Targeting population to evaluate COVID-19 strategies based on activity behaviour

Antoine Goupil de Bouillé, Cloé Cortes Balcells, Tom Häring, Michel Bierlaire
Transport and Mobility Laboratory, EPFL

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Abstract

The propagation of viruses, such as Covid-19, can vary significantly based on group segmentation, including age, geographical location, and socioeconomic status. Different groups may have different levels of vulnerability, exposure, and risk factors that influence the spread of viruses. Therefore, it is crucial to tailor restricting policies accordingly when implementing measures to mitigate virus propagation.

This project presents a methodology for finding optimal sets of activity reduction measures based on group segmentation. The optimization framework utilizes the Variable Neighborhood Search (VNS) algorithm to identify the optimal parameters that reduce both the number of cases and deaths from a pandemic, as well as the economic costs of implementing measures. The economic spread modeling is based on an Agent-Based Model (ABM). The proposed methodology offers a systematic approach for optimizing pandemic mitigation strategies by considering group segmentation and economic factors.

Contents

1 Introduction

1.1 Motivation

The propagation of viruses, such Covid-19, can vary significantly based on group segmentation, such as age, geographical location, or socioeconomic status. Different groups may have different levels of vulnerability, exposure, and risk factors that influence the spread of viruses. Therefore, when implementing restricting policies to mitigate virus propagation, it is essential to take into consideration the characteristics of different groups and tailor the policies accordingly.

For instance, the impact of a virus may be more severe among certain age groups, such as the elderly or individuals with underlying health conditions. These groups may have a higher risk of severe illness or complications from the virus, and thus, policies may need to prioritize their protection through measures such as targeted vaccinations, increased access to healthcare, and strict infection control protocols in settings where they are more likely to be exposed, such as long-term care facilities.

Geographical location can also play a significant role in virus propagation. Urban areas with dense populations and high levels of social interactions may experience faster spread of viruses compared to rural or less populated areas. Therefore, policies may need to be adapted to account for the specific dynamics of different regions, such as imposing stricter restrictions on gatherings, public transportation, or businesses in urban areas, while allowing more flexibility in rural areas with lower population densities.

Socioeconomic status can also impact the spread of viruses. Lower-income groups may have limited access to healthcare, higher levels of crowding in living conditions, and jobs that require close physical proximity or frequent interactions with others, which can increase their vulnerability to virus propagation. Policies may need to consider measures such as increased testing, contact tracing, and support for income and housing to mitigate the disparities in virus spread among different socioeconomic groups.

In Switzerland, when analyzing historical data, we can observe differences between age groups, as shown in Figure 1.1. The graph depicts the proportion of positive cases by age group during the second wave of Covid-19 in September and October 2020. It is evident that the proportion of positive tests is much lower among children under 9 years old compared to individuals aged 70-79 years old. This suggests that there are disparities in the prevalence of Covid-19 among different age groups in France (Switzerland's data was not as granular) during the specified time period.

Hence, considering the variation in virus propagation among different age groups, it is crucial to incorporate age segmentation when implementing restriction policies. This highlights the significance of tailoring restriction policies to account for age-specific dynamics in order to effectively mitigate the spread of the virus and protect vulnerable populations, such as older adults, while also considering the unique needs and characteristics of different age groups in the overall management of the pandemic.

1.2 Project description

This project aims to design a methodology to find optimal targeted activity reductions, reducing the epidemic spread and the economic impact of measures.

The methodology utilizes a multi-agent disaggregated model to simulate the spread of the virus at a granular level. An optimization algorithm is then employed to identify and implement the most effective policies for reducing both the economic and health costs associated with the pandemic. By combining modeling and optimization approaches, the project aims to

