Pandemic Skylines: Digital Twins for More Realism in Epidemic Simulations

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ABSTRACT

In the recent months, many measures have been taken by governments to fight the COVID-19 pandemic. Due to the unknown properties of the disease and a lack of experience with handling pandemics, the effectiveness of measures taken was often hard to evaluate the effectiveness of measures, leading to inefficient measures and late execution of efficient measures. Many models have been proposed to evaluate the performance of these measures on the spreading of a pandemic, but these models are commonly vastly simplified and, thus, limited in expressiveness. To extend the expressiveness of the models, we developed a epidemic simulation inside of a flexible and scalable city simulation game to analyse the counter measures to a pandemic in this city and spot common places of infection on a microscopic level. The configurability of our developed epidemic simulation will also be useful for potential future pandemics.

Keywords

Simulation, disaster communication, pandemic.

INTRODUCTION

Finding new ways to solve complex real-world problems often means modeling the real world and experimenting with different approaches to identify optimal solutions. Many such models share similar properties and challenges, especially if human behavior is involved. Researchers try to answer this question by implementing these models in simulations that range from the evaluation of communication protocols over vehicular traffic management to the exploration of different epidemic countermeasures. Often specialized solutions are focusing on a single aspect of simulation, e.g, networking (Riley and Henderson 2010, Stingl et al. 2011, Varga and Hornig 2008) or urban mobility (Lopez et al. 2018). For practical and more realistic What-If analyses, such simulations need to model human behavior more realistically. Thus, the agents in the virtual world need to have a daily routine instead of just random movement, realistic traffic patterns and daily requirements and social interactions should be considered. These factors also influence how effective, e.g., disruption-tolerant networking routing protocols can be. Global pandemics such as COVID-19 also show the usefulness of realistic simulations to predict and evaluate different countermeasures such as closing schools, using masks, or providing contact-tracing apps to citizens. Here, realistic models of daily routines and social interactions are even more important.

An approach used more and more by governments and researchers is building digital twins of, e.g., urban environments (Baeder et al. 2019). These serve as sandboxes to safely explore different solutions and their effects on the environments. Again, the quality and usefulness of such analyses are strongly connected to the models and parameters driving the simulated environment as well as how good of a copy this digital twin is. Thus, having public transportation, roads and even different dedicated areas for shopping, living, and industry modeled after a real city is key for successful analyses. Besides high-quality models, accessibility and useful visualizations are essential for non-academic professionals to adopt such solutions for What-If scenarios.

In this paper, we present our approach of using a commercial city building game, *Cities: Skylines*, that we modified to make it usable for research simulations. Other researchers (Pinos et al. 2020; Olszewski et al. 2020) as well as educators (Haahtela et al. 2015) have also built their work on this game in different areas. The benefit of building upon the game engine is that we already have AI for human behavior including work duties, schools and shopping, a functioning traffic and public transportation system, and power grid functionality plus the bonus of an excellent visualization. Furthermore, there are responses to accidents and disasters such as fires and earthquakes. Our approach modifies the engine to make the relevant data like agent positions available to external tools, e.g, for incorporation in dedicated network simulator. Also we integrated functionality to simulate proximity-based interactions such as spreading a disease or exchanging data on a device-to-device basis. This allows us simulate a epidemic including spreading behavior, symptoms and effects of masks as well as contact tracing apps within the same environment. Furthermore, parameters such as infection rate in indoor and outdoor environments as well as different lockdown actions can be configured. Finally, we offer various analysis tools for subsequent evaluation of the simulation. In our evaluation, we show how our models are in line with different predictive models for COVID-19 often cited and the real numbers observed in 2020. Thus, it shows the power of our simulation system even for complex disasters such as epidemics spreading in urban environments and its usefulness for What-If analyses.

To summarize, we make the following contributions:

- A novel, flexible simulation toolkit build upon proven an urban city planning simulation
- A unique epidemic model with different spreading behavior and symptoms
- A novel way to study the effects of a pandemic and different governmental measures like masks, quarantines, and shutdowns in local environments including travel patterns and living arrangements
- An integrated way to simulate external influences such as digital contact tracing and virus testing capacities
- A thorough evaluation showing the power of our approach in scenarios with different countermeasures and spreading behaviors.

The remainder of this paper is organized as follows. First, we present related research regarding different simulation environments as well as COVID-19-specific work. In the next section, we give an overview our system's design, describing the models used to drive our epidemic simulation. How this was implemented in *Cities: Skylines* is shown in more detail in the following section. In the next section, we present an experimental evaluation with various scenarios and configurations. Finally, we conclude the paper in the next section, giving a summary and short outlook on future work.

