Modeling & Simulation

SIR Model - Mass Tests

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Abstract

In 2020 the COVID-19 pandemic caused worldwide suffering and deaths and the whole world is waiting for a vaccine. In winter 2020/2021 countries in Europe came up with the idea of executing nationwide mass tests to reduce the number of unconfirmed cases. This strategy should serve as an alternative to lockdown measures that force people to reduce their contacts. In this project we want to contrast these alternatives qualitatively and quantitatively by constructing a modified SIR Model to simulate the spread of the disease. With our model we want to answer the question: How many days of lockdown are necessary with different strategies of mass-testing?

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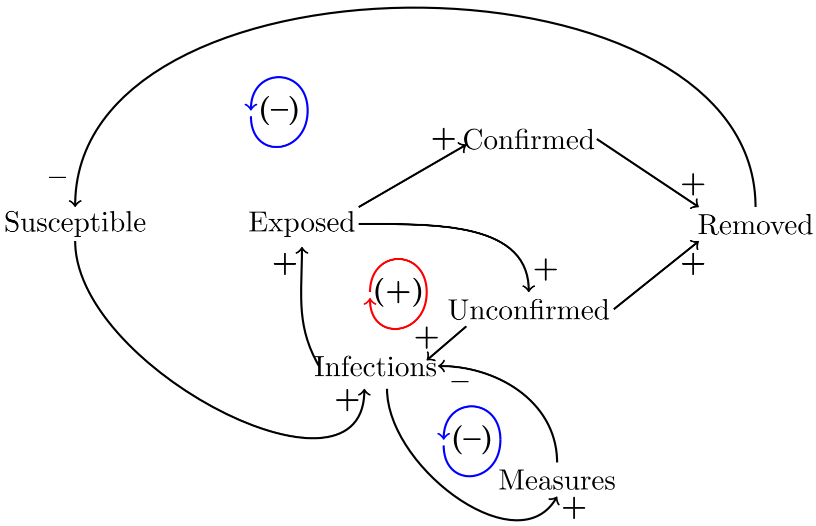
1 Model Description

Our model is based on the classical SIR Model by Kermack and McKendrick, but in addition to the standard compartments Susceptible, Infectious, Recovered we introduce an extra Exposed compartment between the Susceptible and the Infectious. Furthermore we split the Infectious compartment into two seperate compartments: Confirmed and Unconfirmed.
In our model we assume, that the persons in the Confirmed compartment are in quarantine and do not contribute to the infection rate anymore. To capture the causal relations within our model we first sketch a basic causal loop diagram.

1.1 Causal Loop Diagram

As one can see in the figure below, there are two main balancing loops in our model and one reinforcing loop. The upper balancing loop only becomes relevant after a big portion of the population has already recovered from the virus and therefore our model will focus on how the disease can be controlled with different strategies of countermeasures.

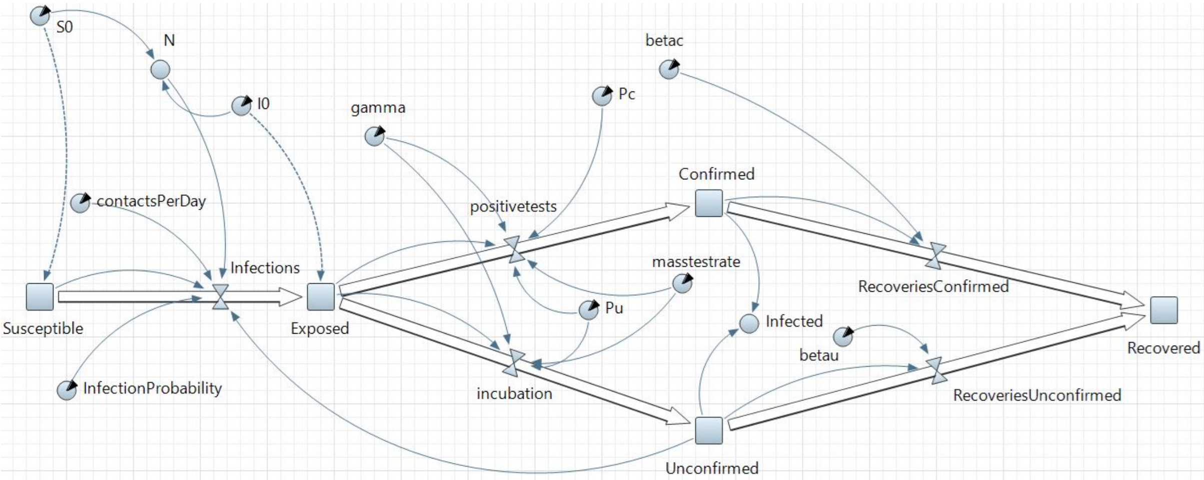
Figure 1.1: Causal Loop Diagram



1.2 Stock and Flow Diagram

For the Stock and Flow Diagram of our model we jump directly into our AnyLogic-Implementation. As already mentioned, the stocks in our model are the Susceptible, Exposed, Confirmed, Unconfirmed and Recovered compartments.