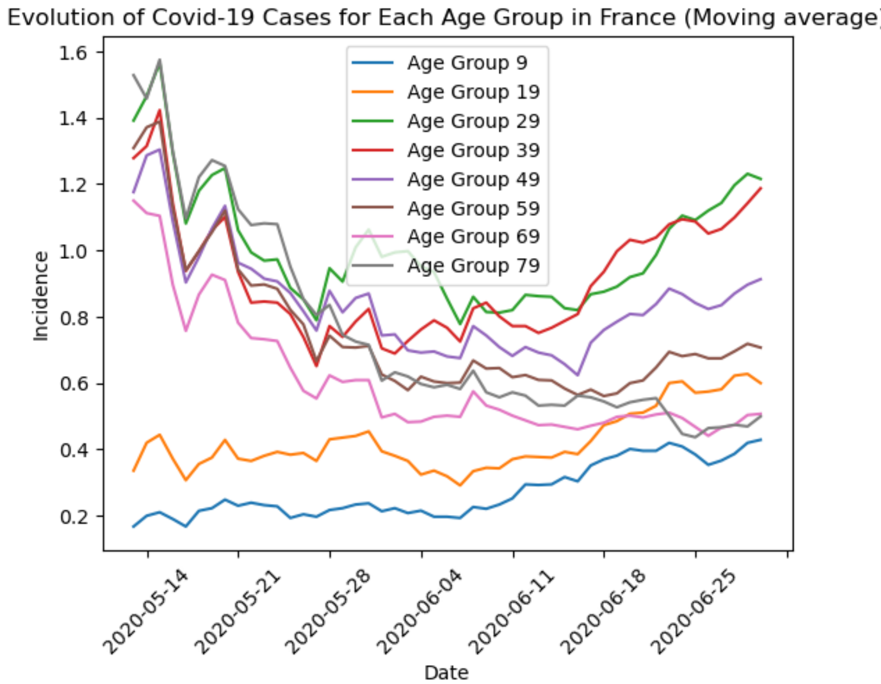


Figure 1: Incidence of Covid-19 positive test by age class in France[1]

develop targeted policies that strike a balance between mitigating the spread of COVID-19 and minimizing the economic cost of the measures and pandemic.

The policies will be tailored based on a population segmentation, to implement activity-restraining measures. These measures will be designed to target specific activities, such as education, work, and leisure, in order to effectively reduce the spread of COVID-19.

1.3 Literature review

The literature review reveals that while there are existing solutions related to Agent-Based Models (ABMs), contagious disease spread, optimization problems, and restriction policies, there is a gap in the literature when it comes to addressing the specific problem of finding optimal targeted activity reductions to simultaneously reduce epidemic spread and minimize economic impact.

The first identified solution is a stochastic ABM for post-lockdown measures[2]. While this research focuses on post-lockdown measures, it does not specifically address the optimization of targeted activity reductions or consider the economic impact of the measures.

The second solution is an ABM model for dynamic modeling of contagious disease spread[3]. Although this research contributes to understanding the dynamics of disease spread, it does not encompass the optimization aspect necessary for identifying optimal targeted activity reductions.

Another relevant study is the optimization of two loss-function problems based on an ABM model[4]. However, this research does not specifically apply the optimization to mobility restric-

[2]Hoertel 2020.
[3]Perez and Dragicevic 2009.
[4]Oremland and Laubenbacher 2014.

tions and epidemics, which are central to the present project.

Furthermore, a simulation of virus spreading using a synthetic population and a disaggregated model is discussed in a different paper[5]. While this simulation provides valuable insights into virus spreading dynamics, it does not address the optimization of targeted activity reductions or consider the economic impact of the measures.

Finally, a neural network approach to optimizing restriction policies in an SIR model is proposed[6]. However, this research focuses on SIR models rather than agent-based desegregated model used in this paper.

In summary, the existing literature lacks comprehensive solutions that specifically tackle the problem of finding optimal targeted activity reductions to reduce epidemic spread and minimize economic impact. Thus, this project aims to bridge this gap by combining an ABM model with an optimizer to develop a novel methodology tailored to address these specific challenges.

1.4 Overall scope of the project

The present research represents a subpart of a comprehensive model focused on analyzing the spread of a pandemic. The larger model, currently under development, utilizes the IBM model, albeit not yet calibrated, to estimate the propagation of a pandemic based on activity schedules. Subsequently, the OASIS Model is employed to recompute these schedules. However, due to the unavailability of the fully integrated model, the current project aims to integrate existing components and employ an optimization algorithm. The initial step involves the definition of various restriction scenarios encompassing diverse activities reductions. Subsequently, the optimization algorithm is applied to refine these scenarios, aiming to minimize the impact of the pandemic. The optimization process focuses on reducing two loss functions associated with the spread of the pandemic, as determined through simulation. This research contributes to the development of effective mitigation strategies by aggregating existing components and applying optimization techniques in the absence of a fully integrated model.

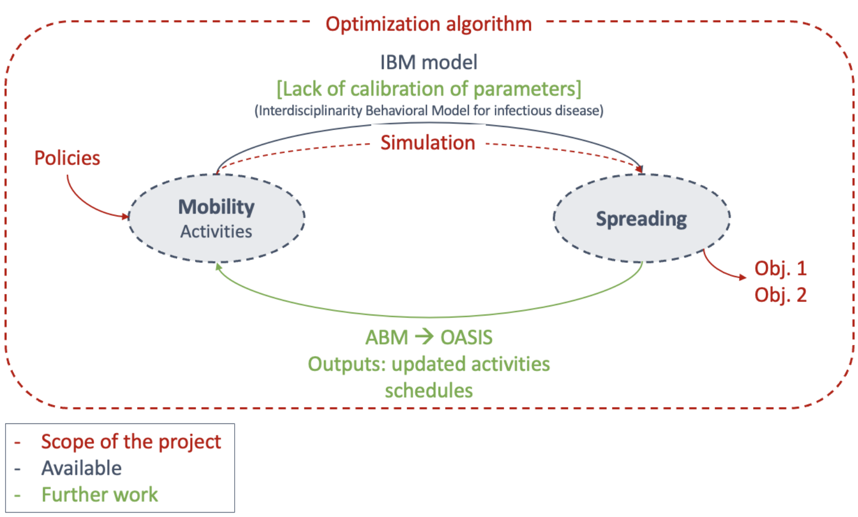


Figure 2: Schematic vision of the overall scope

[5]Bissett KR 2021.
[6]C. Courtès 2022.

