

Bridging Epidemiology and Mobility: Creating a Policy-Aware Activity-Based Model for Epidemiological Studies

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SHORT SUMMARY

This paper presents an Activity-Based Model (ABM) for modeling epidemiological responses, during or after a pandemic. The objective of the model is to include mobility restrictions, such as imposed curfews or other activity-restriction policies when computing the activity schedules. The proposed ABM builds on the foundation laid by (Pougala, Hillel, & Bierlaire, 2022), adding new terms in the objective function and constraints. Moreover, we incorporate a dynamic programming algorithm to solve the above-mentioned optimization problem in a computationally efficient way. This method allows us to solve the optimization problem for large-scale populations and thousands of activities, addressing one of the main limitations of the work (Pougala et al., 2022). By realistically modeling the interactions within a given setting, the method ensures that all possible contacts are accurately represented, capturing the true dynamics of infection transmission within the population.

Keywords: activity-based modeling, agent-based simulation, and decision-making.

1 INTRODUCTION

The global pandemic of COVID-19 has caused significant changes in how populations move and interact, resulting in profound modifications to mobility patterns. These changes are rooted in two primary factors: psychological and imposed restrictions. The fear of the virus, or the memory of it, has led people to voluntarily alter their daily routines, reducing their movements, avoiding big crowds, or embracing the new normality of teleworking. In addition, governments implementing various degrees of restrictions to control the spread of COVID-19 has collectively reshaped individual mobility within society.

Within this context, significant research has been conducted on the interplay between mobility and epidemiology, especially regarding the spread of diseases like COVID-19 ((Hancean, Slavinec, & Perc, 2021), (Mazzoli, Mateo, Hernando, Meloni, & Ramasco, 2020), (Palguta, Levinsky, & Skoda, 2022)). Additionally, studies have focused on estimating and simulating virus propagation based on mobility ((Tuomisto et al., 2020), (Kerr et al., 2020), (Aleta et al., 2020)). In a previous study (see (Cortes Balcells, Krueger, & Bierlaire, 2023)) the authors have proposed tools to drive policymakers by aggregating epidemiological models with ABMs, to propose optimal Non-Pharmaceutical Interventions (NPIs). However, while (Cortes Balcells et al., 2023) proposes an accurate epidemiological model, it lacks in modeling the reaction of the population to the restrictions of NPI. In particular, when an NPI is considered, the study simply reduces the number of contacts of the target activity, without considering the possibility of activity rescheduling from the individuals. This limitation can be addressed by the implementation of an Agent-Based Model (ABM). ABMs offer a more dynamic and flexible framework, allowing for the simulation of individual behaviors and decisions in response to changing conditions, such as NPIs. This approach not only accounts for the direct impact of restrictions on activity participation but also captures the adaptive strategies individuals might employ, such as changing the time, location, or nature of their activities, thereby providing a better understanding of how population behavior evolves in response to public health policies. Existing models such as MATSim (Muller et al., 2020), lack the capability of allowing individuals to reschedule a different type of activity when their preferred activity is removed from the choice set. On the other hand, the Activity Scheduling with Integrated Simultaneous Choice Dimensions (OASIS) model proposed in (Pougala et al., 2022) can allow for rescheduling, but it is unable to handle entire city populations and their numerous facilities.

In this paper, we propose an adaptation of the ABM proposed in (Pougala et al., 2022), to consider NPIs, making it a suitable tool to be coupled with epidemiological models. This framework simulates how in-

dividuals and populations respond to various NPIs, providing a more accurate context for understanding and predicting the spread of diseases in complex social systems. Moreover, we propose an efficient way to solve the problem, allowing the study of a larger population and many facilities. By leveraging dynamic programming, we enable the scalable analysis of behavioral adaptations and mobility patterns, significantly improving the model’s applicability to diverse public health scenarios.

The proposed model offers a powerful approach to managing pandemic-induced challenges, contrasting with more generalized models. This comprehensive solution fills a critical void in the literature, providing a direct link between the imposed NPIs and the reaction of the individual subjected to them.

The paper is divided as follows: Section 2 contextualize the framework, defining inputs, outputs and objective, while Section 3 presents the methodology and mathematical formulation of the problem. Section 4 presents the ABM results on the study case of the city of Lausanne, Switzerland, consisting in population of 100,000 individuals and considering 86,207 facilities.

2 CONTEXT AND PROBLEM STATEMENT

Context Previous work from the authors, i.e. (Cortes Balcells et al., 2023), integrated an epidemiological behavioral model, an economical model, and an optimization algorithm into a tool to drive the choice of NPIs in pandemic management. A graphical schematic of this work is proposed in Figure 1. The figure presents the proposed tool linking mobility restrictions, epidemiological behavior, and an economical model. The last two models calculate health and economic costs, which are optimized using a Variable Neighborhood Search (VNS) algorithm to balance the trade-off between health implications and economic fallout. While the epidemiological behavioral model, the economical model, and the optimization algorithm are already exhaustively described in (Cortes Balcells et al., 2023), this paper focuses on a formulation of the mobility restriction model as ABM. As visible from Figure 1, the ABM takes as input the characteristic of the individuals x_t and of a set of facilities x_a . Moreover, the AMB is fed with the restriction selected from the optimization framework \mathcal{P} . The expected output is a schedule of individual activity.

