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`. It contains the persons that have been freshly infected but do not contribute to the infections yet. After some time-delay they get `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 reinforcing loop illustrates the impact the `Unconfirmed` have on the dynamic behaviour of the pandemic. 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.

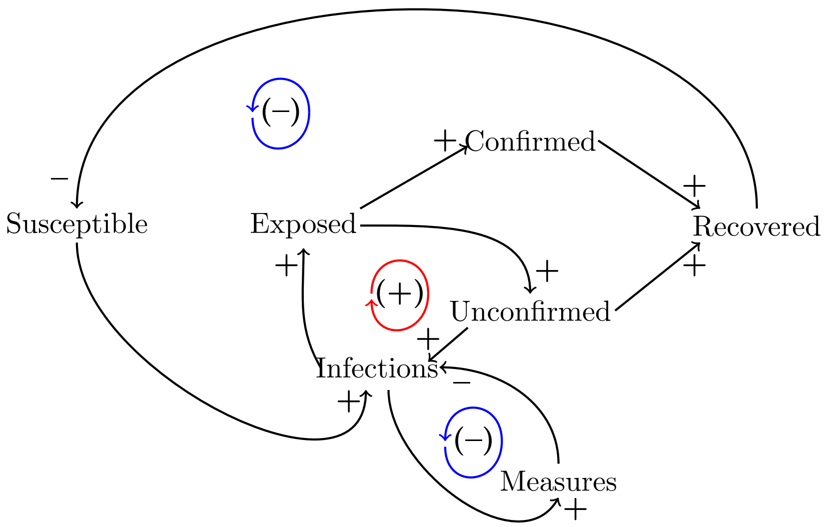


Figure 1.1: Causal Loop Diagram

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.
The number of infections determines the flow from the `Susceptible` to the `Exposed` compartment, which in turn is dependent on the number of contacts per day, the infection probability, as well as the number of `Susceptible` and `Unconfirmed` people. To determine how many people of our `Exposed` department get `Confirmed` or `Unconfirmed` we introduce the parameter *pc* and *pu*, which represent the probability that an infection is detected or not detected, respectively. Furthermore the parameter *gamma* models the average number of days it takes for an infected person to become infectious.
Lastly the flow of the `Confirmed` and `Unconfirmed` to the `Recovered` compartment is determined by their respective recovery rates *betac* and *betau*.

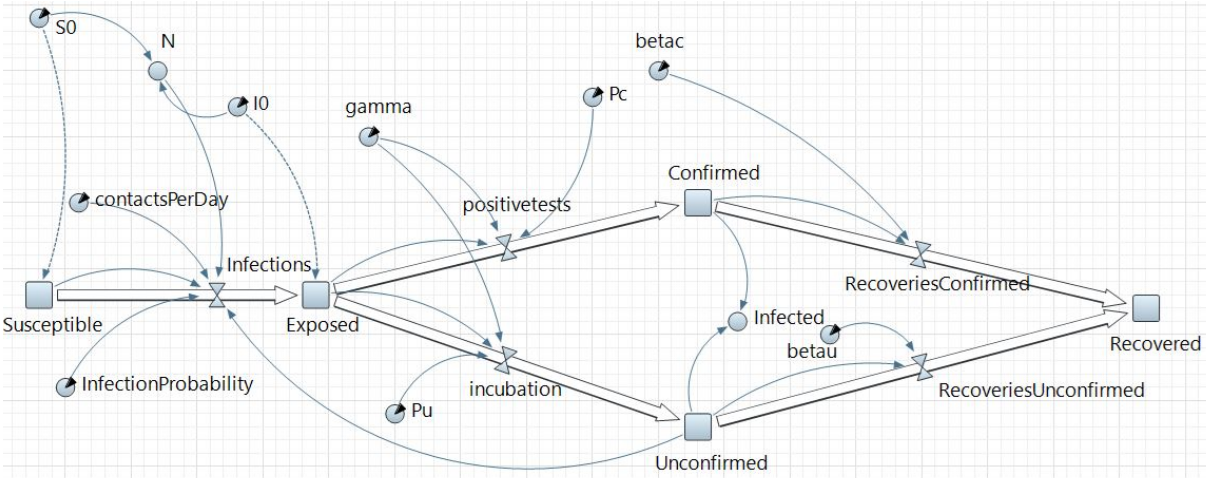


Figure 1.2: Stock and Flow Diagram

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 ourselves to 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 yields 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 instantaneous 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 [**MassTests**], 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.

