Epidemiology modeling

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1 Task 1

As the aspect of epidemic outbursts to explore, we have chosen the Mortality, but also the influence of the vaccination effectiveness and fluctuation between gaining and losing immunity.

2 Task 2

Aims and general properties We aim to model the dynamics of an epidemic with a focus on the impacts of vaccination and mortality. We would like to understand how vaccination influences the spread of the disease and the overall mortality rate. By introducing additional compartments to the traditional SEIR model, we aim to capture the complexities introduced by vaccination and death cases.

To capture the targeted aspects of the epidemic, we will:

1. Introduce a death compartment to account for fatalities due to infection.
2. Include a compartment for vaccinated individuals who are still susceptible, recognizing that vaccines are not always fully effective.
3. Incorporate a vaccination compartment for the individuals who have been vaccinated.
4. Use differential equations to model the transitions between compartments based on specific parameters.
5. Moreover, we also provided a parameter for those, whose vaccination failed - we allow them to return to *Susceptible* compartment and get another vaccination which this time might be successful and give them immunity.

Our main goal is to investigate the *Dead*, *Vaccinated*, and *Failed vaccination* and also therefore analyze the influence of the change of the corresponding parameters. The compartments and parameters are presented and described in Task 3.

To estimate the parameters of the model, the potential sources of data could be:

- the vaccine efficacy from clinical trial data,
- statistics about mortality or severity of the disease for a specific period of time
- information about possible mobility of infectious individuals, lockdowns, and restrictions in society.

3 Task 3

The key elements of the model include the following compartments:

- **Susceptible (S):** Individuals who are not yet infected but can contract the disease.
- **Exposed (E):** Individuals who have been exposed to the disease but are not yet infectious.
- **Infected (I):** Individuals who are currently infectious.
- Recovered (R): Individuals who have recovered from the disease and gained immunity.
- **Vaccinated (V):** Individuals who have been vaccinated and gained immunity.

- **Failed vaccination (V**$_{f}ailed) : Individualswhohavebeenvaccinatedbutremainsusceptibleduetoineffectivevaccine.$**De**
  Due to the introduced compartments, we are obligated to include the following parameters:

- β: infection rate - it is influenced by the *number of contacts* and *probability of infecting.*
- γ: recovery rate,
- σ: infection rate in exposed individuals,
- α: rate at which individuals leave the *Recovered* compartment,
- α**_v**: rate of immunity loss after the vaccination,
- α**_v_failed**: rate at which individuals leave the *Failed vaccination* compartment - enables them to revaccinate,
- **v_rate**: vaccination rate,
- **v_success**: rate of vaccine efficacy,
- δ: mortality rate.

4 Task 4

We have decided to put our project into the Streamlit app, which lets us change the parameters easily. **Initial conditions:**

- Population size:
- Initial number of infected individuals:

5 Task 5

Scenario 1: Hospital Capacity

The parameters that can be controlled by social restrictions are:

- *prob_of_infecting*: 'Probability of Infecting', which can be reduced by social distancing, wearing masks, disinfecting social spaces, etc.;
- *avg_no_contacts_per_individual*: 'Average Number of Contacts per Individual', which casually can be minimized by the well-known approach *Stay Home, Save Lives*,

which have a direct impact on the β parameter.

Below, we present the way to find optimal values for the above parameters. Our attention should be attracted by the bold green line, which represents *Infected* individuals.

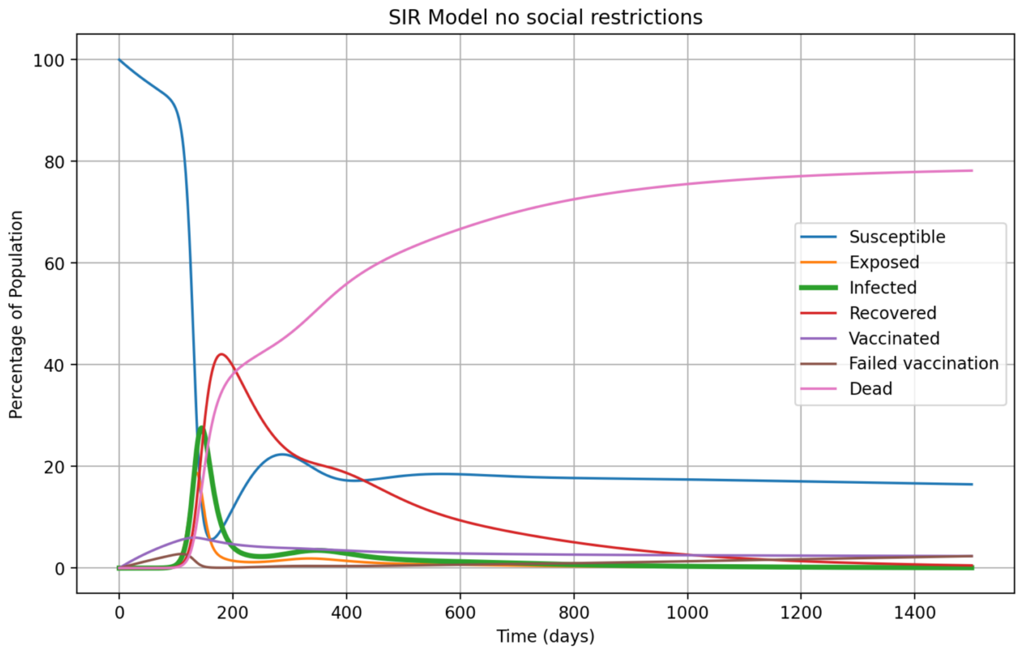

Figure 1: Parameters: *prob_of_infecting*: 0.02, *avg_no_contacts_per_individual*: 20

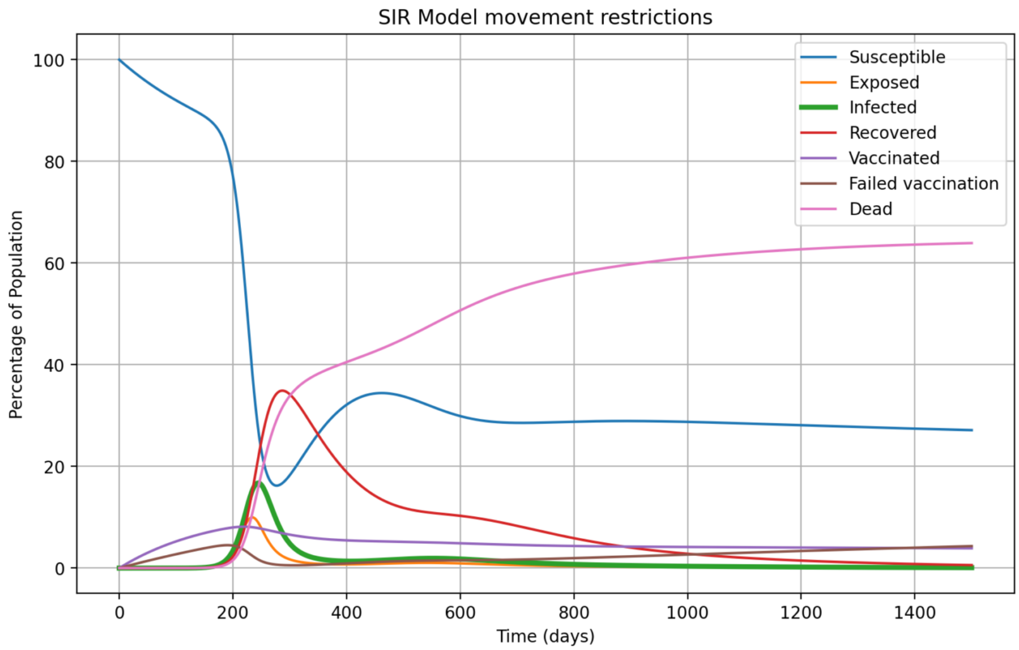

Figure 2: Parameters: *prob_of_infecting*: 0.02, *avg_no_contacts_per_individual*: 12