2 Methodology

2.1 Simulation

2.1.1 Modeling the epidemiological spread - IBM model

The Interdisciplinary Behavioral Model for infectious disease (IBM) is an agent-based model that simulates the interactions and behaviors of individual agents within a system to study the emergent properties of the system as a whole. In the context of pandemic spread modeling, an IBM can simulate the interactions between individuals within a population, their movements, and the transmission of the virus between them.

This study utilizes an IBM model that adopts a disaggregated approach, enabling a microscopic simulation of pandemic spread[7]. The model specifically focuses on capturing the propagation of the virus within a population, taking into account various factors such as geo-schedules, socio-economic and health data, as well as testing strategies[8,9]. To achieve this, the model incorporates activity schedules that provide detailed information on the synthetic population's locations at 30-minute intervals, utilizing the MATSIM framework. By considering these spatiotemporal dynamics, the IBM model provides a comprehensive representation of individual behaviors and interactions, facilitating a more accurate assessment of the virus's transmission dynamics. This agent-based approach offers valuable insights into the complex dynamics of pandemics and supports the evaluation of intervention strategies aimed at mitigating their impact.

The agent-based model employed in this study simulates the dynamics of various facilities, including schools, workplaces, and shops, using 30-minute time steps. It considers factors such as the number of individuals present, their socio-economic and health characteristics, and the number of infected individuals within each facility to determine the probability of infection for individuals. Moreover, the model incorporates the probability of individuals getting tested for the virus, which is influenced by their socio-economic and health features. If an individual tests positive, they are required to self-isolate at home for a random duration.

At the end of each day, the model calculates the number of infected and tested individuals, enabling the tracking of pandemic spread within the population. The simulation period in this study spans 60 days, mirroring the timeline of the initial Covid-19 pandemic.

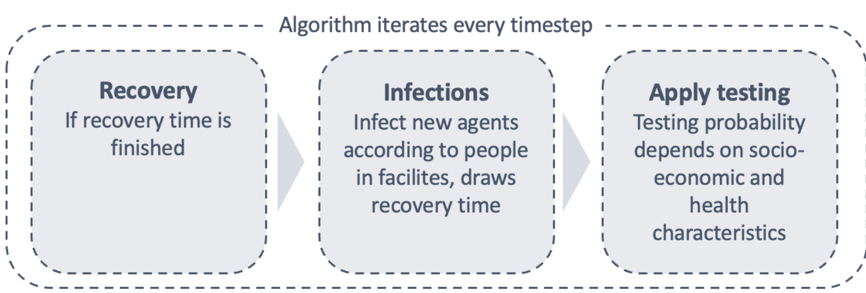


Figure 3: Schematic vision IBM Model

[7] Axhausen and Gärling 1992.
[8] Cortes Balcells C. 2021.
[9] Cortes Balcells C. 2022.

2.1.2 Implementing of restriction policies

In the absence of an operational OASIS Model, this study adapts the IBM model to incorporate activity restriction policies as a mitigation measure. The implementation of these policies follows a step-by-step process:

1. Definition of Activity-Reduction Scenarios: The study defines a set of S activity-reduction scenarios, each representing a specific combination of restrictions. These scenarios account for variations restrictions for each different types of activities.

2. Selection of Restriction Scenarios: For each population segment $j \in [1, J]$, one restriction scenario $s_j \in [1, S]$ is chosen. This selection process determines the specific combination of restriction measures for each segment.

3. Application and Duration of Restrictions: The selected restriction scenario is applied at the start day, T_{begin}, and remains in effect until the end day, T_{end}. The duration of the restriction period is a variable to be optimized.

4. Adjustment of Activity Schedules: The activity schedules of individuals are modified according to the chosen scenario. Activities are replaced with "home" to reflect the restricted mobility and social distancing measures.

5. Optimization of policies: To optimize the effectiveness of the implemented policies, an optimization algorithm seeks to determine the optimal combination $(s_1, ..., s_J) \in S^J$ of scenarios for each population segment. Additionally, the optimization process considers a single reduction period, with the beginning and end dates, T_{begin} and T_{end}, respectively, treated as optimization variables.