RELATED WORK

Digital twins are digital images or representations of real-world objects, systems, services, or processes (Barricelli et al. 2019) and are used in almost all areas of application. For example, digital twins find application in cyber-physical systems and Industry 4.0 (Tao et al. 2018), healthcare and medicine (Björnsson et al. 2020), critical infrastructures (Farsi et al. 2020) or climate forecasts (Voosen 2020). They are created from both existing systems, as well for future systems (digital prototyping). In the virtual space, these twins can be modified, stressed, or linked to other twins, and accordingly, the systems response, performance, or resilience can be captured and measured without the need to interact with a physical system. It quickly becomes apparent that a digital twin is only valuable if both the representation and all influencing factors (linked systems, environmental parameters, user behavior) can be realistically transferred, integrated, and represented in the digital space.

One of the biggest challenges in representing real systems in digital space is modeling realistic human behavior. Guo et al. 2019 call this challenge the "digital mirror of the physical world". This representation is essential for digital twins used or influenced by people, such as critical infrastructures (transportation systems, power grid, ICT). Such representations often rely on recorded user behavior data, for example movement (Aschenbruck et al. 2011) or energy-consumption traces (Kelly and Knottenbelt 2015), which represent realistic behavior on the one hand but can usually only be applied to the recording's original scenario on the other hand. Necessary for the creation and use of digital twins that interact with humans, is the use of human population models that can generate realistic behavior for arbitrary scenarios.

In particular, human mobility behavior is tremendously important for such a system evaluation and is a significant research challenge. In the last decades, more and more realistic mobility models have been developed. They range from simple random-based behavior models, such as random walk or random waypoint (Camp et al. 2002), to more sophisticated models, such as SLAW (K. Lee et al. 2009), SWIM (Kosta et al. 2010) or the *Working Day Movement Model* (Ekman et al. 2008), which are able to map environmental features like streets, social interactions or routines. Thus, the used mobility model of city inhabitants in the computer game *Cities: Skylines* is very well suited for the simulation of the everyday workflow of citizens, as it models all required actions taken during the day.

In the current situation with COVID-19 and containment efforts, digital twins of the population, especially movement and social interactions (person-to-person contacts) are more important than ever to perform meaningful cause-and-effect (e.g. vaccination, social distancing) analyses regarding the dynamics of infectious-disease transmission.

There exist well known mathematical or epidemiological models that use differential equations to describe disease dynamics, such as the forces of infection in combination with statistical movement characteristics (Kermack and McKendrick 1991; S. Del Valle et al. 2005). However, such models have been replaced by modern agent-based models, which allow for more realistic and diverse assumptions and configurations (S. Y. Del Valle et al. 2013). For example the *object-oriented platform for people in infectious epidemics* (OPPIE) (Mniszewski, S. Y. Del Valle, Priedhorsky, et al. 2014; Mniszewski 2012) which extends the *Los Alamos Epidemic Simulation System* (EpiSimS) (Mniszewski, S. Y. Del Valle, Stroud, et al. 2008) supports a description of social contact networks and human behavior based on the National Household Transportation Survey (NHTS)[1].

In this work, we aim at increasing the realism of these models using a city-scale simulation, which encodes the everyday life of citizens of every age group. In addition, any city can easily be recreated in the simulation to analyse the effect of different measures to the city itself.

DESIGN

In the related work, we identified a challenge of realistic citizen movement (Guo et al. 2019), which is a heavy influence factor to the spreading of a epidemic. For this purpose, we rely on the city-building simulation game *Cities: Skylines* (*Cities: Skylines* 2015). In this game, the player has the task to build and manage an city of increasing size. The game has a very high level of detail in simulating individual citizens based on their needs and their character. For example, the daily routine of an adult citizens can include going to work, shopping, relaxing, and going out for a walk. Furthermore, children will go to school and seniors will not have any obligations during the day. For their daily commute to work, the adult citizens have multiple possibilities like walking, driving with the car, or using public transportation. Thus, we expect to be able to capture the influence of parts of society on the spreading of the epidemic. As an example, the influence of the closing of schools can easily be evaluated by analysing how many infections actually happened in schools. This is easily possible in simulations and may provide an insight on the effectiveness of measures when shutting down different parts of society. This can then be used as valuable information before taking these measures in the real-world. In the remainder of this section, we discuss the necessary features of a epidemic simulation. As a first feature, we highlight the configuration options of the epidemic, followed by the possibilities to configure measures taken by the government.

Epidemic Modeling

In this section, we describe our modeling of the epidemic in the simulator. For that purpose, we divide the properties into two aspects, first the spreading behavior of the disease and second the symptoms associated with it. While the first directly influences the speed with which the epidemic spreads in society, the second is using for measuring for the consequences of the spreading disease.

Spreading Behavior

An epidemic is majorly characterised by the possibility of the disease to spread fast among the citizens. We model the spreading behavior based on known properties of the COVID-19 pandemic, with some modifications to keep the computational complexity low. The progress of the disease is as follows:

In general, an infected citizen will not immediately start spreading the disease itself, but only after a certain amount of time, the so-called latent period. We use this time as a parameter to control the simulation and to be adaptable to potential future diseases with different characteristics. This time-span might be even before the end of the so-called incubation period, in which the citizen is infectious without having any symptoms. To reflect this disease behavior

[1]https://nhts.ornl.gov/

in the simulation, we track the infection times of each citizen, and only consider him as infectious after the end of the latent period.

