

A TUTORIAL ON HOW TO SET UP A SYSTEM DYNAMICS SIMULATION ON THE EXAMPLE OF COVID-19 PANDEMIC

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ABSTRACT

The Covid-19 virus has substantially transformed many aspects of life, impacted industries, and revolutionized supply chains all over the world. System dynamics modeling, which incorporates systems thinking to understand and map complex events as well as correlations, can aid in predicting future outcomes of the pandemic and generate key learnings. As system dynamic modeling allows for a deeper understanding of the manifestation and dynamics of disease, it was helpful when examining the implications of the pandemic on the supply chain of semiconductor companies. This tutorial describes how the system dynamics simulation model was constructed for the Covid-19 pandemic using AnyLogic Software. The model serves as a general foundation for further epidemiological simulations and system dynamics modeling.

1 INTRODUCTION

The pandemic caused by the Coronavirus Disease 2019 (Covid-19) can be classified as a low-probability, high-impact disruptive event (Simchi-Levi et. al. 2015) that severely impacted global and local supply chains (SC). The disruptions were primarily caused by government-issued lockdowns and public restrictions on social and day-to-day life aimed at slowing down the pandemic. To foresee SC changes and make well-informed decisions, it is crucial to understand the past and future implications the pandemic disruption has had and will continue to have on a global scale.

To comprehend, evaluate, and predict the development of the Covid-19 pandemic, a system dynamics (SD) model was created. The model was created by extending the epidemiological SEIR model to mimic the pandemic development in several countries. This was made by taking vaccinations, reinfections, behavioral change, and stringency levels into account to address the complexity and expressions of the Covid-19 pandemic. Simulations and SD modeling arise from a need to understand and map the increasingly complex world we live in as well as the actors and events within it. System thinking is required to efficiently take well-grounded decisions and learn from the accelerated and dynamic reality (Sterman, 2000). The following paper demonstrates a tutorial on how to build and simulate the pandemic.

2 BACKGROUND

2.1 System Dynamics Modeling and AnyLogic

There are four simulation and modeling techniques available to address a spread of a pandemic: discrete event simulation, agent-based modeling, SD, and hybrid simulation. The choice of the appropriate modeling technique depends on a multitude of factors such as the decisions, time, geographical scale, and the emergency management phase i.e. preparedness or response. According to Currie et. al (2020), SD is the most suitable modeling technique for complex systems modeling at a global level. Additionally, SD is capable of capturing the different states of the pandemic, the transition between them, as well as the quarantine strategies used to control the spread of the disease. SD is an appropriate method for global simulations as it encompasses simplifying assumptions. Other techniques such as the afore mentioned would be more suitable for an organizational level as they provide a higher level of granularity and realism.

SD is both an abstract and general way of modeling, it distinguishes itself by overlooking the finer details of a system, creating overall depictions of complex systems (AnyLogic, 2022). This characteristic, and offered methodology, make it suitable for larger-scale problems. Feedback loops are the foundation and basic concept of SD allowing for complex relationship modeling. For example, the larger the population of chickens, the more chickens that will give birth, influencing the probability of more chickens crossing the road and potentially being struck by an automobile which in turn would decrease the population of chickens. These interconnections are built on positive and negative feedback loops, otherwise denoted as reinforcing or balancing loops. Describing these loops and models through SD is done by utilizing stocks, flows, and information that impacts the flows. Please refer to John D. Sterman's book (Sterman, 2000) for a more granular description of the world of SD.

The epidemiological model is built in AnyLogic Software version 8. AnyLogic (AL) serves as a beneficial tool for performing SD modeling using multiple structures and tools including stocks, flows, diagrams, array variables, etc. For the pandemic simulation presented, the Professional AL is needed and more information on installing AL and a quick 3-day guide on how to use it can be found in Ilya Grigoryev's [book](#) (Grigoryev, 2021). Other programs with the same criteria for SD modeling can be utilized however, the following model was constructed using AL.

2.2 Epidemiological Modeling of Covid-19: From SIR to SEIHDR

The most commonly mentioned epidemiological mathematical model when working with SD modelling is the SIR-model. This is based on a susceptible population (S) that becomes infected by a disease (I) and finally recovers (R) and thereafter remains immune. To read further about this simple model SIR and its applications please be referred to John D. Sterman's book (Sterman, 2000).

The SIR-model is however not sufficient to capture the complexity of the Covid-19 pandemic. The mentioned complexity arises from the specific characteristics of the virus including incubation time, mutant development, degrees in transmissibility, governmental stringency levels, fatigue, reinfection, and vaccinations. To capture these phenomena the SIR model was initially extended through exposed (E), hospitalized (H), and dead (D), creating a SEIHRD-model. To understand this extension and the further background behind it please be referred to Ivorra et al (2020).

In addition, the model is extended by adding vaccinated stock as well as multiple virus mutations. It is assumed that after a certain period, the population, regardless of vaccination status, does not remain immune and is susceptible to reinfection. Furthermore, for simplicity, births and Covid-19 independent deaths as well as people immigrating and migrating to and from the country have been disregarded in the simulation model.