This approach allows for the integration of activity restriction policies within the adapted IBM model, enabling the evaluation and selection of optimal scenarios to mitigate the spread of the pandemic within the population. The number of solutions is proportional to $\mathcal{O}(\frac{T_{sim}(T_{sim}-1)}{2}J^S)$, where T_{sim}, is the length of the simulation, J the number of segmentation, and S the number of scenarios.

2.2 Optimization

2.2.1 Optimization framework

This project aims to find the optimal set of policies to reduce both the sanitary impact of the disease, and the economic impact of mobility restraining measures. We can formulate a two-objective optimization problem to identify these optimal policies. The objectives are represented by a sanitary and an economic loss function. We seek to minimize them while satisfying certain constraints.

$$\begin{aligned} \underset{s, T_{begin}, T_{end}}{\text{minimize}} \quad & \begin{bmatrix} \mathcal{L}_{sanitary}(s, T_{begin}, T_{end}) \\ \mathcal{L}_{eco}(s, T_{begin}, T_{end}) \end{bmatrix} \\ \text{subject to:} \quad & \\ & 0 < s_i \leq S \\ & 0 \leq T_{begin} \leq T_{end} \end{aligned}$$

where:

N : number of scenarios
s_j : choice of scenarios for each segment
s : set of scenarios for each segment $(\mathrm{s}_1, s_2, ..., s_J)$
T_{sim} : number of days simulated

2.2.2 Sanitary loss function

The sanitary loss function is defined as a mathematical function that quantifies the impact of the pandemic in terms of deaths and infections. The function is designed to capture the severity of the pandemic and the associated impact on public health. It takes into account the number of casualties caused by the pandemic, as well as the number of infections. The importance of infections versus casualties is decided with a coefficient denoted as κ. One could model this coefficient to represent the proportion of severe forms of Covid-19 cases, which are highly vulnerable. However, ethical considerations, such as fairness and potential biases, should be addressed. Careful review of literature and expert consultation is needed to ensure an ethically sound approach in modeling studies.

$$\mathcal{L}_{sanitary} = C_{casualties}(s, T_{begin}, T_{end}) + \kappa \sum_{\tau=1}^{T_{sim}} I_\tau(s, T_{begin}, T_{end})$$

$C_{casualties}$: Number of casualties during the simulation
T_{sim} : Number of days simulated
I_τ : Number of infected people on day τ
κ : Importance of number of infected people ≥ 0

2.2.3 Economic loss function - Cost of policies

In our model, we account for the economic impacts of the imposed activities restrictions. To guide our approach, we draw insights from relevant literature, including the works of Shami and Lazebdnik[10]. By considering the economic consequences of the associated policy measures, we

[10]Shami and Lazebnik 2022-12.

aim to provide a holistic assessment of the potential economic impacts of the proposed targeted activity reductions.

In our model, we consider the number of remote-working periods due to restrictions imposed during the pandemic. This is important as remote work has become a common strategy to mitigate the spread of the virus. However, we acknowledge that not all types of work are equally efficient or even possible to be done remotely. Some jobs may require on-site presence, while others may have reduced productivity when done from home. Therefore, we take into account the impact of remote work on different types of occupations and sectors.

Additionally, we recognize the need to model the cost of education in our model. The pandemic has disrupted traditional education systems, leading to changes in learning environments, such as online and hybrid models. These changes may have short-term and long-term impacts on education, including potential loss of learning opportunities, changes in educational outcomes, and economic consequences. Therefore, we aim to incorporate the cost of education, including potential disruptions and changes in learning models, in our economic impact assessment.

By considering the effects of remote work and education disruptions, our model will provide a more comprehensive understanding of the economic impacts of the pandemic and associated restrictions, capturing the nuanced impacts on different sectors, occupations, and education systems.

$$\mathcal{L}_{eco}(s, T_{begin}, T_{end}) = (T_{end} - T_{begin})\epsilon\psi \sum_{i=1}^{k} \alpha_i H_i(s)$$

α_i : economic loss due to restrictions for activity i
$H_i(s)$: number of hours of activity i modified due to policies
ϵ : proportion of remoteless works/activities
ψ : reduction of efficiency working at home

2.2.4 Optimization process

We will utilize a meta-heuristic algorithm to search for an optimal set of policies that simultaneously minimize both loss functions, accounting for economic impacts and sanitary effects of the pandemic.

A meta-heuristic is a high-level optimization algorithm that guides the search for solutions in a problem space. It is designed to handle complex optimization problems with multiple objectives or constraints. Meta-heuristics are versatile and can be used to explore various solution spaces and find near-optimal or good-quality solutions in a reasonable amount of time. At each iteration (see Figure 2.2.4), the algorithm will firstly update the restriction scenarios and therefore adapt the agents schedules. Then, it runs the agent-based-model IBM to compute the epidemic spread according to the new epidemic spread. Finaly, it computes the loss functions.