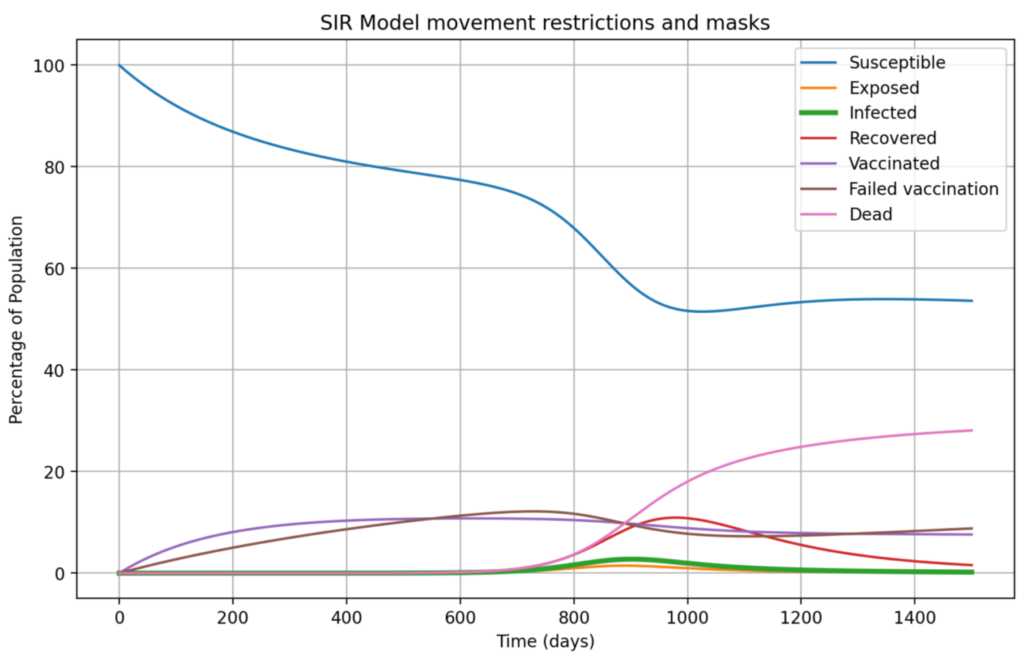

Figure 3: Optimal parameters proper for this scenario: *prob_of_infecting*: 0.01, *avg_no_contacts_per_individual*: 12. As we can see, the *Infected* line is below 10%.

Social restrictions led to a refined line, decreased the value of infections to only a few percent of the population, and delayed the "peak" of the infections, which led us to the conclusion that wearing masks, social distancing, and restrictions are effective ways to fight the epidemic.

Scenario 2: Seasonal Variation

To investigate how the epidemic would evolve with seasonal variation we created a special tab on our Streamlit app, which allows us to choose the parameter, number of changes per year, and the value of the selected parameter in each part of the year.

The parameter of my choice is the *alpha* - the rate at which individuals leave the *Recovered* compartment. I decided to check, how four variations per year would impact the trajectory and development of the epidemic. If the individual goes to *Susceptible* compartment, he gets another chance to:

1. fall sick,
2. receive a vaccination and immunity,
3. die,

so this parameter might have big impact on number of Infected people and fatalities.