3 METHOD

The following section explains the structure of the epidemiological AL model in a step-by-step manner used to simulate the Covid-19 pandemic by introducing all major stocks. In addition, crucial parts like

events and variables are summarized in tables in the sub-subsections and the parameters are summarized at the end of every sub-section in tables with a short description for model acquisition and understanding. For accessing all code needed to create the dynamic variables and events presented in this tutorial please be referred to the [simulation GitHub page](#) (Infineon Technologies AG, 2022). Additional general features such as: importing data and historical values from excel files to compare with simulation results, can be further investigated using Ilya Grigoryev’s [book](#) (Grigoryev, 2021).

Figure 1 depicts the major stocks and flows that define the structure of the model. The stocks are additionally explained in Table 1. The first step is to construct this initial structure, seen as the model’s backbone or skeleton. The stocks are always calculated as people, and flows are in people/day.

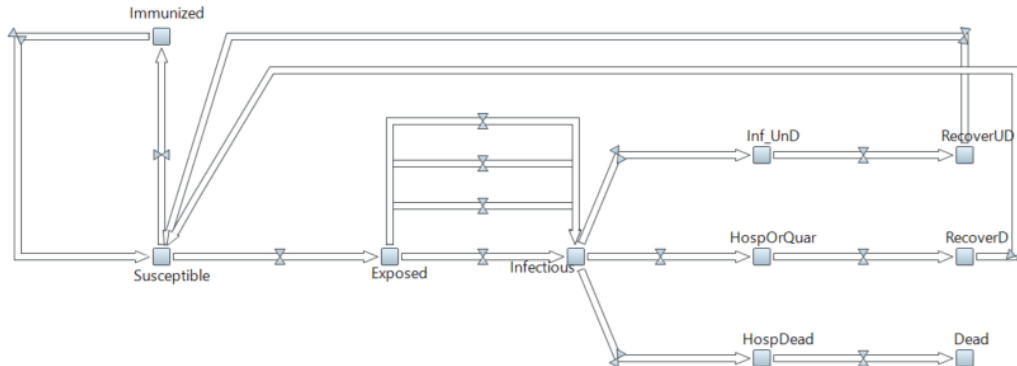


Figure 1: Stock and flow diagram of Pandemic Simulation.

Table 1: List and description of major stocks.

Major Stocks		
Name	Description	Initial Value
Susceptible	Susceptible population	Total Population
Immunized	Immunized population	0
Exposed	Exposed population	0
Infectious	Infectious population	initialInfected / hiddenFraction
Inf_UnD	Infected population where the disease remains undetected leading to recovery	initialInfected / hiddenFraction
RecoverUD	Recovered population where the disease remained undetected	0
HospOrQuar	Infected population which led to hospitalization/quarantine leading to recovery.	initialInfecte
RecoverD	Recovered people previously hospitalized/quarantined.	0
HospDead	Hospitalized/quarantined population that will eventually die.	0
Dead	Dead population	0

3.1 Susceptible

As previously stated the susceptible stock denotes the number of people at risk of being infected by the virus. The susceptible stock is overall affected by three feedback loops; vaccination, immunization, and reinfection representing the in- and outflows of the susceptible stock, see Figure 2.

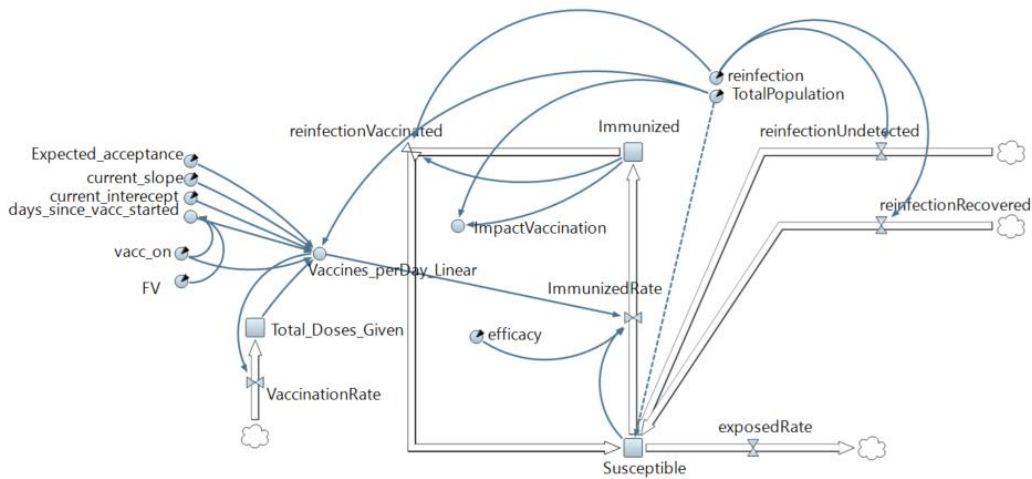


Figure 2: Screenshot of the model part specifically including the susceptible and immunized stocks and linked parameters.