An infectious citizen may infect other healthy citizens. We do not consider the exact way of the transfer of the disease, e.g, physical contact, air-borne etc., but assume that citizens in the same building or flat (if they are inside), the same vehicle (if they are in a vehicle), or in a certain distance (if they are outside) may be infected by infectious citizens. We modeled the degree of the spread of the disease by a transmission probability p_{inf} per hour, which can be set independently for indoor, vehicle, and outdoor occasions. p_{inf} can be configured at the start of the simulation to account for possible future pandemics. If the contact duration of two citizens is different to one hour, the probability for an infection can be calculated as shown in Equation 1. In this equation, t is the contact duration in hours, and p_{inf} the infection probability for an one hour long contact. This equation is derived by calculating the probability that the citizen does not get infected over the duration t, and then reversing it. That is, as a citizen must not be infected at any point in time to remain healthy. Additionally, a citizen cannot be infected twice, i.e., the infection probability converges to one for very long exposure periods. We assume that the infection probability is constant and does not change, for example, during the night.

$$p_{inf}(t) = 1 - (1 - p_{inf})^t \qquad (1)$$

Similarly, the range in which the disease may spread outdoors can be configured freely. After the end of the infectious period, the citizen remains ill, but is not considered in the spreading of the disease anymore, which is similar to the behavior of Sars-CoV-2. If required, the infectious period can be configured to be the full duration of the disease. However, he remains ill until the lifetime of the disease expires.

Symptoms

In addition to the infectious period of a citizen, he might develop various symptoms. In reference to current knowledge of the COVID-19 pandemic, we introduced a probability with which a person gets infected. Citizens without symptoms will not notice that they are infected if they are not tested, and thus will not follow all governmental measures. Also, only citizens with symptoms are potential candidates for dying through the consequences of the disease. We modeled the death of the citizens based on their age group (junior, teen, young adult, adult, and senior). With that, we are able to differentiate between the consequences of a disease for the different age groups. Each citizen has a certain probability to die during the disease, which is based on his age group. Chosen citizens will then be declared dead and removed from the simulation. In future work, we plan to extend the modeling by sending severely sick people to the hospitals instead of just using the overall death percentages independent of the workload of the hospitals. This will enable an even more fine-granular analysis of the epidemic.

Governmental Measures

For governmental measures, we implemented similar ones to those taken by the German government throughout the COVID-19 pandemic. These measures include: wearing masks, sending infected people to quarantine, and going into lockdowns of various degrees. In the following, we will describe our design choices for each individual measure.

Masks

The wearing of masks in public is a promising approach to reduce the spreading of the epidemic without decreasing the mobility of the citizens. Depending on the type of masks that is used, the influence of the infectiousness of people may be different. We capture this difference by reducing the spreading probability described previously by a predefined factor. While this approach of modeling cannot capture different types of masks among the citizens (some wearing everyday masks and mainly protecting others, some wearing FFP2/N95 masks, protecting both themselves and others), it provides a good and easy-to-configure overview on the general influence of masks on the spreading of disease. We plan to extend the configurability further by, for example, having different types of masks for senior people.

In addition to that, we allowed for different types of strictness regarding the wearing of masks. These types are masks only worn in buildings, in buildings as well as vehicles, and masks worn in public. For the masks only in buildings case, we excepted residential buildings as the citizens will not comply with wearing masks at home or when visiting friends. Especially with strict masks policies, we will show in the evaluation that the majority of infections is related to private meetings in residential buildings. For the masks in buildings and vehicles case, we had the same restrictions as previously, but added the need for citizens to wear masks while driving in vehicles.

This has mainly an influence to public transport and drastically limits the infections taking place in busses and trams. For the last case, masks are required everywhere, meaning citizens will also wear masks when walking anywhere in public.

Quarantine

The government can send infected or potentially infected citizens to quarantine to reduce the spreading of the disease. This aspect is pivotal for controlling a disease, as the number of contacts of potentially infectious people is reduced drastically.

We offer four modes for quarantine: No quarantine at all, quarantine of infected citizens, quarantine for infected people including their families, and quarantine for infected citizens including their contacts. People will be sent to quarantine either if they have been sick (are infected and show symptoms) or they have been tested positive for the disease. We allow for configuring the quarantine behavior of the citizens, by either sending all citizens with symptoms and tested citizens to quarantine, or by only sending tested citizens to quarantine. While being at home in quarantine at home, further infections might still happen within the same household. These potential infections are acknowledged and handled by the third quarantine mode, in which the family is proactively also sent to quarantine to prevent the further spread of the disease. While this already proves quite effective, we added the possibility to also send the contacts of the quarantined citizen into quarantine. The share of contacts that is send to quarantine depends on the reliability of the contact tracing. Contact tracing will be explained later in Governmental Tools.