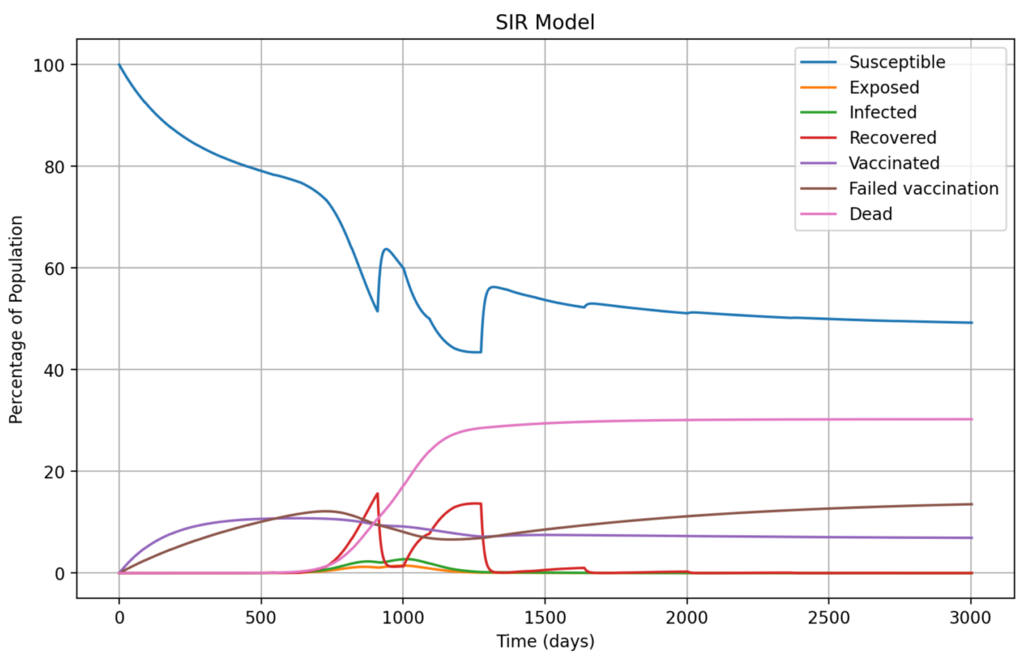

Figure 4: Parameter α variation: 0.1%, 0.1%, 10%, 1%

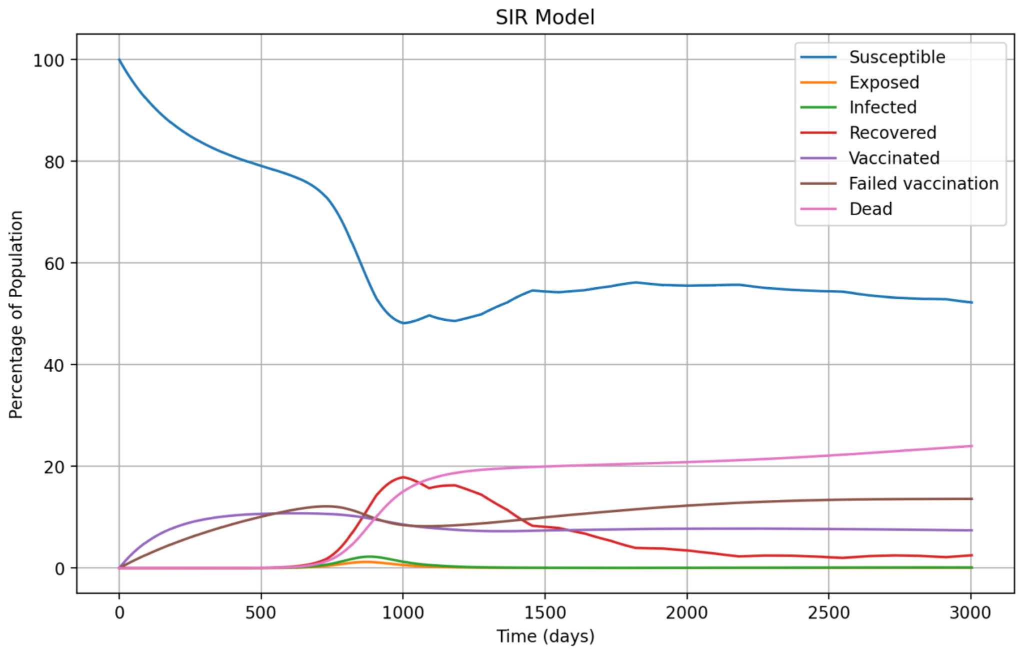

Figure 5: Parameter α variation: 0.1%, 0.2%, 0.3%, 0.4%

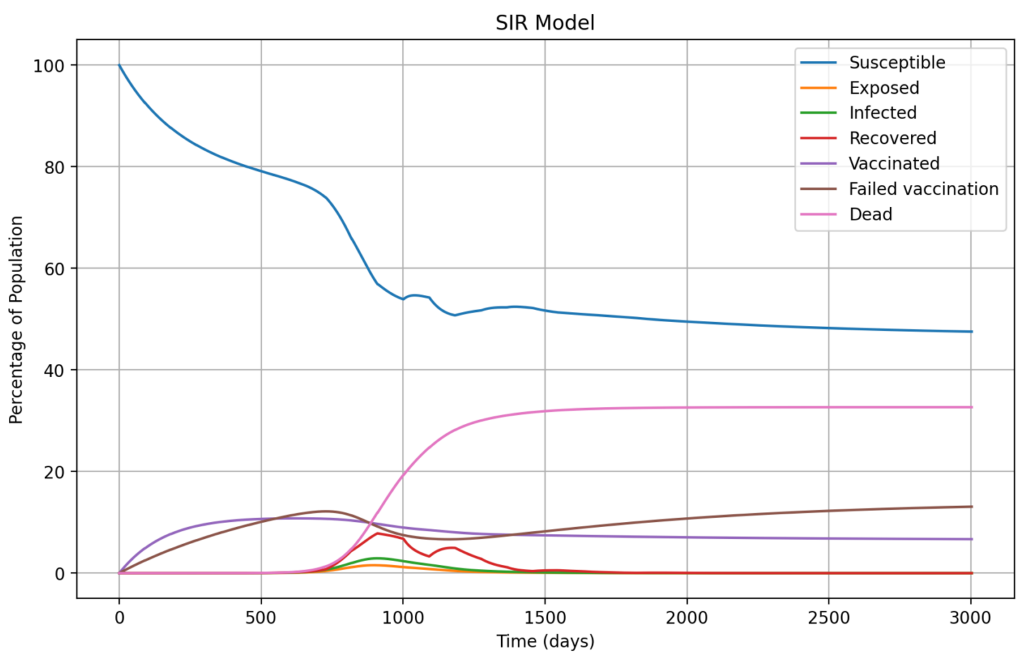

Figure 6: Parameter α variation: 1%, 1.5%, 2%, 3%

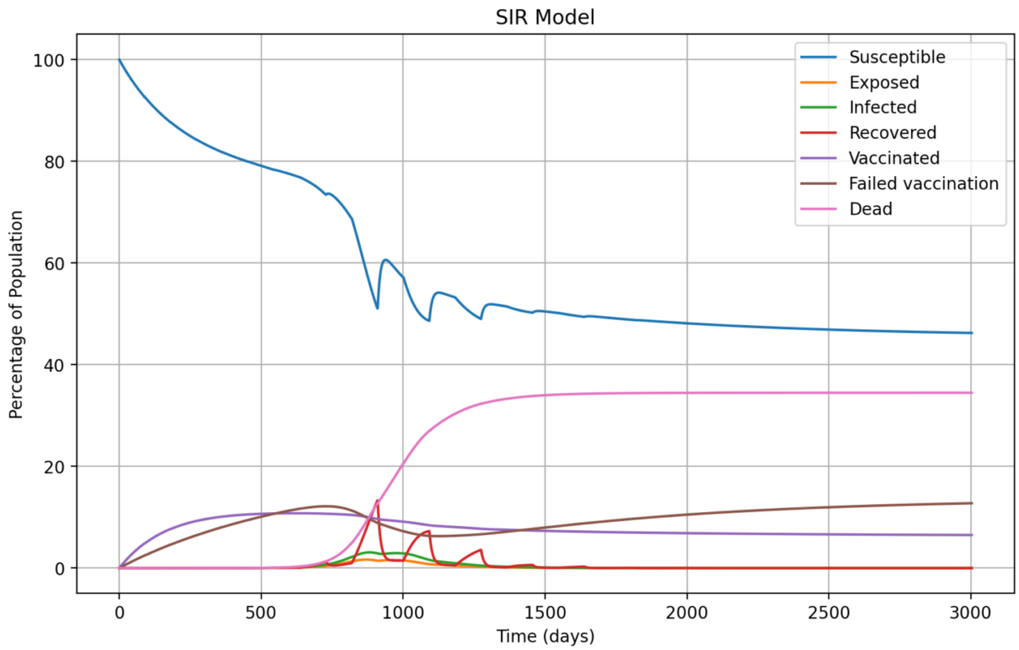

Figure 7: Parameter α variation: 10%, 0.1%, 10%, 1%

Those changes are extreme so we can see 3 ”stairs” around the 1000th day of the simulation.