3.1.1 Vaccination

One year after the pandemic outbreak, vaccinations were introduced to help control the spread of the virus. Vaccinations are necessary to add to the model due to the way they altered the course of the pandemic. For the simulation of the vaccination, the approach is similar to that of (Feng et al. 2011). The action is implemented through the stock “Immunized” representing the number of people immunized by the vaccines. This is affected by vaccine efficacy and the number of vaccines administered per day among other parameters.

The rate of the daily doses of vaccines administered per day is assumed non-constant in the Covid-19 pandemic model. It is assumed to differ depending on when during the pandemic the simulation was made. This leads to an approach modeling the rate as three linear approximations, rather than a constant value, depending on the time since the vaccinations started, the maximum vaccination capacity, and a varying vaccination interval. In this tutorial, the intercept and the slope are only described through the “current” value as written in table 5.


An additional stock is added and indicates the total amount of given vaccine doses, see Table 2. The flow, VaccinationRate, is the input to the total amount of given doses and is defined by the rate of vaccinations administered per day as well as the rate of the immunized stock, see Table 3.

Table 2: Summary of the stocks related to the vaccinations that haven't already been introduced.

<input type="checkbox"/> Vaccination Stocks	
Name	Description
Total_Doses_Given	The cumulative amount of vaccine doses given.

To further acquire the immunized stock, the days since the vaccination started must be considered. The VaccinesperDay_Linear is calculated using the stock of total doses given, the expected vaccine acceptance, and the current slope and intercept of the vaccination rate. All of these additions to the model represent a balancing feedback loop that removes people from the susceptible which in turns decreases exposed and infectious population etc. It is however assumed that people are at risk of reinfection so additional loops are added further explained in the following section.

Table 3: Summary of the flows related to vaccinations.

 Vaccinations flows	
Name and Description	Formula
VaccinationRate: The rate of vaccination doses per day	$(VaccinesperDay_{linear} < 0)? 0: VaccinesperDay_{linear}$
ImmunizedRate: The rate of people being immunized through vaccinations.	$(Sustptible > 0 \ \&\& \ VaccinesperDay_{linear} \geq 0)?$ $delay\left(\left(\frac{VaccinesperDay_{linear}}{2}\right) * \left(\frac{efficacy}{100}\right), 14\right) : 0$

To further acquire the immunized stock, the days since the vaccination started must be considered. In addition, the VaccinesperDay_Linear is calculated using the stock of total doses given, the expected vaccine acceptance, and the current slope and intercept of the vaccination rate. All of these additions to the model represent a balancing feedback loop which removes people from the susceptible which in turn decreases exposed and infectious population etc. However, it is assumed that people risk reinfection so additional loops are added further explained in the following section.

Table 4: Summary of the dynamic variables related to vaccinations. Formulas can be found in GitHub page linked in section 1.



 Vaccination Dynamic Variables	
Name	Description
Days_since_vacc_started	Calculates how many days have passed since the vaccination started in the country.
Vaccines_perDay_Linear	The amount of vaccination doses per day.
ImpactVaccination	The impact the vaccinations had in reference to the deadliness. Further used in calculation of the death rate.

Table 5: Summary of all parameters related to vaccinations.

 Vaccination Parameters	
Name	Description
Expected_acceptance	Percentage of people assumed to accept the vaccination
maxCapa	Maximum capacity of daily vaccines given
Vacc_on	Binary parameter vaccination (0-off; 1-on)
FV	Day of the first Vaccination (country specific)
Efficacy	Average efficacy of all the vaccines used in the country. In this model, only one vaccination efficacy rate determines the efficacy of the whole vaccination effort. However, in reality, all countries simulated are using several vaccinations with different efficacies.
GivenHerdImmu	Static herd immunity, assumed by health institutes or calculated
Current_intercept	The current intercept of the linear approximation used for the vaccinations
Current_slope	The current slope of the linear approximation used for the vaccinations


3.1.2 Reinfection

As the pandemic evolved, the cases of reinfection increased, which introduced the risk of stocks previously seen as immunized and recovered to be reinfected. The rate at which this happens is based on the reinfection fraction and the size of the stocks getting reinfected. The model, therefore, adds a flow back to the

susceptible stock from the recovered undetected, recovered hospitalized, and the vaccinated, see the reinfection rates described in Table 6. This creates reinforcing loops increasing the amount of susceptible and further the amount of infectious and recovered. The reinfection is delayed by 180 days converting to around 6 months (Thomas, et al., 2021).

The parameter “reinfection” is a fractional, constant parameter value denoting the fraction of the stock to be reinfected. For this model that value has been assumed to be the same for all stocks.

Table 6: Summary of the flows related to reinfection.