Governmental Tools

There are different tools available to the government that can be used to control the epidemic. The first one is tracing the contacts of infected people, such that the exponential growth in active cases can be prevented. Secondly, the government can deploy testing centers, which also aim at isolating infectious citizens, such that they can cure and recover without infecting any other people.

Contact Tracing

Contact tracing can either be done manually, e.g., by the health department, or using a smartphone app that people must have installed. For the manual contract tracing, we implemented the probability p_{bui} to track citizens that are in the same building. Notice that the probability of successfully detecting a contact between two persons, each with p_{bui}, is equal to p_{bui}^2, as it is required that the presence of both people at the particular building has been traced. This is inspired by one measure in Germany, in which the presence of people in restaurants had to be documented to track the chain of infections. For this measure, we enable the possibility to define a conformity ratio, as it has happened that people filled out wrong information to avoid being traced. In addition, we provide the possibility for an app-based contact tracing, which can also be configured to reflect the number of citizens that use the app. The app recognizes a contact when two citizens are in a configurable range, such that potentially infected citizens can be send to quarantine precautionally. This is much more effective compared to the building-based tracing, as the app is able to trace contacts even outside of buildings and in public transport. The acceptability of this solution strongly depends on the trust of the citizens in the provider of the app and the technical requirements of the app. Thus, we enabled to configure the percentage p_{app} of citizens that uses the app. Notice again that the probability a successful contact detection between two people, each with p_{app}, is equal to p_{app}^2, as both citizens need to be using the app for the detection to work.

Testing Capacities

As a last governmental tool considered in our simulation, wide-spread tests can be used to detect and isolate infected citizens before they can spread the disease to others. In the general case, the government will not have sufficient test capabilities to test all citizens, which is why we choose to limit the testing capabilities. This limitation is done by setting the share of people that can be tested per week. We support both testing of sick citizens only or testing citizens randomly. Additionally, we allow to reserve a configurable share of tests for people with symptoms, while the remaining tests can be used to test random persons. The targeted testing of citizens has the advantage that infectious persons can quickly be isolated, without sending people with other diseases into quarantine. However, the infected persons without symptoms will not be detected and, thus, cannot be isolated. This is the advantage of testing citizens randomly, but the large number of tests required for this strategy makes large-scale testing of random people often impossible.

IMPLEMENTATION

We implemented our epidemic simulation as part of the *RealTime* mod (dymanoid 2020), that is already available for *Cities: Skylines* (*Cities: Skylines* 2015). In the following, we will briefly introduce the functionality provided by *Cities: Skylines* and the *RealTime* mod, and then highlight contribution[2].

Cities: Skylines (*Cities: Skylines* 2015)

Cities: Skylines is city-building simulation based on the Unity engine, in which the player tries to build a large-scale city. We chose this game as our simulation environment due to its open modification API and the realistic behavior of the citizens. This behavior consists, beyond other, of shopping trips, working days, taking walks, and traveling. Most citizens have a family, which is managed by the game, and shares their home building. From there, the people travel to their work place every day, and come back in the evening. For their commute to work, they can either walk, take their personal car, or use one of several public transports like buses, trams, and trains that are available to increase the realistic behavior of the citizens. A citizen may become sick, but there is no spreading implemented in *Cities: Skylines*. Thus, we needed to extend the game to be able to simulate a epidemic inside of one of our cities. For configuration purposes, we use the option panel provided by *Cities: Skylines*. In that option panel, parameters for the pandemic like the efficiency of masks and the spread of the disease can be configured.

RealTime Mod (dymanoid 2020)

The *RealTime* mod is a modification of *Cities: Skylines* aiming at increasing the realism in the game. For that purpose, they reduced the high simulation speed of the game, which did not match the movement of the citizens in the city. Additionally, they decreased the aging of citizens, allowing citizens to live longer than originally implemented in *Cities: Skylines*. These modifications are important for our simulation, as people will more rarely die of other causes then the ongoing epidemic and, thus, will not forge our simulation result.

Additionally, the mod improves the everyday behavior of the citizens, by sending adults to work only on work days, and sending children to school. For relaxation and recreation, this mod makes citizens watch football matches, go to party places (if available), or do shopping trips. This increases the realism of the simulation, as citizens move around the city to fulfil their responsibilities and needs. While there are other features available in this mod, these are not necessary for our epidemic simulation and, thus, will not be discussed further in this paper.

Epidemic Simulation

In this section, we describe our extension of the *RealTime* mod, which is one of the contributions of this work. While both the game itself and the modification provide close-to-realistic human behavior, they do not provide the necessary tools to simulate and evaluate the spread of an epidemic.