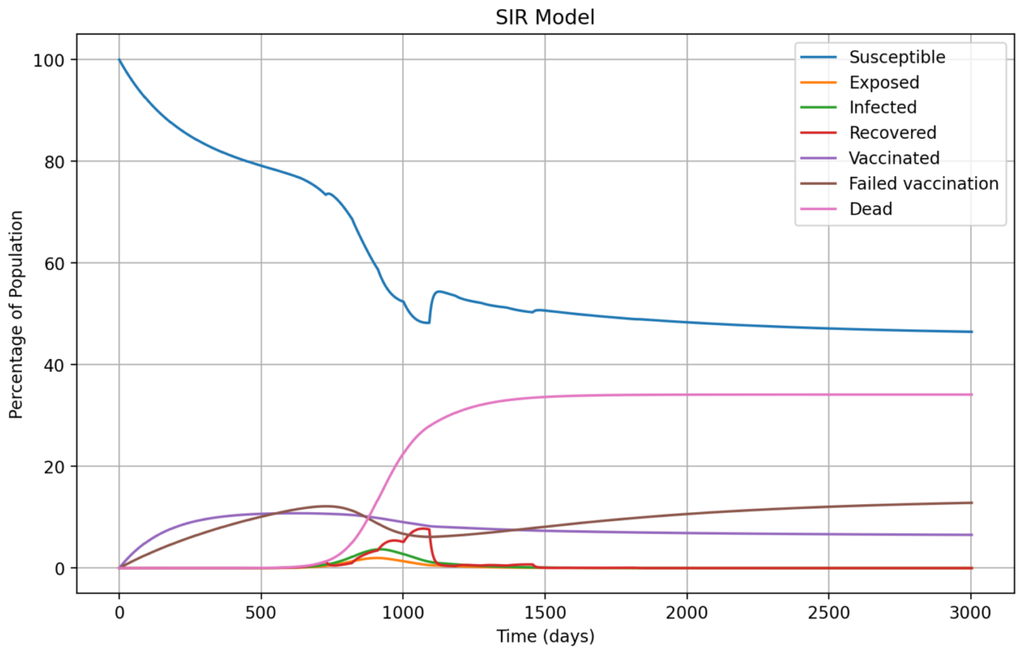

Figure 8: Parameter α variation: 10%, 5%, 3%, 1%

What's interesting, is those seasonal variations of the alpha parameter happen every 91 days, but the visible change and impact are always seen only after almost 1000 days.

We can notice sharp falls or growth of *Susceptible* and *Recovered* each time the alpha parameter drastically around the 1000th day of the simulation. From my point of view, even one high value of the parameter leads to the growth of the *Dead* compartment.

For example in Figure 15 when the changes in the parameters are not drastic, the number of fatalities is definitely lower than in other cases.

Scenario 2: Seasonal Variation ver. 2

To investigate how the epidemic would evolve with seasonal variation we created a special tab on our Streamlit app, which allows us to choose the parameter, number of changes per year, and the value of selected parameters in each part of the year.

I decided to investigate the *gamma* - the recovery rate - the rate at which *Infected* individuals join the *Recovered* compartment. I decided to check, how two seasonal variations per year would impact the development of the epidemic and the sizes of the compartments.

I tested five sets of parameters - more or less extreme and diversified. All parameters excluding *gamma* remained the same.