 Reinfection Flows	
Name and Description	Formula
reinfectionRecovered: The flow of people from the Quarantined/Hospitalized recovered that become susceptible again.	$\text{delay}(\text{RecoverD}, 180) * \text{reinfection}$
reinfectionUndetected: The flow of people from the undetected recovered that become susceptible again.	$\text{delay}(\text{RecoverUD}, 180) * \text{reinfection}$
reinfectionVaccinated: The flow of people previously vaccinated and by that note immunized that become susceptible again	$(\text{Immunized} > 0) ? (\text{delay}(\text{Immunized}, 180) * \text{reinfection}) : 0$

3.2 Exposed

As a way to incorporate the effect that general governmental measures have on the spread of Covid-19 the model includes the exposed stock. This stock refers to the number of people that have been infected but exhibit no symptoms or clinical signs and still are in the incubation period meaning they test negative but still risk infecting people. The size of this stock is mainly related to the contact rate, governmental measures, and several mutant variations. The definition and the formula of the exposedRate used in AL is presented in Table 7 and the different formula inputs are visualized in Figure 3.

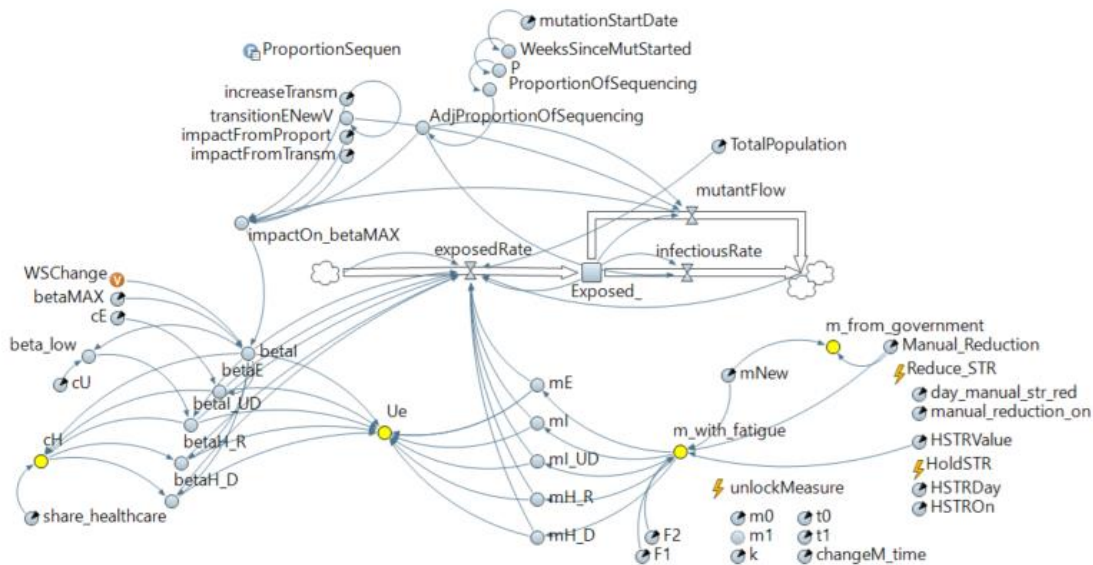



Figure 3: Screenshot of the model part specifically including the exposed stock and linked parameters.


Table 7: Description and formula of the exposedRate.

 Exposed Flows	
Name and Description	Formula
exposedRate: The rate at which susceptible people become exposed by the virus.	$\text{exposed Rate} = \frac{\text{Susceptible } S}{\text{Total Population} * ((mE * \text{beta}E * \text{Exposed} + mI * \text{beta}I * I + mI_{UD} * \text{beta}I_{UD} * \text{hiddenfraction} * \text{Inf}_{UD}) + \frac{\text{Susceptible } S}{\text{Total Population}} * (mH_R * \text{beta}H_R * \text{HospOrQuar} + mH_D * \text{beta}H_D * \text{HostDead})}$

3.2.1 Beta Values

The rate by which people move from the susceptible compartment to the exposed one and further the infectious stock is largely based on the contact rate of people multiplied by the infectivity and the fraction of infected people within the total population. The product of the contact rate and the infectivity is the transmission rate and called the beta-value and represents a large part of the value of the exposed rate. In the model, the beta value varies depending on the respective stock presenting an additional complexity that adds more resemblance to the Covid-19 pandemic. However, they all emanate from the same beta value Beta_I, the transmission rate in the infected compartment. The other specific compartments are distinguished through corresponding coefficients multiplied by Beta_1. For further understanding please be referred to the GitHub page linked in section 1 and Table 8 for the descriptions.

Table 8: Summary of the dynamic variables that are related to the beta values.

 Beta Dynamic Variables	
Name	Description
Beta_I	Transmission rate in the infected compartment
Beta E	Transmission rate in the exposed compartment
Beta UD	Transmission rate in the undetected compartment
BetaH_D	Transmission rate in the hospitalized/quarantined compartment HD
BetaH_R	Transmission rate in the hospitalized/quarantined compartment HR
cH	Share of transmission rate of the infected compartment beta I for hospitalized/quarantined. Based on calculations incorporating the number of infections coming from infected health care workers.
Beta_low	The lowest beta value considered to be that of the people in the undetected state.