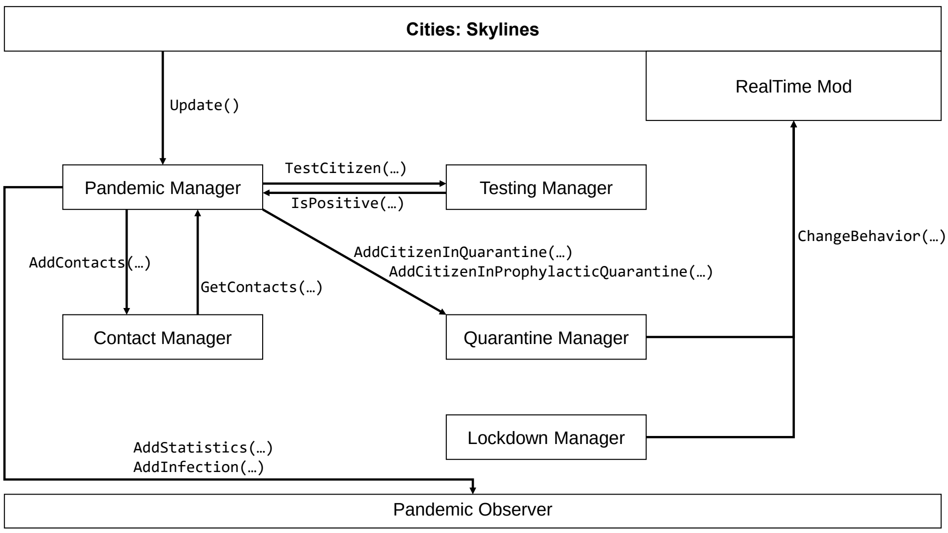


Figure 1. Architecture of our developed extension.

[2]The source-code is available at `https://dev.kom.e-technik.tu-darmstadt.de/gitlab/tobiasm/pandemic-skylines`.

For that purpose, we developed four components, a *Pandemic Manager*, a *Testing Manager*, a *Quarantine Manager*, and a *Lockdown Manager*. Their interaction between each other and with *Cities: Skylines* and the *RealTime* mod is shown in Figure 1. Each of these components contains important functionality for the simulation of an epidemic, which was injected into the functionality of the *RealTime* mod to adapt the citizens' behavior. These components are used in conjunction with the *Pandemic Observer*, which is responsible for persistently storing the results.

Pandemic Manager

The *Pandemic Manager* is responsible for the spreading of the disease from infected to healthy citizens and for the tracking of infection time and deaths. Based on the configuration, the *Pandemic Manager* starts infecting citizens at the start of the simulation, such that a certain number of citizens is infected with the disease at the start of the simulation. On the call of the *Update* function of Unity, we force a pause of the simulation. At a first step, the *Testing Manager* is called to decide on which citizens will be tested. Based on the configuration, this decision may either be done randomly within the set of citizens with symptoms or with the whole population. To prevent unnecessary tests from already tested citizens, we decided that a citizen may not be tested more often than once a week. Without that precaution, the randomness of the decision might lead to a few citizens being tested repetitively, while others might not be tested at all. Tested citizens will then be sent to quarantine.

After the testing has been performed, the contact manager is called to trace contacts. Then, the spread of the disease is performed as described in Design. The modeling of the spreading of the disease for large residential buildings was especially difficult. In the early stages of our approach, the infected cases in large residential buildings skyrocketed due to the high number of people living in this particular building. To address this issue, we limited the spreading of the disease inside of residential buildings to family members, and used a lower infection probability to account for random infections in the hallway. Consecutively, we determine the death of citizens based on a similar formula like Equation 1, and set the *Dead* flag of the citizens to true if he died. Once this flag is set, the *RealTime* mod will take care for the handling of the dead citizen. In the end of each *Update* call, the current state of the simulation is transferred to the *Pandemic Observer*.

Testing Manager

The *Testing Manager* is responsible for simulating testing of citizens. Its main challenge was to transfer the configured number of tests per week into an actual testing system. To not exceed the configured number of tests, we developed a virtual queuing system considering this number to decide on the testing order of the citizens. As a certain share of tests may be reserved for sick citizens (infected citizens with symptoms), we use two virtual queues for the testing, one for sick people only and one for all citizens. While healthy people may only use the second virtual queue, sick citizens can be queued into both. Each queue is processed with the speed possible based on the number of available tests and has a configurable maximum length in processing time, such that the queues are not filled with outdated tests. Additionally, we ensure that citizens tested positive are not tested again, as we assume some form of immunity after recovery. Thus, testing these citizens would not provide any additional insight, while consuming important testing resources.

We provide the possibility to set the false-positive and false-negative rate of the respective tests, such that the effects of the test quality can be investigated. Due to the queuing of tests, the executing of a single test may take a while. As the citizen might continue infecting other citizens in that time, we implemented the possibility to precautiously send tested citizens to quarantine. In that case, their contacts will not yet be notified, but the notification of the contacts will only happen when the positive test results is there. The handling of the quarantine measures is then left to the *Quarantine Manager*.

