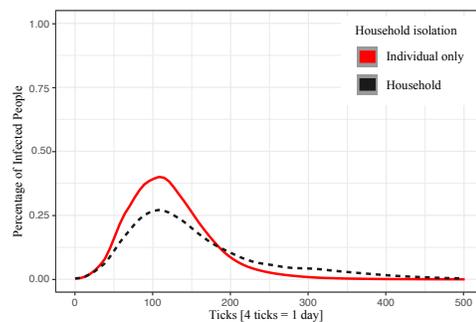


Figure 5: Ratio of infections over time depending on the isolation policy, for the “everyone” test regime and “healthcare and the education workers” high-priority groups. Testing makes family isolation much more effective when the whole household is isolated (vs. no testing as in Figure 2).

A slightly counter-intuitive result can be seen in Figure 6. When prioritizing healthcare workers in testing, the hospital effectiveness goes down. This will be discussed in the next section.

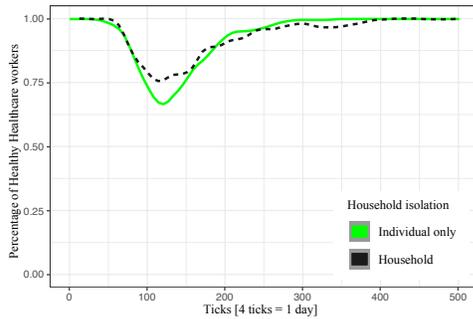


Figure 6: Hospital effectiveness for the best regimes, prioritizing healthcare and education workers in combination with testing everyone with leftover tests.

Figure 7 shows the results for prioritizing both, healthcare and education workers, and then testing everyone with leftover tests. Again we can see the effect of families isolating. This shows that this deducted, as most compelling, regime is the best to spread the hospitalisations as much as possible.

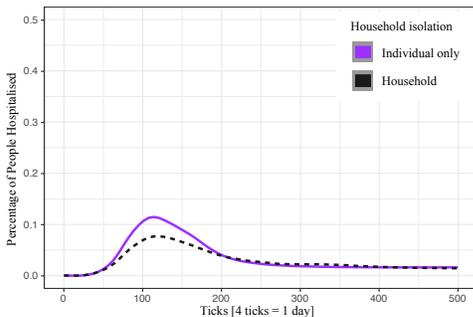


Figure 7: Hospitalisations for the best regimes, prioritizing healthcare and education workers in combination with testing everyone with leftover tests.

The same data showed that the mortality of the disease remained similar regardless of the testing or prioritizing regime.

4 Discussion

The results of the adaptive testing scenario show how advanced distinctions of groups of agents allows the exploration of effects when applying different policies such as testing policies.

The importance of the division between different agent groups based on various characteristics is strengthened by the results, as they show that single interventions have only a marginal effect in lowering the spread of the virus. Therefore, it is important to use a combination of different strategies to lower the spread most effectively. The ASSOCC model is useful here because it provides insight into the effect of different measures and interdependence between them. A fine-grained analysis can be done while exploring a wide array of small interventions which can then accumulate to a large effect. This is shown by the small effects in figures 2 and 4 leading to the best result shown in Figure 5, with the combination of prioritizing healthcare and education workers, isolating households with an infected member, and testing everyone with leftover tests.

Isolating the household when one member is infected is effective in reducing the spread, because then fewer persons are outside to spread the virus. The ASSOCC model is able to provide insight

into the strength of this measure since different cultures can be represented, including their respective different household distributions of: families, adults living together, elderly couples living together, and multi-generational households. In this case, the settings have been adapted to Italy and its distribution of households.

As mentioned, it is slightly counter-intuitive that the hospital effectiveness decreases that much when prioritizing healthcare workers in testing, as seen in Figure 6. The reason for this could be that infected healthcare workers are identified faster, since they are prioritized in testing. The hospital workforce could decrease faster as they go into self-isolation earlier, unable to work.

As a surprising result, testing elderly alone did not lead to a substantial benefit (Figure 3). This can be explained by the schedules of the agents. Retired people do not go to work and thus they have fewer potential contacts with other age groups, only at the shops and leisure places. But when they go there, the rest of the population is either at work, school or university during the week. In general, all age groups have a higher chance of meeting agents in the same age group.

The results presented and the effectiveness of the testing regimes may vary for different countries and cultures. This is one option for further research. Furthermore, the simulation was run with only about a thousand agents. Therefore, it can be possible that effects of measures can not be distinguished so clearly. The number of agents in each age group and professions is limited. This means several of the tested policies were only applied to a limited number of agents, limiting their effects. Given more agents, it can be possible that the small differences will become larger and more noticeable. In addition, only 50 people were tested daily, which can also limit the effectiveness of the measures.

While the effectiveness of these measures can change, the results presented in this paper show the value of the ASSOCC model as a tool and how it can help to explore different interventions for the COVID-19 crisis and how to get through it.

5 Conclusion

This paper presented a novel simulation model called the ASSOCC model, which enables advanced, many-faceted simulations of the COVID-19 crisis. We have described one potential application for supporting decision makers: optimizing the use of testing facilities in order to best protect the population depending on the specifics of various cultural backgrounds. The use of advanced agent models makes this tool unique and adaptive. The presented scenario focuses on adaptive testing techniques for Italy. The simulation outcomes show that testing is needed in combination with isolating the household if one of its members is infected; that first maintaining testing of education and healthcare workers is very important, then everyone with leftover tests. In conclusion, the ASSOCC project is a valuable tool for decision-makers to gain insights into the effect of different policies on the population. Given the broad scope of the ASSOCC model, different possibilities for future work exist. For instance, still addressing adaptive testing, different professions or age groups could be prioritized and different countries and cultures can be investigated, given the implementation of cultural diversity.

As future work, the ASSOCC model is being migrated to a Repast simulation, which eases the design of even more advanced agents and enables us to run simulations with many more agents. At the same time, we will be able to work more extensively on calibrating the different parts of the model. Currently, ASSOCC is calibrated with socio-economical data and the coupling of the mechanisms to different theoretical models (in part themselves based on empirical data) but not the mechanisms involved or their interaction.

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