3.2.2 Governmental Measures and Stringency

Governmental measures and stringency refer to the governmental and social restrictions in place and how severe these respective items are. Their impact on the pandemic is to be considered in the simulation.

The parameter denotation m, meaning measure, is implemented and simplifies the governmental measures to one value. This m value is individual for each stock due to the way the different measures affect different groups. Up until a certain point during the pandemic simulation, these m-values are taken from a data source with historic data on stringency. After that certain point, the model simulates new values through the event formula “UnlockMeasure” calculating and implementing the outcome of new measures, see Table 11. To access and read the formula for this event please see GitHub page linked in section 1. The event UnlockMeasure means that once $t = t_1$, a new measure is applied converting m_0 to m_1 and t_0 to t_1 ,

see Table 14 for the parameter explanations. This yields a m_{New} value which is further fed into the measures for the specific stocks and further to the exposed rate and the U_e value.

This new calculation and m simulated m value are built on the relationship between new cases and stringency level. This relationship is described using a table function named TF in the model. To standardize the measurement of government restrictions historic stringency values are taken for different amounts of new cases from the Oxford Covid-19 Government response tracker (Blavatnik School of Government, University of Oxford, 2022)

To capture “lockdown fatigue” meaning the possible reduction of stringency level due to non-compliance with governmental measures a reduction factor is incorporated. A reduction factor table function presenting a decrease in value from 1 when a stringency value condition is fulfilled follows a reduced stringency value simulating the reality of fatigue.

The implementation of new measures features a two-week delay to mimic a government reaction time before restrictions are put into place, this delay is constant throughout the simulation. These delays in the SD model create oscillations around the affected time but overall these parameters and implementations are assumed to decrease the effect of the pandemic.

Table 9: Summary of the dynamic variables related to governmental measures and stringency.



 Dynamic Variables	
Name	Description
recalculation	Recalculates the m_I value, meaning the value of the new measure.
$m_E=m_I=m_{I_UD}=m_{H_R}=m_{H_D}$	The m -values used to implement change caused by governmental measures in the specific compartments (Exposed; Infectious; Undetected; Hospitalized-Recovered and Hospitalized dead). All equal to $m_{with_fatigue}$ (see below)
$m_{from_government}$	The stringency and level of measurement from the government, meaning ignoring the fatigue and the reality of what people are actually doing.
$m_{with_fatigue}$	The “reality“ of the measurements including a possibility to manually reduce and hold the stringency level at a certain level.
U_e	Input to the effective reproduction rate based on government measure inputs.
Re	Re is the effective reproduction rate
XXX	Variable calling upon the Stringency table function implementing a delay between action and outcome
New_cases	The amount of new cases from the past week.
AvgStringency	The average stringency
XXX1	Variable calling upon the Reduction factor table function implementing a delay between action and outcome
M_I	The value of the current measure

Table 10: Summary of the events used to implement stringency effects.

 Events	
Name	Description
Reduce_STR	Implements a reduction of the stringency, this is done through a function on the front end.
HoldSTR	Implements the holding of the stringency at a certain level, this is done through a function on the front end.
new_case_calc_t0	Calculates the new daily cases using the difference between cumulative cases today and yesterday
Inflection_point	Checking whether the cases are increasing or decreasing and from that deciding how long the governmental reaction time is.
Populating_sinks	Populating sinks

UnlockMeasure	Unlocks a new measure and changes the m values accordingly.
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Table 11: Summary of the variables related to the stringency.

Dynamic Variables	
Name	Description
Newcase_t1	The amount of new cases at a certain point in time.
Newcase_t0	The amount of new cases at a certain point in time.
Relative_increase	The relative difference between two amounts of cases at certain times.
Cum_cases_t0	The amount of cumulative cases at a certain point in time.
Cum_cases_t1	The amount of cumulative cases at a certain point in time.
Delay_str	Variable displaying the delay_stringency in Table 16.
Delay_adj	Variable displaying the delay_adjustment in Table 16.

3.2.3 Virus and Mutant Flows

For the infectious flow from the exposed to the infected different measures and add-ons are made to capture the multiple variants of the Covid-19 virus. It is assumed, for the simplification of the model, that the variants following the original one are dominant to the original Covid-19 infection and the Delta and Omicron variants are assumed to be dominant over all previous, cumulative variants. For the original Covid-19 model the infectious rate decides the flow of exposed to infectious individuals that become infected with it, see Table 12.

Table 12: Description and formula of the flow rate of the Original Covid-19 variant as used in the model.

Original Flow	
Name and Description	Formula
InfectiousRate: The rate of people moving from the exposed to the infectious stock.	$\max(0, (1 - \text{AdjProportionOfSequencing}) * (1/5.5) * \text{Exposed})$

Regarding the analysis and the number of mutant shares in detected cases it is important to know about sequencing as it is a big part of the mutant rate, see Table 13. Sequencing means testing what mutant infected people have to understand how big part of tested cases a certain mutant has. To capture the spread of the mutation, country and mutant specific table functions of the proportion development are created based on the development of the mutant, namedProportionSequen in the model. The table functions plot the proportion over the time since the mutation started. The data for these table functions are taken from the covSPECTRUM (2021) website, which gathers data on mutation spread. This creates the proportion of sequencing graphs and for adding additional mutants these values have to be altered through an adjusted proportion of sequencing due to the difference in the dominance of mutants.