`Infected`	-	≥ 45.000	≤ 10.000	≤ 5.000
contactsPerDay	12	2	6	9

Table 1.1: Numbers for first *Lockdown*

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

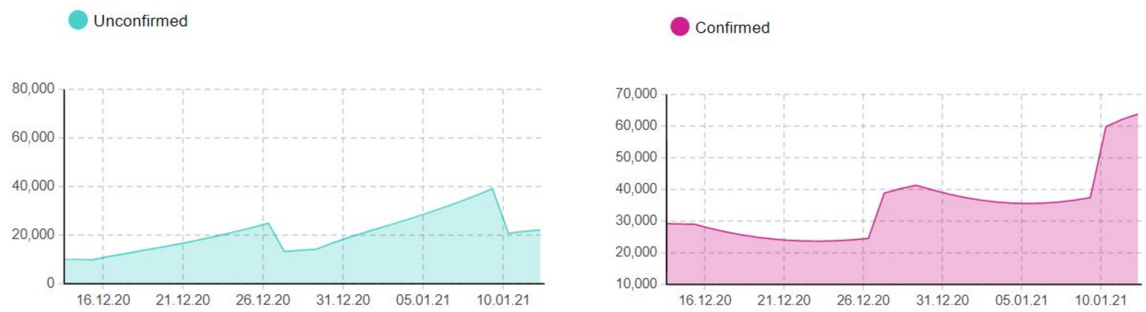
`Infected`	-	≥ 115.000	≤ 30.000	≤ 20.000
contactsPerDay	9	3	6	9

Table 1.2: Numbers for other *Lockdowns*

once the number of `Infected` people (`Confirmed` plus `Unconfirmed`) reaches a certain level. 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. In addition to that, we modeled the first *Lockdown* in Spring 2020 to be more restrictive than following *Lockdowns*, where we use the numbers in Table 1.2. For the first *Lockdown*, we lift the *Lockdown* restrictions after the number of `Infected` people sinks below 5.000. However, we do not increase the number of *contactsPerDay* entirely to pre-pandemic levels to simulate the safety measures, which are still in place without the *Lockdown*. For the other *Lockdowns*, we already lift the restrictions at less than 20.000 `Infected`.

2 Simulation Results

In Figure 2.1 we can see the effect of the *Masstests* (in the graphic with 50% participation rate every 14 days): a steep dropoff of the `Unconfirmed` cases and simultaneous growth of `Confirmed` cases. As we can see in the graphs below, even with this relatively optimistic participation rate and a high frequency of *masstesting*, this strategy alone is merely enough to slow down the exponential growth of cases. To effectively reduce the number of infections, however, we have to make use of our *lockdown* events.



(a) `Unconfirmed` (b) `Confirmed`

Figure 2.1: Change of `Unconfirmed` and `Confirmed` cases with *Masstests*

To compare the different parameters for our *Masstest* events, we measured the amount of days in *Lockdown* after 12. 12. 2020. Since the first *Lockdown* in our model only takes place in Spring 2020, we only need to look at the numbers for the other *Lockdowns* to quantitatively measure the time spent in *Lockdown*. To do this, we created a different stock and assumed a flow of 1 during full lockdown ($contactsPerDay = 3$) and 0.5 during the first level of reopening ($contactsPerDay = 6$). As soon as the lockdown ends ($contactsPerDay = 9$) the flow is set to 0. We can see the results in Table 2.1.

	30 days	21 days	14 days	7 days
25% participation	138	124	95	81
35% participation	123	94	87	67
50% participation	96	87	79	39
70% participation	88	78	48	5
90% participation	78	47	37	4

Table 2.1: Days of *Lockdown* with different participation rate and interval between *Masstests*

In comparison, 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 [**MassTests**]. 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 *Masstests*, ideally both. The sweetspot seems to be at the rates/intervals highlighted in green, there we see a significant dropoff in the days of *Lockdown* needed. We could significantly impact the epidemic wave with just *Masstests* and no *Lockdown* at that cutoff. Since the numbers at that cutoff are highly unlikely to be reached in reality, it seems that masstesting should be done alongside lockdowns instead of replacing them.
To reach a participation rate high enough politicians would probably need to enact laws making participation mandatory. There have been tries to do it but the opposition parties heavily criticised it, questioning the legality.

In Table 2.1 we see that the days of *Lockdown* needed is roughly equal if we compare the *Masstests* with 25% participation every 14 days to the *Masstests* with 50% every 30 days. More generally, we can observe that the days of *Lockdown* needed is roughly constant for a given ratio *days between tests/participation rate*. Only in the comparison of 35% participation every 7 days and 70% participation every 14 days we get a significant difference. This called for some more testing.

Masstests per month / participation per month	one	two	three	four
20%	142	142	142	142
40%	112	118	120	120
60%	90	87	87	87
80%	82	85	85	85

Table 2.2: A set number of participants per month; participation per *Masstest*: p.p.m. /number of *Masstests*

In Table 2.2 we compared the number of days of *Lockdown* for a fixed ratio x/y where x is the participation rate and y is the number of days between tests. We set a fixed participation rate per month, where a month is assumed to have 30 days, so the ratios are the percentages in the table divided by 30. We compared doing one *Masstest* per month, so 30 days between tests, to up to four *Masstest* per month, so 7.5 days between tests. So in the first row we first do one *Masstest* with 20% participation, then two *Masstests* with 10% participation and so on.
In some cases, namely in the second and fourth row, we get better results when doing one „big" *Masstest* compared to a higher number of „small" ones, while in the third row we get the opposite result. All in all it seems that the number of days in lockdown is roughly equal for *Masstests* with the same ratio.

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. Another limitation of our model is test sensitivity. Even if we assumed 100% of the population would participate at the mass test, we still would not catch 100% of the infections. Neglecting that, we assume that the participation rate is equal to the rate of detected infections.