Figure 1.2: Stock and Flow Diagram



1.3 Parameters

We choose our contactsPerDay to be 12 before the start of the pandemic, based on [3]. With our lockdown events, which we will discuss later, this value will vary through the course of the pandemic. Inseperably intertwined with the contactsPerDay parameter is our parameter for the InfectionProbability. Since our formula for the Infections states

$$\text{Infections} = \text{Susceptible} \cdot \text{contactsPerDay} \cdot \text{InfectionProbability} \cdot \text{Unconfirmed} \cdot \frac{1}{N},$$

a change in the first parameter would have the same effect on our model as the analogous change in the second parameter. This posed the challenging task of finding realistic values for those parameters. Therefore we determined our parameter for the InfectionProbability by comparing our model results with the data provided by [1] and finally settled for the baseline

$$\text{InfectionProbability} = 0.06.$$

Furthermore to reflect the seasonal differences in the course of the pandemic, we lowered the InfectionProbability in the summer to 0.02.
Next we needed to determine the value of gamma, which is determined by the time it takes from contracting the virus to becoming infectious oneself. We refer to [4], where a feasible parameter value of 5 is given.
For the rate of positive tests, we took a look at the current state in Austria, where approximately 65% of infection go by unnoticed [2]. Of course one constant value for the rate of positive tests cannot perfectly modeled an ever changing pandemic, however, continuously changing the value

throughout the pandemic seemed to be a too daunting task to handle.
For the recovery parameter the only value that truly matters in our model is the recovery rate for the Unconfirmed compartment, since the people in the Confirmed compartment already do not contribute to the spread of the pandemic anymore. For the value of RecoveriesUnconfirmed we oriented us on the average number of days it takes to recover from the virus, which we assumed to be around 7 days. The inverse of this value roughly yield our parameter value of

$$\beta_u = 0.15.$$

Finally we address the starting values for our model. We choose our start date to be the 25th of February 2020 and assume an initial 300 infections. Our parameter for N is simply chosen as the current population of Austria, which yields the approximate value of $N = 8,900,000$. We end our simulation on 28.01.2022, exactly one year after the presentation date.

1.4 Events

First of all, we of course implemented a mass test event. In our implementation this immediately transfers a predefined fraction of our Unconfirmed compartment to the Confirmed compartment. In addition to this instantaneous shift we also adjusted the rate of confirmed cases for the next three days after the start of the mass test accordingly. We experimented with different participation rates for our masstests, starting from 25%, roughly the average participation rate for the previous masstests in Austria, all the way up to the illusive rate of 90%. For the recurrence of the masstests, we implemented them to occur cyclically, experimenting again with different time intervals for the cycle. The first masstest starts on the 12th of December, just like in reality.

The second big event we implemented was of course the Lockdown. To be precise, we modeled multiple different version of Lockdowns, but all with the same basic idea: The Lockdowns triggers, once the number of Infected people (Confirmed and Unconfirmed combined) reaches a certain level. Precise numbers for this are found in the table below. We chose the value of Infected people over the value of the Confirmed people as the main indicator for our model Lockdown, even though in reality only the number of Confirmed people is accurately known. Our reasoning for this was, that the total number of Infected people in our model should be the best indicator for the strain of the virus on our health system, which would be a major deciding factor in the decision to implement a Lockdown in reality. The effect of a Lockdown in our model is simply a reduction of the contactsPerDay parameter. To account for the multiple levels of reopening like we have seen in previous lockdown, we implemented different levels of lockdown, which gradually increase the number of contactsPerDay to pre-pandemic levels.

Nr. Infected	-	$\geq 45,000$	$\leq 10,000$	$\leq 5,000$
contacts per Day	14	2	6	9

Table 1.1: Numbers for first lockdown

Nr. Infected	-	$\geq 115,000$	$\leq 30,000$	$\leq 20,000$
contacts per Day	9	3	6	9

Table 1.2: Numbers for other lockdowns

2 Simulation Results

To compare the different masstest parameters we measured the amount of days in Lockdown after December 12th. To do this we created a different stock and assumed a flow of 1 during a lockdown and 0.5 during the first level of reopening.

	30 days	21 days	14 days	7 days
25% participation	119	96	86	60
35% participation	96	86	78	36
50% participation	86	77	49	5
70% participation	75	45	6	4
90% participation	39	4	4	3

Table 2.1: Days of lockdown with different participation rate and interval between masstests

To compare: without any masstests at all the number of days in lockdown would be 156. The actual participation rate ranged from $14 - 36\%$ (averageing about 25%), depending on state, with the lowest rate in Vienna and the highest in Lower Austria. The first two masstests happened in the middle of December and January, respectively, so the parameters that best fit reality would be the 25% participation with a 30 day interval between the masstests.
Our simulation now suggests that to really get the most out of masstesting we would need to either heavily increase the participation rate or decrease the interval between masstests, ideally both.

One thing we want to stress is, that in our model no vaccinations are done at all. Since the first vaccinations are already happening right now our model might make the situation look more grim than it really is.