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 two questions: How many days of lockdown are necessary with different strategies of mass testing? What would happen if lockdowns are foregone, but regular mass tests are established instead?

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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.
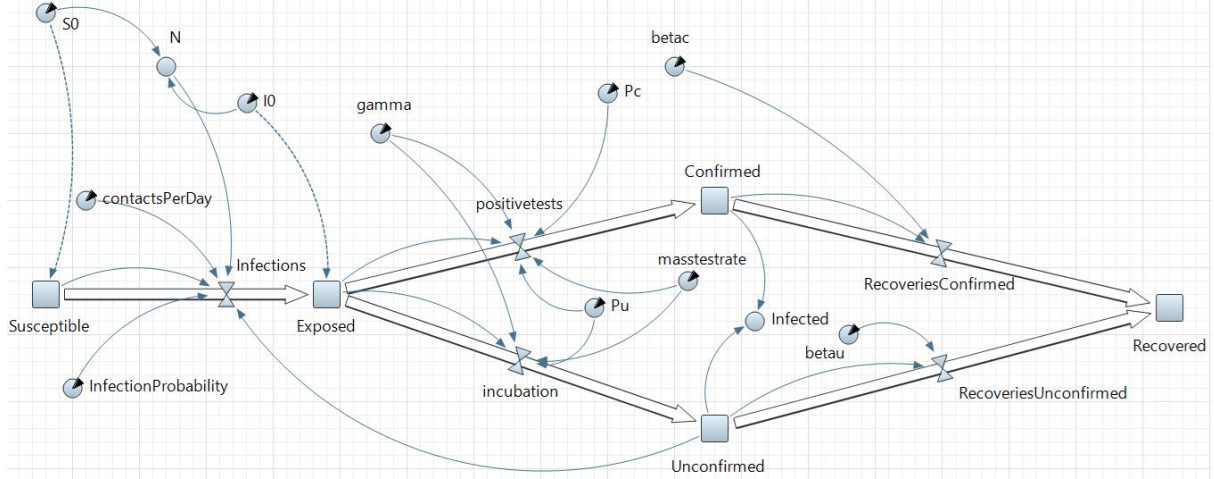
Figure 1.1: Causal Loop Diagram
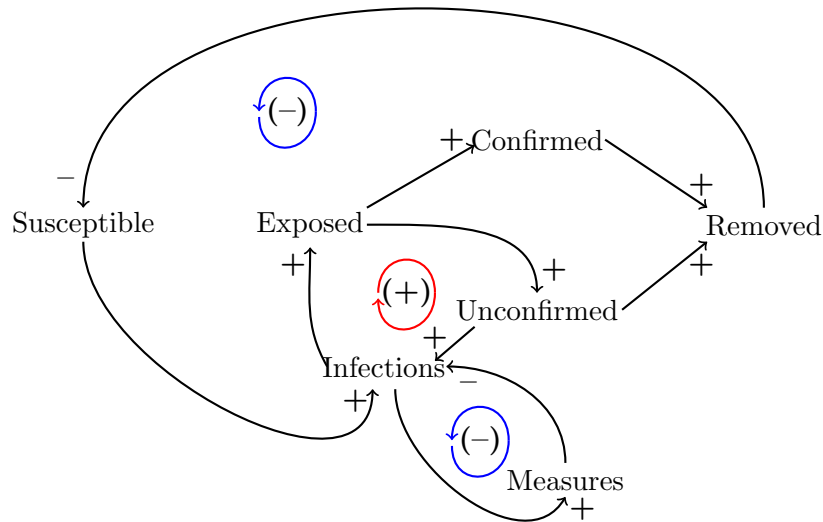
1.2 Stock and Flow Diagram

For the stock and flow Diagram of our model, we jump directly into our implementation in AnyLogic. 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 the parameter *contactsPerDay* to be 12 before the start of the pandemic, based on [**Spiegel**]. 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 the parameter *InfectionProbability*. From our formula

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

we can deduce that 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. We determined our parameter for the *InfectionProbability* by comparing our model results with the data provided by [**OrfCorona**] 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 represents the time it takes from contracting the virus to becoming infectious oneself. We refer to [**RobertKochInstitut**], where a feasible parameter value of 5 is given.

For the number of undetected cases, we took a look at the current state in Austria, where approximately 65% of the infections go by unnoticed [**MassTests**]. Of course one constant

value cannot perfectly model an ever changing pandemic, however, continuously changing the value throughout the pandemic seemed to go beyond the scope of this model.

For the recovery duration, 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 $25.02.2020$ and assumed 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 *Masstest* event. In our implementation this immediately transfers a predefined fraction of our `Unconfirmed` compartment to the `Confirmed` compartment. In addition to this instanteous shift, we also adjusted the rate of `Confirmed` cases for the next three days after the start of the *Masstest* accordingly. We experimented with different participation rates for our *Masstests*, starting from 25%, roughly the average participation rate for the previous mass tests 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 one starts on $12.12.2020$, just like it did 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 events trigger once the number of `Infected` people (`Confirmed` plus `Unconfirmed`) 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 *Lockdown*, even though only the number of confirmed people is accurately known in reality. 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 lockdowns, we implemented different levels of *Lockdown*, which gradually increase the number of *contactsPerDay* to pre-pandemic levels.

Infected	-	≥ 45.000	≤ 10.000	≤ 5.000
contactsPerDay	14	2	6	9

Table 1.1: Numbers for first *Lockdown*

Infected		≥ 115.000	≤ 30.000	≤ 20.000
$contactsPerDay$	9	3	6	9

Table 1.2: Numbers for other *Lockdowns*

2 Simulation Results

To compare the different parameters for our *Masstest* events, we measured the amount of days in *Lockdown* after 12.12.2020. 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 $14 - 36\%$ (averaging about 25%), depending on the state, with the lowest rate in Vienna and the highest in Lower Austria. The first two mass tests 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 mass testing, we would need to either heavily increase the participation rate or decrease the interval between mass tests, ideally both.

One thing we want to stress is, that in our model we ignored the existence of vaccines. Since the first vaccinations are already happening right now, our model might make the situation look more grim than it really is.