Quarantine Manager

The *Quarantine Manager* is responsible for managing the quarantine of citizens. This includes: Sending citizens to quarantine after their test and releasing them if they are either tested negative or recovered from the disease. Additionally, it is important to be able to send citizens to prophylactic quarantine, which is only necessary if one of their contacts was confirmed positive. The decision to send a citizen to quarantine is made by the *Testing Manager* and the *Pandemic Manager*, which state the necessity for quarantine. Once a citizen is sent to quarantine, its behavior in the game changes such that he stays at home until he is released from quarantine.

Lockdown Manager

In addition to sending citizens to quarantine, the whole city can be locked down to reduce the contacts of each individual person. We offer two possibilities for lockdown, the first closing down everything except work and

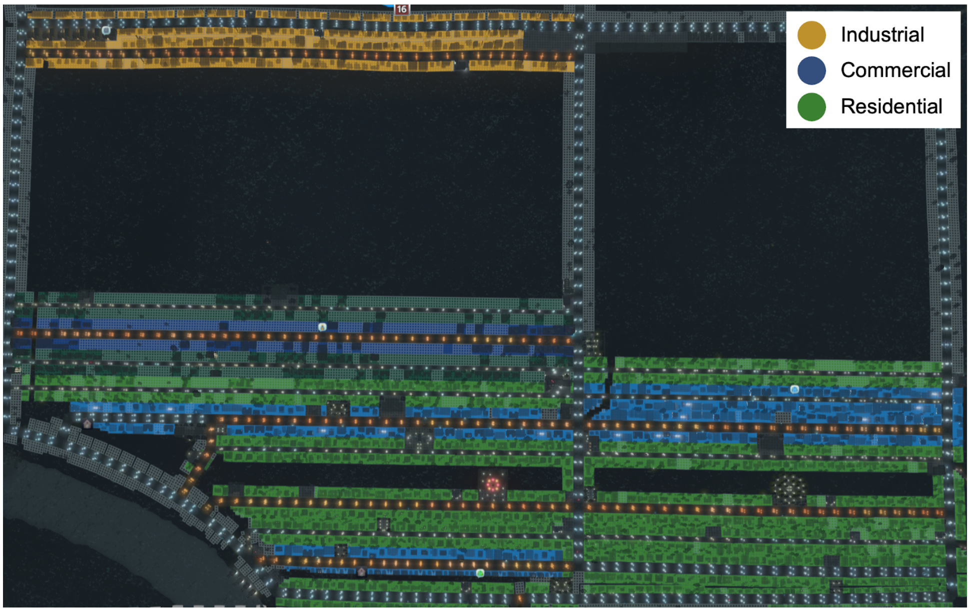


Figure 2. City used for this evaluation. Screenshot of *Cities: Skylines* (*Cities: Skylines* 2015).

schools, and the second closing down everything, i.e., a hard lockdown. In contrast to quarantine, the behavior of all citizens is changed during a lockdown. As a hard lockdown reduces the social contacts to a minimum, it is reasonable to set a relatively high start-infection rate of the citizens to analyse the effects of a hard lockdown.

Contact Manager

The contact manager keeps track of citizens that had contact, depending on the configured policy for contact tracing. If app-based contract tracing is enabled, a contact is detected if the citizens are within a configurable range. If contract tracing in buildings is enabled, a contact is detected if the citizens are in the same building.

Pandemic Observer

The *Pandemic Observer* is responsible for storing the simulation results persistently. For that purpose, data is provided by the other components, which is then exported as csv-file for easy and human-readable access. Based on these csv-files, we generate the plots using external python scripts.

EXPERIMENTAL EVALUATION

In this section, we present experimental results of our epidemic simulation platform. This includes simulating the epidemic with different measures taken by the government and different tools available to them. For this purpose, we build a small city with 11.452 inhabitants, which is shown in Figure 2. The number of citizens is controlled by the game giving the (pre-pandemic) setup of the city. This number can be increased by declaring more zones as residential areas or increasing the living standard of the citizens in the city. The yellow zones are industry buildings, blue zones are commercial buildings, and green zones are residential buildings. Between these zones there is empty land, which could be used for further building. In addition, multiple schools, firefighter stations, police stations, and hospitals are placed in this city. There are several parks available for the citizens to relax and meet, including a Christmas market at the center of the city. While the city layout does not correspond to the traditional German city, using a real city as an example is possible. The complexity of building a city depends strongly on the required level of detail for the simulation. Thus, our developed epidemic simulation can be used on any city, given that a person is willing to create a digital twin of it. With that, majors or governments may get more detailed explanations of the spreading behavior and infection hotspots in their city.

For the configuration of the disease, the default parameters used are shown in the Table 1. Without doubt, these parameters heavily influence the spreading behavior of the disease and need to be chosen carefully. In this work, we aimed at reflecting some properties of the COVID-19 pandemic, without any claim of completeness. For a more accurate modeling of the epidemic, the knowledge of experts in the field of medicine or similar is required. However, the properties of the epidemic we modeled are:

1. The latent period of the disease is shorter than the incubation period, i.e., a citizen is infectious before developing symptoms.