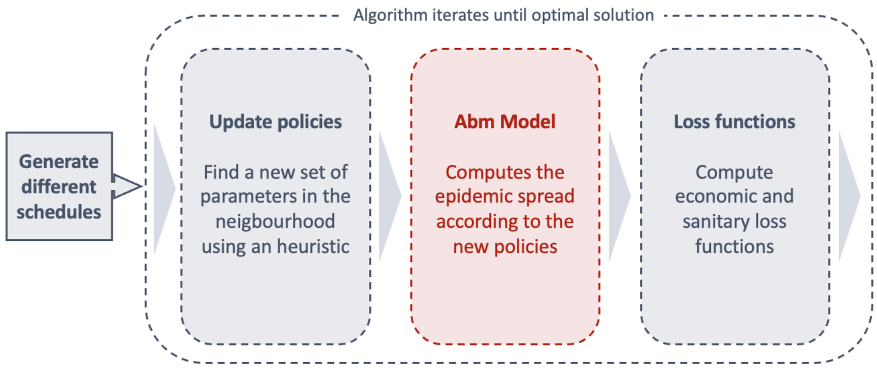


Figure 4: Optimization process description

2.2.5 Choice of a meta-heuristic

These optimization methods are applicable for solving bi-objective loss functions, where the loss function is modeled as a black-box.

- **Variable neighbourhood search** (VNS) explores different neighborhoods of a current solution to find an optimal solution to a combinatorial optimization problem.[11]
- **Bi-Criterion Optimization with Multi Colony Ant Algorithms**[12]
- **Simulated annealing** is a methodology inspired by the annealing process in metallurgy. It is used to find the optimal solution to a problem by iteratively exploring the solution space and gradually "cooling" the system to escape local optima and converge towards a global optimum.[13]

[11] Mladenović and Hansen 1997.
[12] Iredi, Merkle, and Middendorf 2001.
[13] Lin et al. 2008.

3 Results

3.1 Synthetic population

We use activity schedules of a synthetic population, obtained from the MATSIM framework provided by ETHZ. This agent-based model provide valuable insights into human mobility patterns in Switzerland, and more specifically on Vaud. For each person, the model provides an activity schedule with locations at a 30-minute time-step.

3.2 Implementation of the model

We have chosen mutually exclusive scenarios, independent of the age class, so that the algorithm will have to chose the best restriction for each class. We have chosen to focus on 4 mains scenarios :

- Scenario 1: 0% activity reduction for work, 80% for all other activities
- Scenario 2: 20% reduction for all activities
- Scenario 3: 60% reduction for all activities
- Scenario 4: 0% activity reduction for education, 80% for all other activities

The chosen scenarios focus on testing the choice of restraining work and education, which are the most "expensive" restrictions. Indeed, it his the highest daily cost. We could imagine implementing other types of scenarios. The parameters are easy to change based on an Excel file.

In this implementation, the population is segmented based on age into nine groups, with each segment representing a 10-year age range. This age segmentation allows for a more detailed analysis of the impact of the pandemic across different age groups.

The focus of the modeling effort is on the Canton of Vaud, where the spread of the pandemic is simulated over a period of two months. By narrowing the scope to a specific geographic area and timeframe, the study aims to capture the dynamics of the pandemic within a localized context and assess the effectiveness of the implemented mitigation strategies.

3.3 Implementation of the VNS

The Variable Neighborhood Search (VNS) algorithm is employed in this study to optimize the selection of activity restriction scenarios for each population segment. To implement the VNS algorithm, this paper utilizes the Biogeme Python library[14] specifically designed for solving optimization problems. This library provides the necessary tools and functions to define the optimization problem, implement the VNS algorithm, and analyze the resulting solutions. By leveraging the capabilities of this library, the study can efficiently and effectively explore the solution space and identify promising strategies for controlling the spread of the pandemic in the Vaud Canton.

The VNS package requires to code the available operators, the cost functions and the initial solution.

The operators are of two types:

- Temporal operators: shift the beginning or the end of the restriction periods (+1,-1) or shift the whole period
- Increase/decrease the scenario for each age class

[14] "Biogeme 3.2.11 python package" 2018.

3.4 Choice of parameters

The cost functions use hyperparameters in order to be close to reality costs and number of infections. The economic data can be derived from statistics on the Vaud Canton. We also compute the cost of closing activities for each activities.