Apart from the sequencing the mutants mainly alter the model through differences in transmissibility and impact further altering the previously mentioned beta values.

Table 13: Description and formula of the flow rate of a mutant/variant of Covid-19 as used in the model.

Mutant Flow	
Name and Description	Formula
MutantFlow: The rate of infections of a mutant.	$(\text{AdjProportionOfSequencing} > 0) ? (\text{AdjProportionOfSequencing}) * \text{Exposed} * \text{transitionENewV} : 0$

Table 14: Summary of all the parameters used for the model in the parts presented related to the exposed stock; beta values, stringency and mutant development.



 Parameters	
Name	Description
BetaMAX	The highest possible beta value.
cE	Share of transmission rate of the infected compartment beta I for people in the exposed state
ChangeM_time	The time when the simulation changes from PR values to dynamic mode
cU	Share of the transmission rate of the infected compartment beta I for people in the undetected state
Day_manual_str_red	The day at which the stringency is to be manually reduced
Delay_adjustment	The amount of days the adjustment implementation delay is.
Delay_stringency	The amount of days the stringency implementation delay is.
F1	Hold stringency function is off. Off switch used in the front end of the simulation for the Hold STR.
F2	Hold stringency function is on. On switch used in the front end of the simulation for the Reduce and the Hold STR.
freespread	Time om free spreading to population sinks.
HSTRDay	The day at which the stringency is to be held at a certain value.
HSTROn	The switch that turns on the hold of stringency value
HSTRValue	The parameter that is fed into the m_with_fatigue holds the stringency level at given value.
impactFromProport	Represents the impact that is expected to happen to the beta I factor. Proportion meaning how big part of current variants this one takes
impactFromTransm	Represent the impact that is expected to happen to the beta I factor. Transmission meaning how tranmissable.
IncreaseTransm	The change the mutant causes on the rate of people moving from the Exposed to the Infected stock.
K1	It refers to the measure implementation efficiency and defines how quickly the measures become effective.
m0	The value of the previously implemented measure.
Manual_Reduction	The parameter that is fed into the m_with_fatigue manually reducing the stringency.
Manual_reduction_on	The switch that turns on the manual reduction.
mNew	Value of new implemented measure.
mutationStartDate	The start date of the mutation.
Share_healthcare	How big share of infections come from hospitals and health care workers.
T0	The first day where the current measure was applied
T1	The point in time when the next measure is implemented
WSChange	Implements the seasonality into the model.

Table 15: Summary of the dynamic variables used in the model related to the mutants/variants of Covid-19.

 Dynamic Variables	
Name	Description
WeeksSinceMutStarted	Calculating the amount of weeks passed since the specific mutation started

ProportionOfSequencing	What percentage of infections of the given mutant can be found in the population based on the number of weeks since the mutation has started
transitionEnewV	Capturing the new exposed rate for each mutant
impactOn_betaMAX	How much the mutant impacts the maximum beta value further impacting all beta values.
P	Variable calling upon the ProportionSequen table function at the time WeeksSinceMutStarted.
AdjProportionOfSequencing	This adjusts the proportion of sequencing value depending on what mutants are present. In this report only one mutant is added for simplicity but additional and this variable becomes more complex.

3.3 Infectious, Recovered and Deceased

Finally, the last stocks and flows are reached, see a summary in Figure 4. For the Infectious stock following the three different branches, this is implemented to mimic the issue with undetected infections and the possibility to quarantine when notably infected.