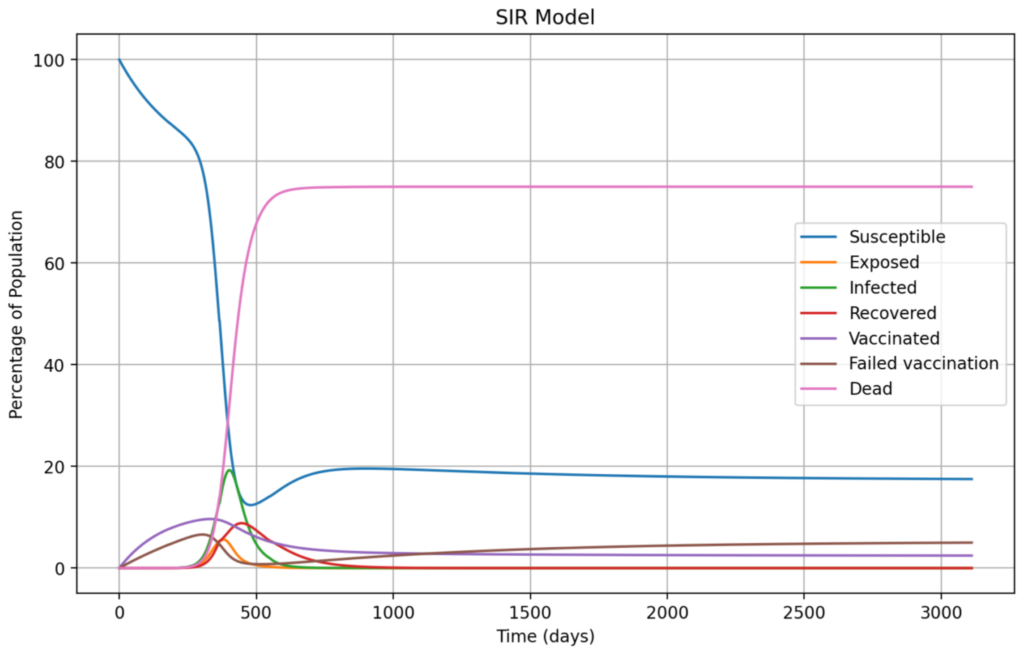

Figure 9: Parameter γ variation: 0.7%, 1.5%

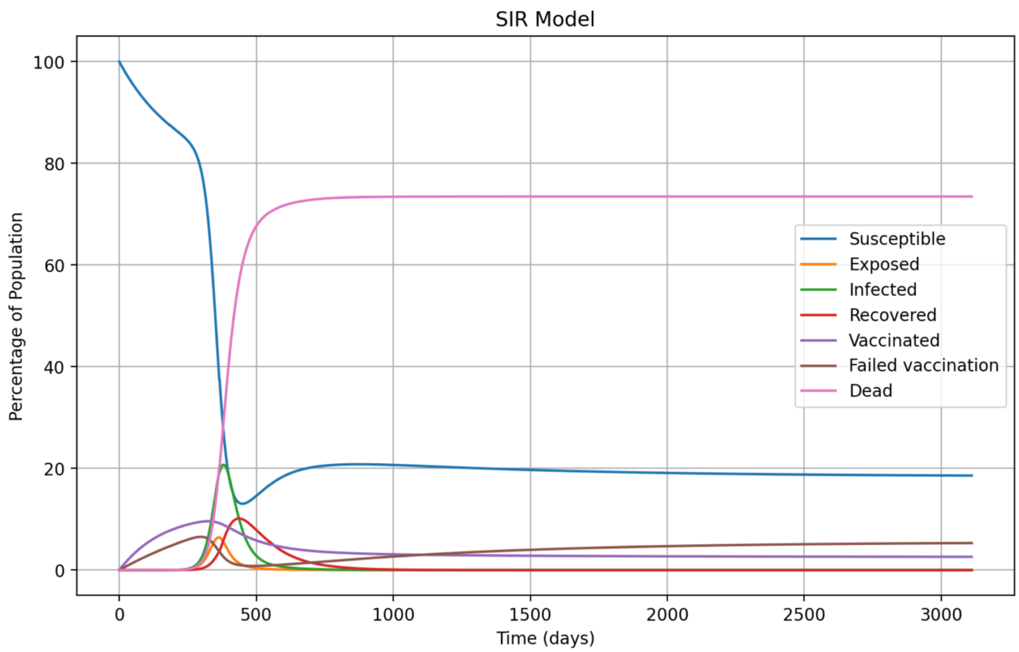

Figure 11: Parameter γ variation: 1%, 0.7%

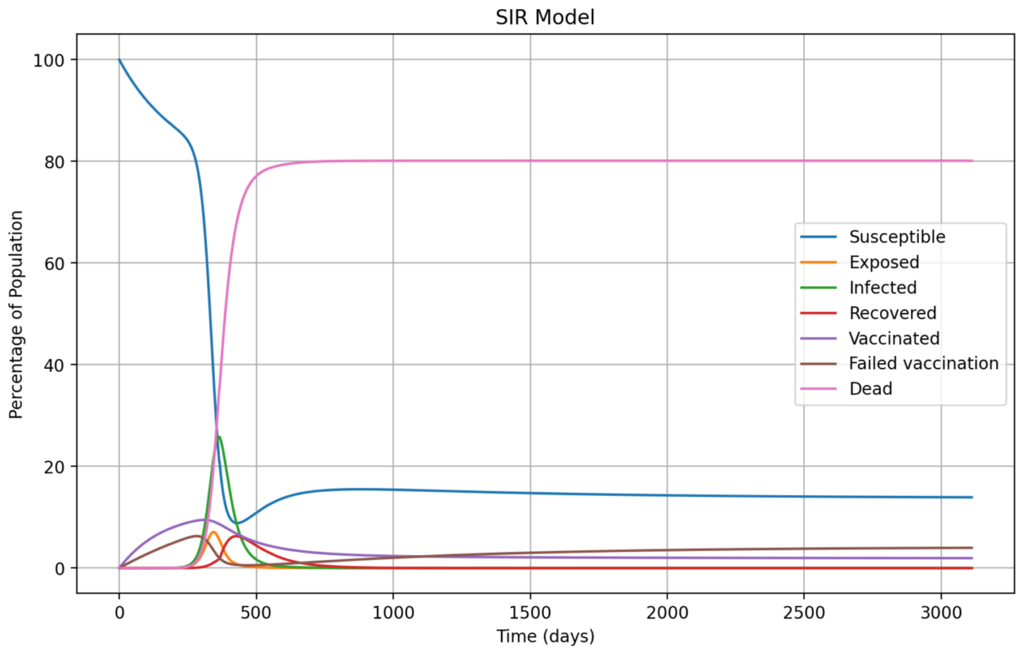

Figure 10: Parameter γ variation: 0.7%, 0.2%

This parameter set was the most extreme and high - we can notice the instant fall around the 1000th day of simulation and violent fluctuations between *Susceptible*, *Recovered* and *Dead* compartments.

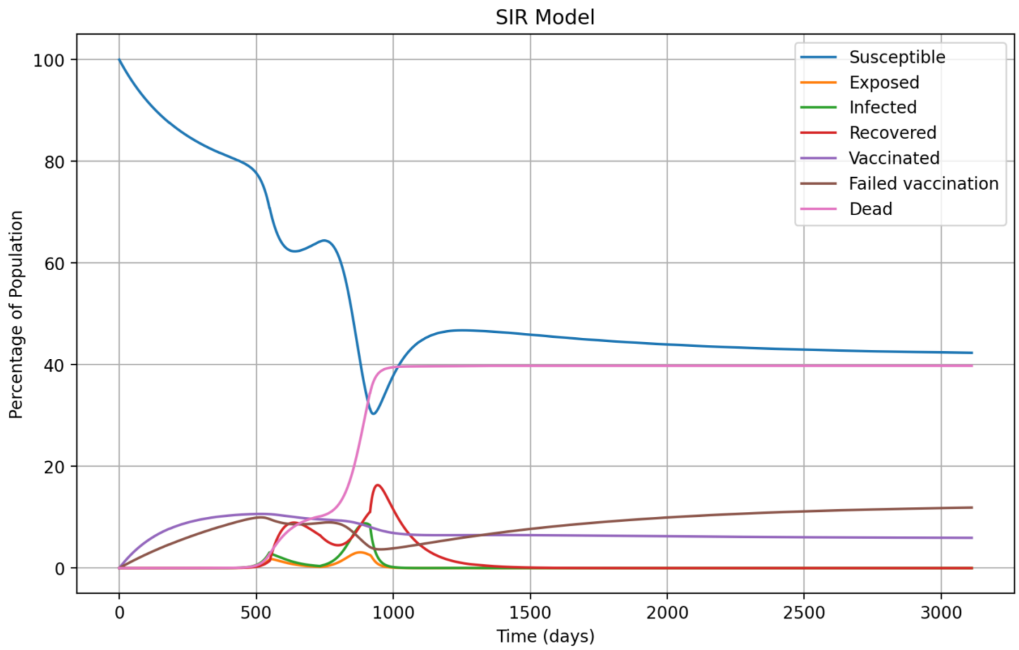

Figure 12: Parameter γ variation: 2%, 7.5%

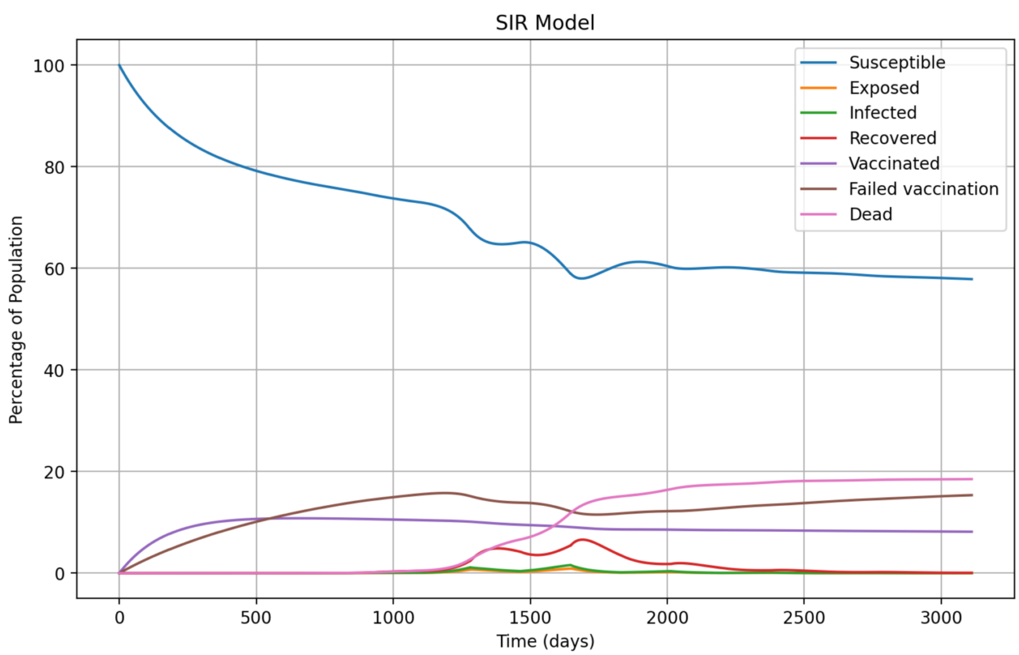

Figure 13: Parameter γ variation: 5%, 7.5%

In this case, both values of the parameter are high, and as a result, most individuals remain in *Susceptible* compartment.

In every situation, the seasonal variation is not noticeable at the beginning or end of the situation. When *gamma* is low, the *Dead* compartment is common to achieve very high levels. By choosing bigger values, we can see the decrease of the *Dead* percentage.

The results aren't the same as I expected, because the variation happens every 183 days, but the fluctuations are only visible when the gap between two parameter values is quite big, and when the values are high. So the conclusion is that the mild seasonal variations don't have a major impact on the epidemic development.