Choice of hyperparameters		
Hyperparameter	Chosen value	Source
Average remaining working years	20 years	Vd.ch
Cost healthcare	4700 CHF/day	Statistica[15]
Pourcentage of severe forms	10%	Educated guess
Pourcentage of death	5%	Educated guess
Normal GDP Vaud	62 Mds CHF	Vd.ch
Population Vaud	814 000 hab.	Vd.ch
Proportion of remote-less works	50%	Educated guess
Proportion of work that can not be done during infection	40%	Educated guess
Reduction of efficiency working at home	20%	Educated guess

Economic loss for each type of activity		
Activity	Economic loss	Source
Work	344 CHF/day/hab.	PIB/Population/225 Working days
Leisure	30 CHF/day/hab.	Educated guess
Home	0 CHF/day/hab.	Educated guess
Shop	40 CHF/day/hab.	Educated guess
Education	344 CHF/day/hab.	Same importance than work
Other	40 CHF/day/hab.	Educated guess

We note that the costs are given by time span in the code (30 minutes periods. We therefore consider 10 hours or 20 active periods a day, so divide these daily cost by 20.

3.5 Pareto front

The Variable Neighborhood Search (VNS) algorithm was executed on the server (jed.epfl.ch) over a duration of 6 hours to obtain a Pareto front consisting of 15 Pareto-optimal solutions. The Pareto front represents a set of solutions that achieve an optimal trade-off between multiple conflicting objectives, in this case, the reduction of the spread of the pandemic and the minimization of associated loss functions.

By utilizing the computational power of the server, the VNS algorithm explored different neighborhoods of the solution space, systematically searching for solutions that provide the best possible compromise between the conflicting objectives. The Pareto front resulting from this optimization process represents a diverse range of solutions, each representing a unique combination of activity restriction scenarios tailored to the population segments.

The Pareto front (see Figure 3.5 obtained through the VNS algorithm serves as a valuable tool for decision-making and policy evaluation. It enables stakeholders to evaluate and select solutions that align with their specific priorities and constraints. The 15 Pareto-optimal solutions offer a range of trade-offs, providing a comprehensive understanding of the implications of different mitigation strategies on the spread of the pandemic and associated losses.

The Pareto front can be further analyzed and visualized to identify clusters of solutions that represent distinct policy alternatives. This information can assist policymakers in making informed decisions based on their specific objectives and the context of the Vaud region.

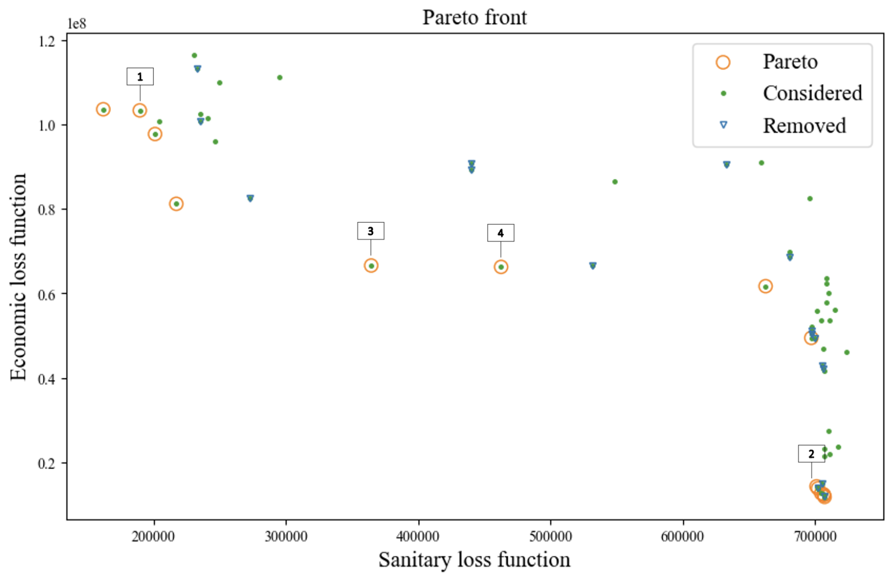


Figure 5: Pareto front of solutions

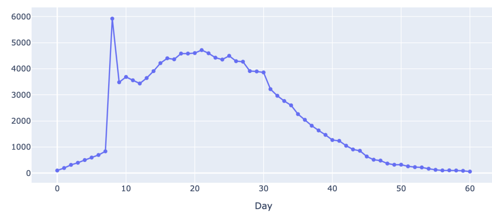
3.6 Epidemic spread

Having obtained a Pareto front consisting of 15 Pareto-optimal solutions, we can now narrow our focus to four main solutions that exhibit distinct characteristics and trade-offs. These solutions have been selected based on their representation of diverse strategies for mitigating the spread of the pandemic while minimizing associated losses.

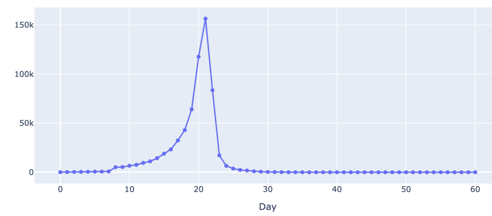
Each of the four selected solutions within the Pareto front represents a unique combination of activity restriction scenarios tailored to the population segments. These solutions have been identified as particularly promising due to their potential to achieve a favorable balance between reducing the spread of the pandemic and minimizing the overall impact on the population.