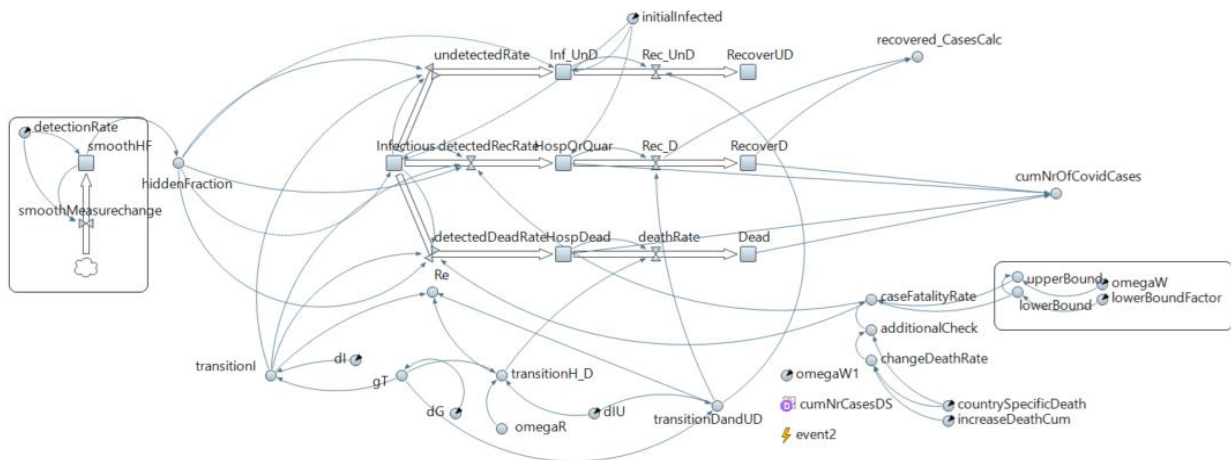


Figure 4: Screenshot of the model part specifically including the infectious, infected, recovered and deceased stocks and linked parameters.

The greatest impacts for this part of the simulation are the transition times, meaning how long people remain in certain compartments, the death rates, detection rates, hidden factors, and disease-specific characteristics, see Table 17 for description and formula for all the rates.

Regarding the transition times, it is assumed that the rate by which people move from the infected to the next stage is partly influenced by stringency meaning a sooner detection follows stricter measures in place. This introduces the parameter g defining how much the duration in the infected compartment can be reduced as a product of government measures. It increases the time spent in HR and HD by the same amount assuming early detected virus increases the amount of time under observation.

The detection rate defines how many of the infected people flow into the infected discovered and recovered compartments. The model follows the same principal as C. Bommer and S. Vollmer (Vollmer & Bommer, 2020). For more information on the meaning of detection rate please be referred to their report. Due to an improvement in detection rates throughout the pandemic, a gradual increase in detection rate is incorporated through a separate stock and flow structure that adapts the detection rate gradually smoothing the values over 5 days. Additionally, it is possible to adapt the detection rate 6 times at indicated times over the simulation run. The flow is defined by the difference in the latest value of the detection rate and the current smoothed detection rate divided by 5. However, at this point, the model implicitly assumes that the

hidden factor for infections and death rates are the same and that all people who die from Covid-19 are detected as such even though this must not necessarily be the case.

The case fatality rate denoted how many of the detected cases die, further explanation in table 17.

Table 16: Description and formula of the stocks related to the infectious, infected and deceased stocks.


 Infectious, infected and deceased flows	
Name and Description	Formula
undetectedRate: The flow from the Infectious stock to the branch of undetected infected.	$(1 - \text{hiddenFraction}) * \text{transitionI} * \text{Infectious}$
detectedDeadRate: The flow from the Infectious stock to the branch of detected infected that will eventually die.	$\text{hiddenFraction} * \text{caseFatalityRate} * \text{transitionI} * \text{Infectious}$
detectedRecRate: The flow from the Infectious stock to the branch of undetected infected that will recover.	$\text{hiddenFraction} * (1 - \text{caseFatalityRate}) * \text{transitionI} * \text{Infectious}$
deathRate: The flow to the dead stock	$\text{HospDead} * \text{transitionH_D}$
Rec_D: The flow to the stock of detected recovered.	$\text{HospOrQuar} * \text{transitionDandUD}$
RecoveredUnD: The flow to the stock of undetected recovered.	$\text{Inf_UnD} * \text{transitionDandUD}$
smoothMeasurechange	$(\text{detectionRate} - \text{smoothHF}) / 5$

Table 17: Summary of the dynamic variables related to the infectious, infected and deceased stocks.



 Dynamic Variables	
Name	Description
AdditionalCheck	It checks if there has been a change in death rate and if yes incorporates this change to the fatality rate.
caseFatalityRate	The proportion of deaths compared to the total number of infectious people.
changeDeathRate	Changes the death rate in accordance to the vaccination impact and mutation death rate variation.
cumNrOfCovidCases	The sum of the hospitalized/quarantined dead and recovered and the detected unrecovered and recovered.
gT	The amount by which dI can be shortened and dHD, dHR and dUD prolonged depending on the strictness of governmental measures currently in place
LowerBound	The case fatality rate when the implemented control measures are fully applied
omegaR	The time of how much longer people who die stay in the hospital compared to those who recover
Recovered_CasesCalc	The amount of recovered detected.
transitionDandUD	The duration of how long people stay in the infected detected and undetected compartments.
transitionH_D	The duration of how long people stay in the Infected soon to be dead compartment
transitionI	The duration of how long people stay in the infectious compartment
upperBound	The case fatality rate when no control measured are applied.
Hidden fraction	

Table 18: Summary of parameters used for the infectious, infected, recovered and deceased stocks.

 Parameters	
Name	Description
CountrySpecificDeath	Collects the specific death rate for the country.

dG	The maximum value parameter g can take on
dI	The basic duration of how long people stay in compartment I
increaseDeathCum	The possible increase in death rate.
Initialinfected	The amount of people initially infected by the disease.
omegaW	The difference between the upperBound and the lowerBound
Detection rate	The fraction of Covid-19 cases assumed detected.