Scenario 3: Restrictions or vaccination

As the third scenario, I decided to check if the epidemic can be fought only by high vaccination level but without any social restrictions (which impact the number of contacts and probability of infection), and opposite - if only social restrictions but without an effective vaccine can be a decisive factor to end the epidemic or decrease the number of *Infected* or *Dead* individuals. All parameters excluding β, *v_rate* and *v_success* will be the same:

- 'sigma': 0.14,
- 'gamma': 1/21,
- 'alpha': 0.005,
- 'alpha_v': 0.005,
- 'alpha_v_failed': 0.001,
- 'delta': 0.03

Therefore, we will investigate two cases and values of the parameters:

1. we will reduce the β parameter, which represents a low infection rate as the result of restrictions and lockdown, and both the *v_rate* and *v_success*, which means that we do not have an effective vaccine.

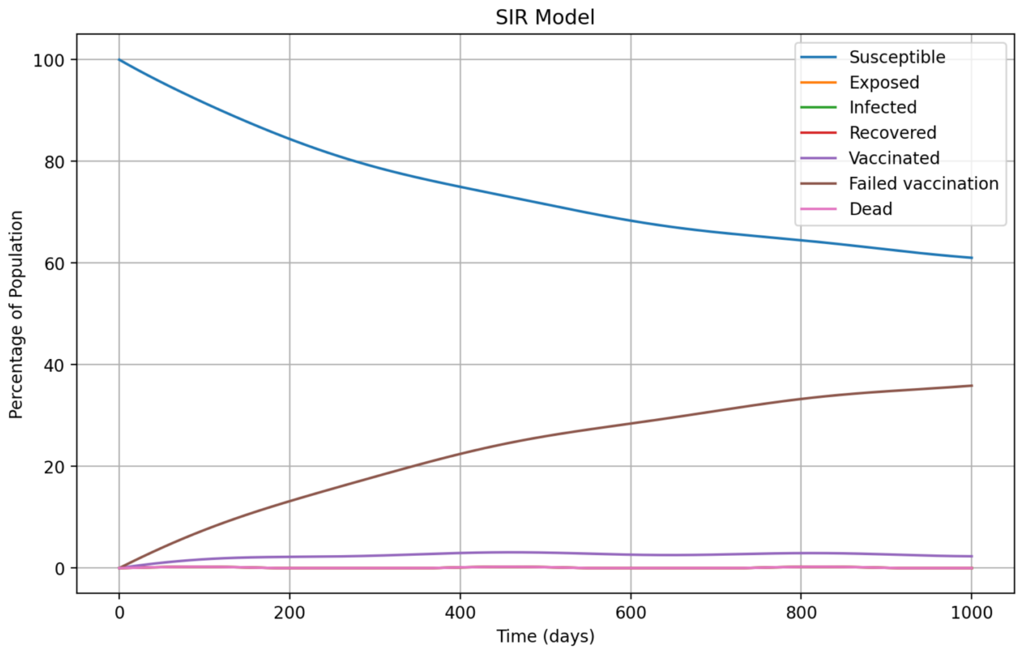

Figure 14: Parameters: *prob_of_infecting*: 0.009, *avg_no_contacts_per_individual*: 6, *v_rate*: 0.001, *v_success*: 0.2

As we can see, the percentage of *Infected* and *Dead* are close to zero. Moreover, most of the population stays in *Susceptible* compartment, which means that social restrictions are quite effective despite the lack of an efficient vaccine.

2. the *v_rate* and *v_success* are going to be extremely high and the same about the β parameter, as the people are willing to receive the effective vaccine, but not to stay at home and wear masks.

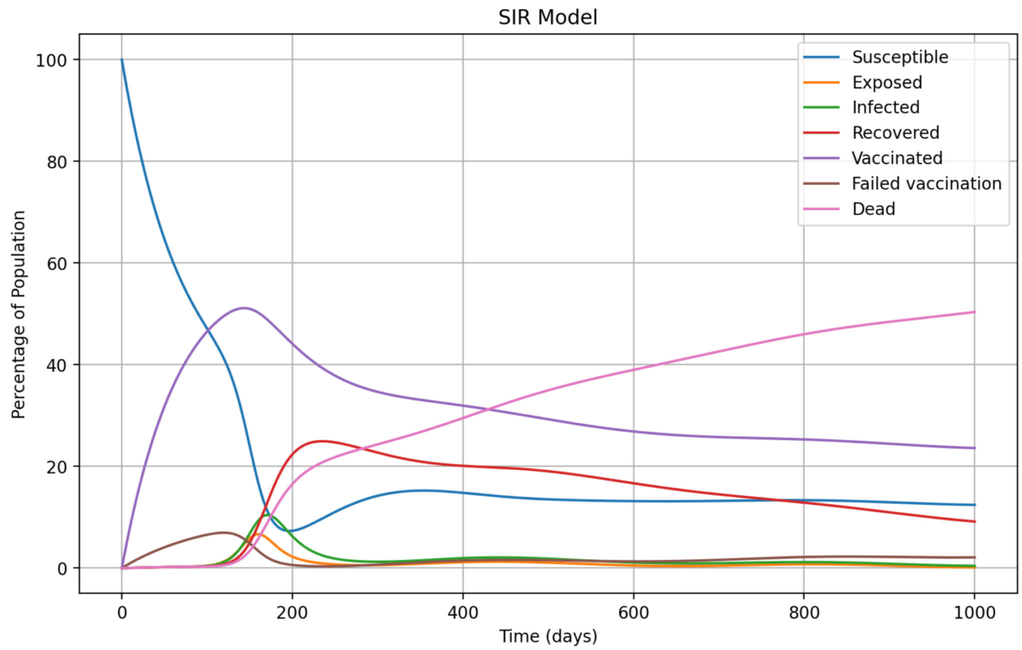

Figure 15: Parameters: *prob_of_infecting*: 0.02, *avg_no_contacts_per_individual*: 25, *v_rate*: 0.01, *v_success*: 0.9

This case leads us to the conclusion, that vaccines can't be the only means to fight the existing epidemic. We can notice quite a high level of *Recovered* and *Vaccinated* compartments, but in the end, almost half of the population died because of the epidemic.

That's why the most effective way to end the epidemic is to combine social restrictions with looking for an effective vaccine.

6 Task 6

Functions generating data disturbed by seasonal variations and random noise are included in code.

7 Task 7

In this task, I decided to check the prediction of the parameters for generated data from scenario 1 - the hospitalization - and scenario 3 - the Restrictions.

Firstly, I generated data with the noise and seasonal variations with selected parameters from Task 5, and then I uploaded it to the prediction function. Below, there is the comparison between actual and predicted parameters for each scenario.

Hospitalisation

Parameter	**Original values**	**Best values**
beta	0.00011999999999999999	0.0000951488789619485
sigma	0.15	0.1404377546708476
gamma	0.047619047619047616	0.0373388468952057
alpha	0.01	0.008748892616182067
alpha_v	0.005	0.004427878640888532
alpha_v_failed	0.001	0.0006386546117298125
v_rate	0.001	0.0008889790758840705
v_success	0.7	0.7131140274256323
delta	0.03	0.02522631853046273

Table 1: Comparison of original and predicted values for hospitalization scenario.