To visualize the daily infections for the four selected scenarios from the Pareto front, we can plot a line graph illustrating the number of infections over time. This graph provides a clear representation of the impact of each scenario on the spread of the pandemic.

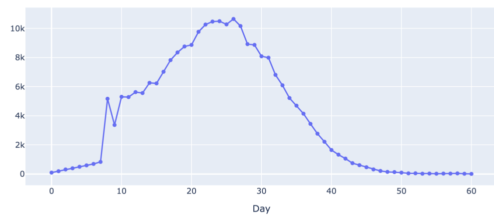
By plotting the daily infections for the selected scenarios, we can observe the differences in the rate and magnitude of infection across the duration of the simulation. This allows us to assess the effectiveness of each scenario in controlling the spread of the pandemic and provides valuable insights for decision-making and policy evaluation.



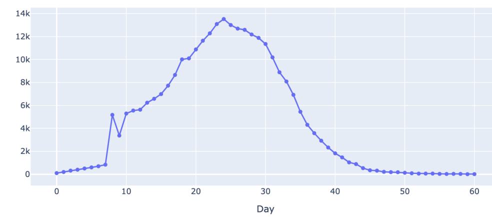
(a) Pareto solution 1



(b) Pareto solution 2



(c) Pareto solution 3



(d) Pareto solution 4

Figure 6: Evolution of infections over time

3.6.1 Pareto solution 1

- Higher economic loss: This solution results in an estimated economic loss of 105 million CHF. The implemented activity restrictions have a significant impact on economic activities, potentially leading to financial losses for businesses and individuals.
- Lower sanitary loss: In contrast, this solution demonstrates a lower sanitary loss with approximately 200,000 infected individuals.day. The implemented restrictions effectively limit the spread of the pandemic, resulting in a lower number of daily infections compared to other scenarios.
- Restrained work for 30-39 year-olds: This solution involves targeted restrictions on individuals aged 30 to 39, aiming to reduce the transmission of the virus within this age group. This restriction leads to a high economic cost.
- 60% restrictions for 50-59 year-olds: Notably, this solution imposes a 60% restriction on individuals between the ages of 50 and 59.
- Restrictions during the whole period: Unlike some scenarios with varying restriction periods, this solution implements continuous restrictions throughout the simulation period. Maintaining strict control measures over the entire duration emphasizes the importance of sustained efforts to manage and curb the spread of the virus.

3.6.2 Pareto solution 2

- Lower economic loss: This solution results in a lower estimated economic loss of 15 million CHF compared to other scenarios. The implemented activity restrictions have a lesser impact on economic activities, potentially mitigating financial losses for businesses and individuals.

- Higher sanitary loss: In contrast, this solution exhibits a higher sanitary loss with approximately 700,000 infected individuals.day. The implemented restrictions are associated with a greater number of daily infections, indicating a higher level of transmission of the virus compared to other scenarios.
- Restrained activities for 70-79 year-olds: This solution involves targeted restrictions on individuals aged 70 to 79. However, this class of the population is less likely to work, therefore reducing the sanitary loss, without reducing the economic loss.
- Less restrictions compared to Solution 1: In comparison to Solution 1, this solution implements fewer overall restrictions. We can observe that the less restrictions imposed, the more likely it is to have a high sanitary loss.
- Start on day 1, end on day 59: This solution initiates the implemented restrictions on the first day of the simulation and concludes them on the 59th day.

3.6.3 Pareto solution 3

- Moderate economic loss: This solution results in a moderate estimated economic loss of 72 million CHF. The implemented activity restrictions have a moderate impact on economic activities, potentially leading to financial losses for businesses and individuals, but to a lesser extent compared to other scenarios.
- Moderate sanitary loss: In terms of sanitary impact, this solution demonstrates a moderate level of sanitary loss, with approximately 360,000 infected individuals.day. The implemented restrictions effectively limit the spread of the pandemic, resulting in a moderate number of daily infections compared to other scenarios.
- Restrained work for 30-39 year-olds: Similar to Solution 1, this solution involves targeted restrictions on individuals aged 30 to 39. These measures aim to reduce the transmission of the virus within this age group, which may be associated with specific patterns of social interactions or occupational activities.
- Start on day 2, end on day 59: In contrast to Solution 2, this solution initiates the implemented restrictions on the second day of the simulation and concludes them on the 59th day.