2. Not every infected person will develop symptoms, but may still be infectious.

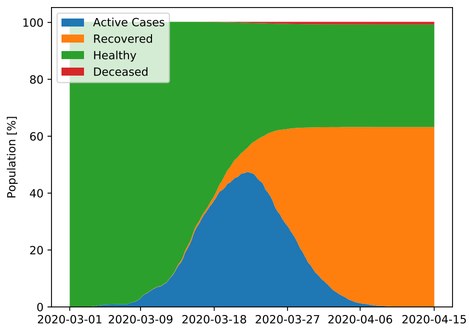
3. The transmission probability indoors seems to be higher than outdoors, which is reflected in our chosen transmission probabilities.

4. The base R-value of Sars-CoV-2 is assumed to be between 2 and 3. Thus, we chose our transmission probabilities such that the R-value is between 2 and 3 if no measures are taken.

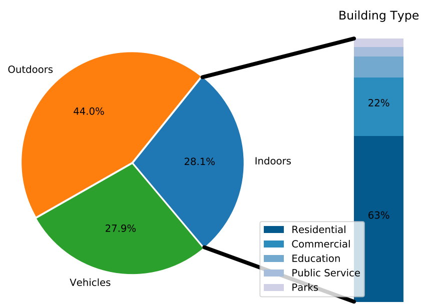
5. Masks can reduce the spreading of the disease significantly, but they alone do not seem to stop the epidemic. Thus, we adjusted the probability reduction through masks such that the R-value is around 1.

Disease Properties	
Disease Duration [days]	10
Start of Symptoms [days]	5
End of Symptoms [days]	10
Start of Infectious Period [days]	4
End of Infectious Period [days]	7
Infected Citizens at Start [%]	0.1
Spreading Behavior	
Indoor Transmission Probability [% / h]	4
Outdoor Transmission Probability [% / h]	2
Probability Reduction through Masks [%]	80
Transmission Range [m]	1.5

Table 1. Default configuration of the experimental evaluation



(a) Number of cases in the city.



(b) Type of infection.

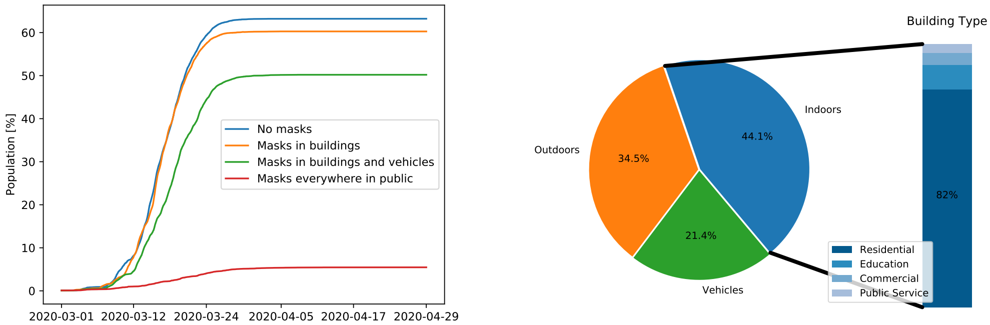
Figure 3. Development of the epidemic without any measures.

To begin with, we analyse the development of the disease if no measures are taken as shown in Figure 3. For that purpose, we first analyse the cases in the city in Figure 3a. In this figure, we see the number of overall infected citizens in blue, the number of recovered in orange, the healthy citizens in green, and the number of deceased citizens in red. We can clearly observe that by simply using the movement of the citizens and the spreading of the epidemic, we obtain the typical behavior of a epidemic. That is, at the beginning, the number of cases raises exponentially until a major part of the citizens is infected, and then reduces again as herd immunity is established. In our simulation, we obtained herd immunity at around 50% of citizens that have been infected, which is a little bit lower than the expected behavior of Sars-CoV-2 (Fontanet and Cauchemez 2020). The behavior of the pandemic can be fine-tuned and the herd immunity target can be adapted using the spreading parameters of the disease. For the infections in the simulation, we show the place of infection (outdoors, indoors, vehicles) including the building type in which they were infected in Figure 3b. There we can see that many infections are taking place outdoors, although the transmission probability there is comparably lower. The reasons for this are crowds at, for example,

Figure 4. Crowded bus stop inside of the city. Screenshot of *Cities: Skylines* (*Cities: Skylines* 2015).

bus stops and parks, which we observed during the simulation as also shown in Figure 4. Similarly, we assume that the higher number of cases in vehicles is not related to the private cars, but to using public transport. For the buildings, it is quite interesting that, even for the no-masks case, the main infections happen inside of residential buildings, while other building types are much less relevant. This might be related to, for example, a low density of citizens in a shop caused by the game model. Never the less, it is interesting that the infections in residential buildings dominate that strongly.