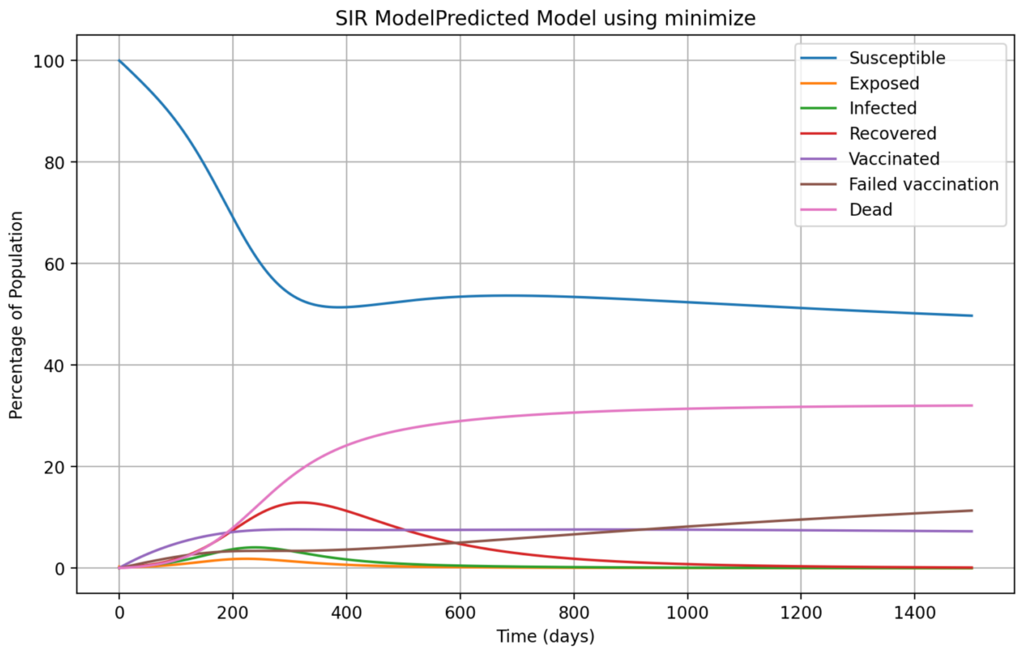

Figure 16: Prediction for hospitalization scenario.

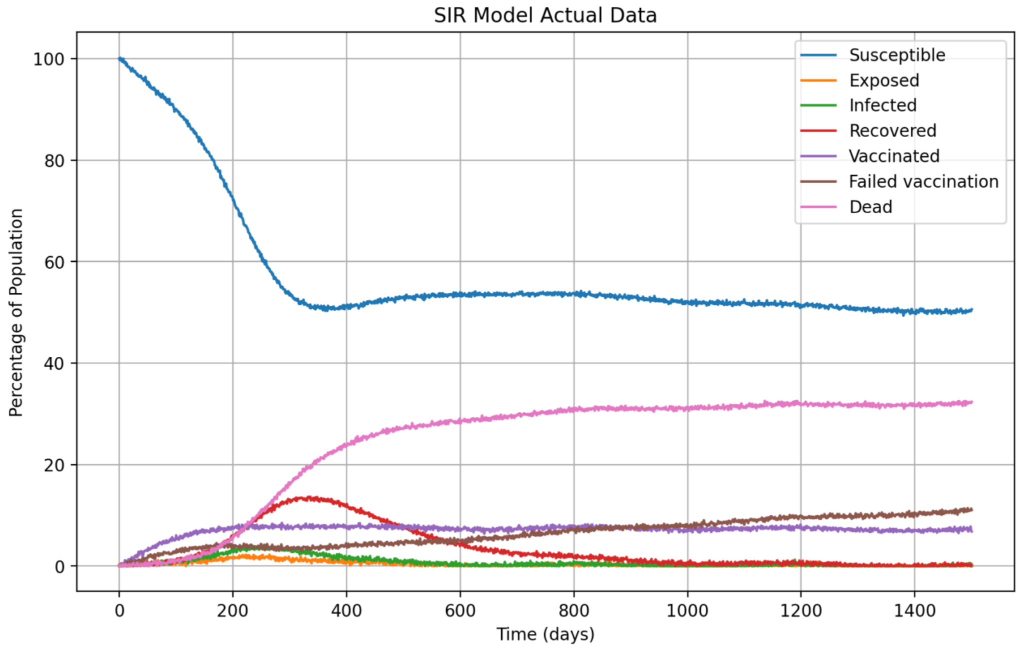

Figure 17: Model for hospitalization scenario.

Restrictions

Parameter	Original values	Best values
beta	5.4000000000000005e-05	0.000001
sigma	0.14	0.15
gamma	0.047619047619047616	0.05
alpha	0.0055	0.01
alpha_v	0.005	0.005
alpha_v_failed	0.001	0.001
v_rate	0.001	0.001
v_success	0.2	0.7
delta	0.03	0.03

Table 2: Comparison of original and predicted values for restriction scenario.

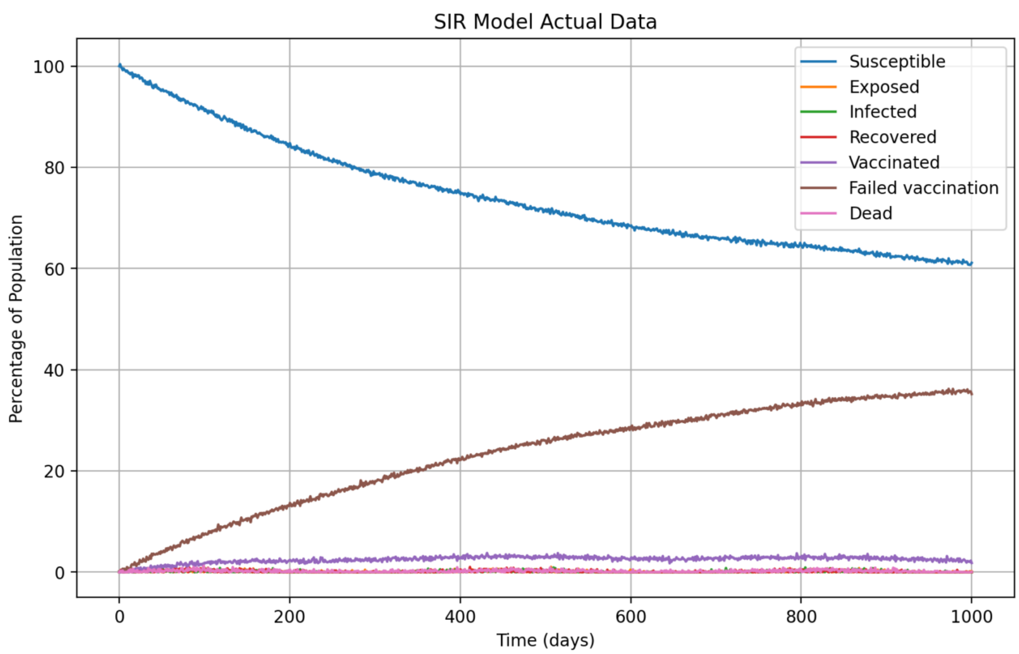

Figure 19: Model for restriction scenario.