3.6.4 Pareto solution 4

- Moderate economic loss: This solution indicates a moderate estimated economic loss of 69 million CHF. The implemented activity restrictions have a moderate impact on economic activities, potentially resulting in financial losses for businesses and individuals, but to a lesser extent compared to other scenarios.
- Moderate sanitary loss: In terms of the sanitary impact, this solution demonstrates a moderate level of sanitary loss with approximately 460,000 infected individuals.day. The implemented restrictions effectively control the spread of the pandemic, resulting in a moderate number of daily infections compared to other scenarios.
- Restrained work for 40-49 year-olds: Similar to Solution 3, this solution involves targeted restrictions on individuals aged 40 to 49. These measures aim to reduce the transmission of the virus within this specific age group, potentially reflecting their higher level of social and occupational interactions.

- 20% restrictions for 70-79 year-olds: Notably, this solution imposes a 20% restriction on individuals aged 70 to 79. This reduction in activities for this age group aims to minimize the risk of infection and control the spread of the pandemic effectively, considering their higher vulnerability to severe illness or complications associated with the virus.
- Start on day 2, end on day 59: Similar to Solution 3, this solution initiates the implemented restrictions on the second day of the simulation and concludes them on the 59th day.

4 Conclusion

4.1 Conclusion on findings

- All policies are applied over the longest possible time-span, emphasizing the need for policymakers to anticipate and take prompt actions in managing the spread of the pandemic. This finding highlights the importance of implementing timely and sustained measures to mitigate the impact of the virus effectively.

- The majority of Pareto-optimal policies choose to retain work and education activities, because of their higher economic costs.

- The analysis of the Pareto front highlights the existence of solutions that achieve significantly lower levels of sanitary optimization with equivalent costs. For instance, comparing solution 3 and solution 4, both exhibit similar economic costs but demonstrate notable differences in terms of sanitary costs. Solution 3 attains a lower sanitary cost compared to solution 4, indicating a more effective control of the pandemic spread while minimizing the impact on public health.

- The model exhibits consistency in its outcomes, as increasing activity reductions lead to a reduction in the sanitary cost (measured by the number of daily infections), but also an increase in the economic cost. This finding implies a trade-off between reducing the spread of the virus and minimizing the economic impact, highlighting the need for careful decision-making when implementing restrictive measures.

- The computational time required to obtain the Pareto front was approximately 6 hours on the Jed Server. This time frame was necessary to evaluate the impact of various policy combinations on a population of 800,000 individuals over a two-month period, resulting in the identification of 15 Pareto-optimal solutions. This information provides insights into the computational requirements for similar modeling studies.

- These findings emphasize the importance of considering multiple objectives when designing and implementing pandemic response strategies. While economic costs are a crucial consideration, prioritizing measures that yield superior sanitary outcomes can lead to more favorable overall outcomes. Policymakers should carefully evaluate and weigh the trade-offs between economic costs and sanitary benefits to identify optimal solutions that effectively balance public health and economic considerations.

- It is important to acknowledge that the presented model is still in the process of calibration and refinement. The scenarios considered in this study may represent extreme cases and should be interpreted with caution. However, despite these limitations, the findings demonstrate the potential of using an optimization algorithm in conjunction with an agent-based model (ABM) to identify optimal policies for mitigating the spread of a pandemic at a lower economic cost.

4.2 Further improvements

To enhance the robustness and applicability of the model, several areas for improvement can be considered:

- Exploration of additional segmentation factors: In addition to age segmentation, it would be valuable to incorporate other factors such as geographic segmentation (e.g., urban and rural areas). This would enable a more nuanced understanding of the impact of different policies in diverse geographical contexts.

- Optimization of segmentation: The number of segments could be reduced to streamline the model and improve computational efficiency while still capturing the essential heterogeneity in the population. This optimization process would help strike a balance between model complexity and computational resources.

- Expansion of simulation scope: The model can be extended to simulate the spread of the pandemic on a larger scale, such as the entire country of Switzerland, encompassing a population of 8 million people. This would provide a more comprehensive evaluation of the effectiveness of different policies and their implications for a broader population.

- Implementation of multiple restriction periods: To better reflect real-world scenarios, the model can be enhanced to simulate the implementation of multiple restriction periods. This would capture the dynamic nature of policy interventions and their varying effects over time, allowing for a more realistic evaluation of long-term strategies.

- Improved calibration of hyperparameters: Continual refinement and calibration of the model's hyperparameters can enhance its accuracy and alignment with real-world data. This iterative process will ensure that the model accurately captures the dynamics of the pandemic and provides reliable insights for decision-making.

- Integration of the OASIS model: Incorporating the OASIS model into the simulation framework would enable the adaptation of activity schedules based on the evolving spread of the epidemic. This integration would enhance the model's ability to dynamically adjust policies in response to changing circumstances, further improving its effectiveness in simulating real-world scenarios.

By addressing these areas for improvement, the model can evolve into a more comprehensive and reliable tool for policymakers, providing valuable insights for effective pandemic management and control strategies.

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