3.4 Frontend and Simulation Results

After the construction of the model, it is essential to acknowledge its frontend processes. It displays and allows for simplified alteration of parameters to adapt to current changes and developments in the simulation in a user-friendly manner. This is created through AL’s Experiment function, which offers the possibility to conduct scenario analysis using built-in experiments such as Sensitivity Analysis experiments, Compare Run experiments, and Parameter Variation experiments. These built-in experiments are at the disposal of decision makers to further analyze the epidemiological situation. For a more in-depth understanding of this function please be referred to AL’s help webpage on Experiments via this [link](#) (AnyLogic, 2022).

After fabrication of the model, a simulation can be made and results can be acquired. In Figure 5 an example of the simulation results made for Germany in June 2022 is presented.

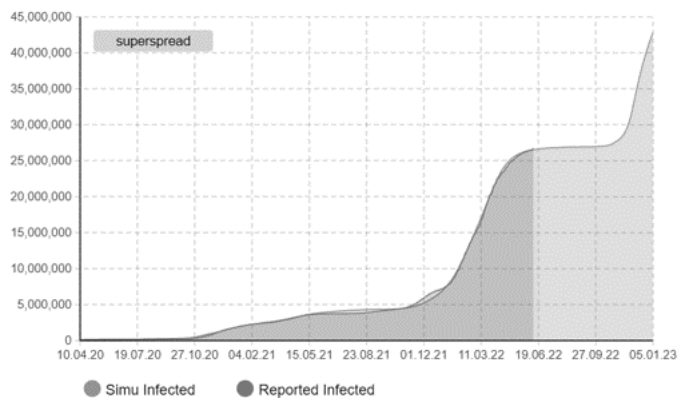


Figure 5: A screenshot of an example result for a Covid-19 simulation performed for Germany in June 2022. The darker curve resembles the reported infected and light grey the simulated.

Visualizing certain areas of interest in the model is easily done through graphs and specifying what parts of the model are requested to examine. Analyses of the future of the pandemic development can then be made through these results.

3.5 Limitations

Mathematical modeling and SD modeling are built on assumptions and include certain limitations in comparison to the real world.

The first and greatest limitation of this model is related to the complexity and uniqueness of governmental restrictions and policies. As an example, in subsection 3.2.2, it is mentioned that the stringency is added to the model through table functions, plotting the cases against the stringency level. However, the stringency and the decisions governments take to handle the pandemic depend on much more than the number of cases and it differs greatly between countries. Some countries, for example, China, implement strict disease control measures, mandatory lockdowns, and isolations, intensive movement tracing, and increased medical facilities (Wang, 2020). Meanwhile, other countries, like Sweden, focus on limiting the spread of infection by recommendations and encouraging voluntary action to reduce the

transmissions while a big focus is also put on reducing the impact on society, socially important activities, citizens, and businesses dampening any concerns that may spread in society (Regeringskansliet, 2020). Reflecting the dependency between cases, death rates, stringency, and society could strongly improve the model accuracy.

Secondly, the model and the infection rate are built on direct human-to-human transmission pathways. However, several studies show that Covid-19 can stay on surfaces for up to nine days and in the air for up to 3 hours (Wang, 2020). This increases the probability to get infected by the disease through indirect contact transmission from the environment to a human host but it is not considered in the model.

Thirdly, a limitation is in regards to how the vaccination is implemented in the model. As explained in subsection 3.1.1. the immunized compartment is added representing those who get vaccinated and are therefore considered immunized. However, it has been made clear throughout the pandemic that the vaccines protect in different amounts the risk of getting infected and the risk of getting severely ill (World Health Organisation, 2022). This means that when someone acquires the vaccine they might still risk getting infected but not risk deadly outcomes. This is something that is not considered in the model. To depict the reality this should be altered implementing the possibility that if a person has been vaccinated they might still risk being infected but to a smaller degree of risk of becoming severely ill.

Due to these mentioned limitations and the complexity of the pandemic, as for all simulation models, this model should be constantly developed and worked on to better depict the reality.

4 CONCLUSIONS

Through this tutorial, a simulation of the Covid-19 pandemic has been constructed. This will hopefully give inspiration to the development of more epidemiological models and create an interest in SD modeling. Considering the limitations, one should always have in mind that SD calls for assumptions and defining of relations which can be problematic and biased if not considered and investigated properly beforehand. The different stock, flows, and feedback loops and the relations between them have to be carefully distinguished and decided. Therefore, for SD simulation in general a conscious decision has to be made at the beginning that discrete event simulation, agent-based modeling, or hybrid simulation does not fit the purpose. This is done bearing in mind mainly the global scale, the scope, and the size of the problem and the study. Then an already proven model, like the SEIRHD in this case, is a good start whenever possible as some of the basic SD relationships can be derived from it. From these basics, add more complex and detailed relationships to further replicate reality while keeping in mind the system thinking. “As simple as possible but as complex as needed” is an adequate guiding principle.

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