Influence of Masks



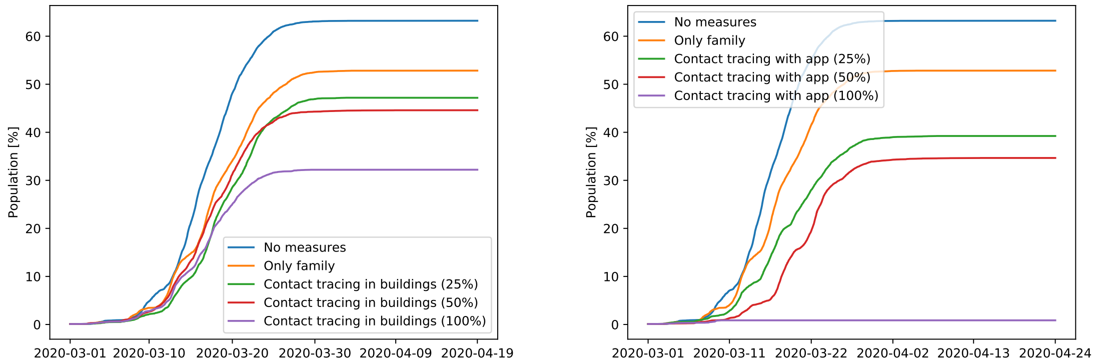
(a) Development of infected people over time. **(b) Type of infection for the mask-everywhere policy.**

Figure 5. Development of the epidemic depending on the mask policy.

Masks can drastically influence the behavior of an epidemic, as it reduces the spread of the disease among citizens. For this simulation, we reduced the infectiousness of citizens by 80% when they are wearing masks. What is evident is that the number of indoor infections increases drastically if masks are required everywhere in public as shown in Figure 5b compared to Figure 3b. The reason why the indoor infections seem to increase is correlated to the lower number of overall infections and the missing masks in private households. We can also observe that the share of infections in residential buildings increases compared to the case without measures, as the infections for all other buildings decrease due to the wearing of masks. In addition, we provide an insight in the behavior of the epidemic in Figure 3a, in which we display the total number of infected citizens over time. We can observe that the policy of wearing masks only in buildings has just a minor effect to the total number of infections and the behavior of the epidemic. The citizens commonly use public transport to get around the city and, thus, get infected already in the buses and at the bus stops, which are commonly very crowded as shown in Figure 4. This also explains minor improvements of the policy of wearing masks in buildings and vehicles, which still does not protect the citizens from getting infected at bus stops.

Influence of Contact Tracing

In Figure 6, we can see the different effects that contact tracing and its acceptance in society have on the spreading of the disease. In Figure 6a, we show the different effects of contact tracing in commercial buildings like shops and



(a) Development of infected people over time. **(b) Type of infection for the mask-everywhere policy.**

Figure 6. Development of the epidemic depending on type of contact tracing.

restaurants. The spread of the disease is influenced depending on the share of citizens that accept contact tracing. We define acceptance as installing and actively using the app (for app-based contact tracing) or providing real data (for building-based tracing). For no additional contact tracing outside of the family, there is already an improvement compared to the case without any measures taken, as tested citizens and their families will be sent to quarantine to prevent the spread of the disease. When we enable the contact tracing in buildings, the improvement increases further. Please notice that for an acceptance level of 25%, only $25\% \cdot 25\% = 6.25\%$ can be successfully traced. Interestingly, the difference between the 25% and the 50% case seem to be rather small, but we explain this minor different through the notification of the family of the infected citizens. If many infections happen inside the family, this explains the minor different between the 25% and 50% cases. For 100% contact tracing in buildings, we see quite a significant improvement, as every infection of a person inside of a building can now be successfully traced. In Figure 6b, we analyse the effect of using an app on the smartphone to trace contacts of the citizens. For all levels of acceptance, we see that the app-based tracing outperforms the manual contact tracing in buildings, which is to be expected as the app can trace infections in all parts of everyday life. Please notice that the disease can be stopped almost immediately when we assume 100% app-based contact tracing, as every citizen in infection range is immediately notified and sent to quarantine when a contact is tested positively.

CONCLUSION

In this paper, we presented an approach to an all-encompassing, realistic disaster simulations. We modified a city building game to act as a digital twin for urban crisis planing and what-if analyses. In addition to existing mobility models, we provide necessary work to research the spreading of pandemics such as COVID-19. Our work enables different spreading behavior and symptoms as well as countermeasures such as various degrees of lockdowns, masks, and digital contact tracing. Furthermore, a thorough evaluation in various configurations has shown that our models are aligned with the observed behaviour in various scenarios and countries during the COVID-19 pandemic.

There are several areas of future work. First, the integration of live statistics as well as interactively triggering countermeasures within the running simulation would benefit researchers and governmental users. Furthermore, a real-time integration of other use-case specific simulation software for more realistic network simulations or the power grid would increase the usefulness of the digital twin even further. Finally, the automatic construction of the urban environment from OSM data can be further improved to get an accurate digital twin with less manual work.

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