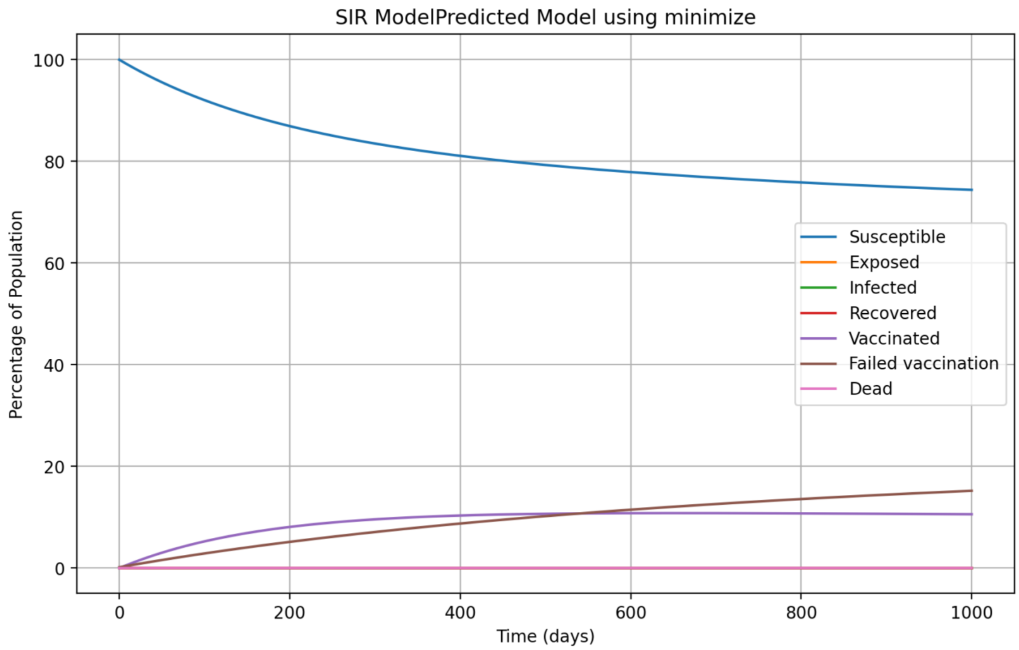

Figure 18: Prediction for restriction scenario.

The problem I noticed:

- when the starting population is too big, the prediction is very inaccurate. Probably that's because of the random fluctuations. The difference was so big and the beta value was even negative, so I decided to put some limitations, but with smaller starting population, it isn't even necessary. It's noticeable on the following plots:

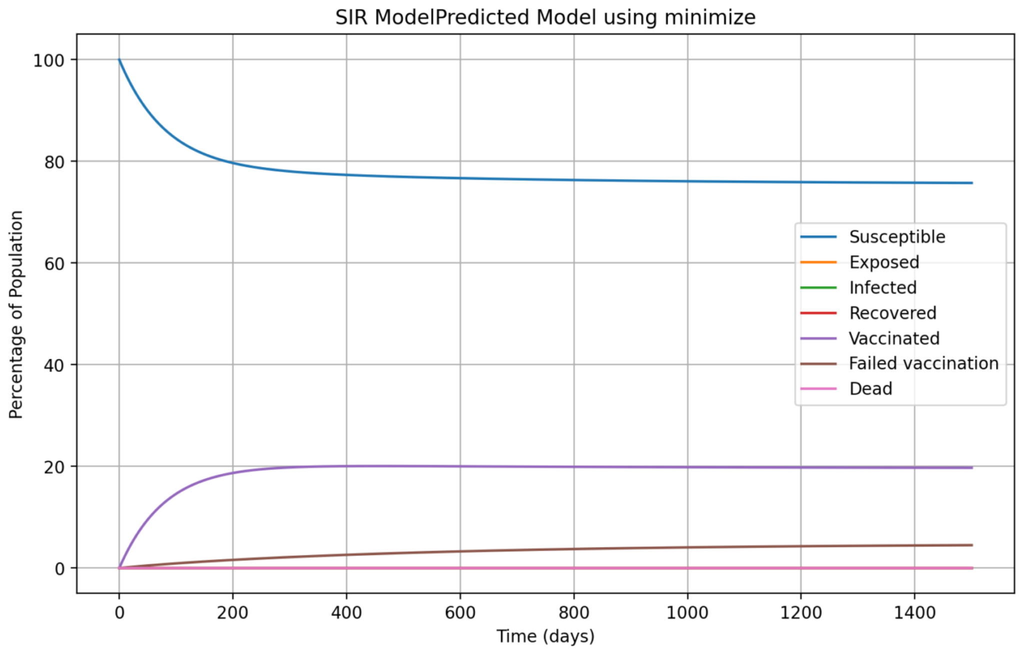

Figure 20: Prediction for hospitalisation scenario with starting population 36000000.

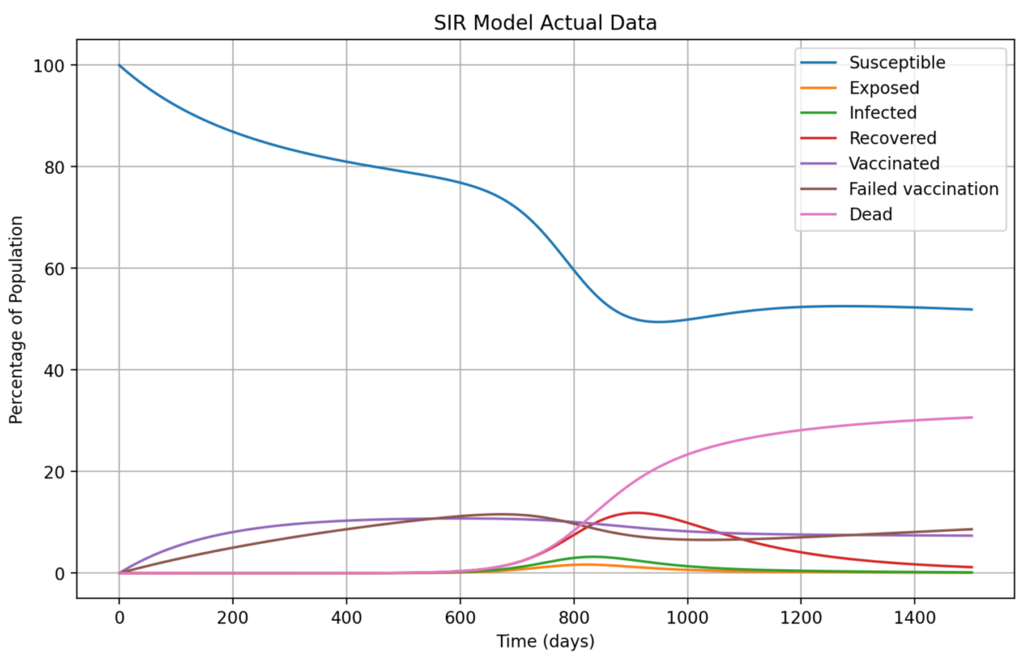

Figure 21: Model for hospitalisation scenario with starting population 36000000.