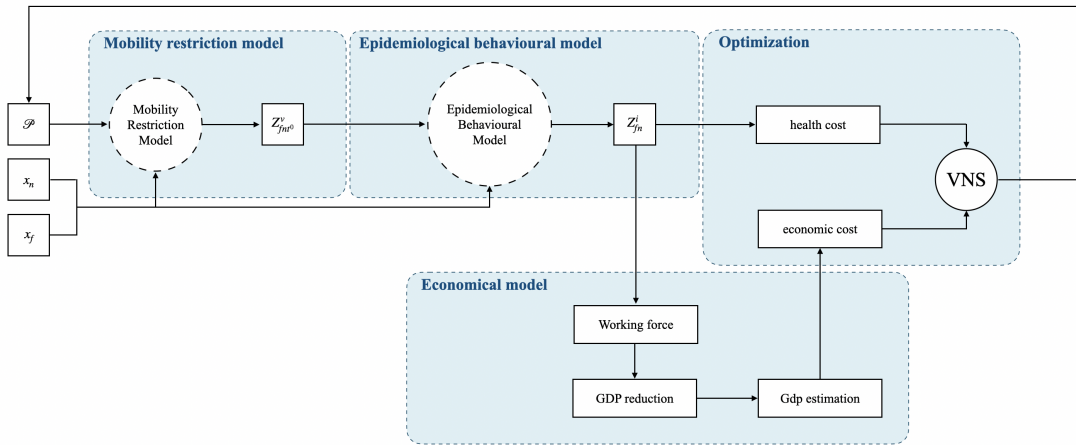


Figure 1: Schematic vision of the overall scope.

The dynamic of mobility is generated using the mobility restriction model and is captured within a day, discretized into T time intervals. For each day, we consider a discretized time horizon into T time intervals of the same length. A typical discretization is 5 minutes, so the time is indexed by $t = 1, \dots, T = 288$. The space is represented by a discrete set \mathcal{F} locations, or facilities, corresponding to the points of the perimeter that we are interested in (a city, a region, etc.), with characteristics x_a . We also consider a discrete list of A activities that individuals can perform during the day. Each activity a is associated with a set of locations or facilities \mathcal{F}_a , and has characteristics x_a . Finally, we define each individual n with characteristics x_n , belonging to the set \mathcal{N} .

Inputs of the mobility restriction model The model operates with three main inputs: individual characteristics, facility characteristics and imposed policies. The input x_n includes the characteristics of the

individual, including attributes such as the personal identifier, the city of residence, the age, the employment status, and the home and work identifiers along with their corresponding coordinates. The second input, χ_a , details the characteristics of the facilities. Each facility is characterized by its identifier, type (education, shop, or leisure), type identifier, and geographic coordinates in the Swiss projection system. The last input of the model the NPI policy p . Every policy p consists in the activation of the set of parameters belonging to \mathcal{P} , where each element of \mathcal{P} is defined as a parameter $\varphi_{\text{restriction}, a}$, $\forall a \in \mathcal{A}$, where $\varphi_{\text{restriction}, a}$ is a parameter that takes value 1 if the restriction is activated for activity a , and 0 otherwise. This includes new convex constraints reflecting multiple interventions, where restriction can be the closure of activities, management of peak hours, travel-time restriction, curfew restriction, and outside time limits.

Problem statement Given a set of activities \mathcal{A} , and a set of restrictions \mathcal{P} for a population with socio-economic characteristics χ_n^e ,¹ we obtain feasible schedules for the population, and define the visits v of an individual n by the following binary variable:

$$Z_{fnt}^v = \begin{cases} 1 & \text{if individual } n \text{ visits facility } f \text{ at time } t; \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

3 MOBILITY RESTRICTION MODEL

Formulation The mobility restriction model is formulated as an activity-utility-based model. The utility function describes the normal behavior of an individual who might want to engage in some activity and does not want to deviate too much from their timing preferences. The foundational structure of the utility function is adapted from (Pougala et al., 2022). This work builds upon the existing framework by introducing additional terms in the objective function and incorporating new constraints to address the mobility restrictions. Given a set of activities \mathcal{A} , and restrictions \mathcal{P} , the optimization problem can be defined as:

$$\max_{\omega, Z, \chi, \tau} U_0 + \sum_{a=0}^{\mathcal{A}} Z_a^0 (\chi_a + V_a^1 + V_a^2 + \varphi_{\text{traveltime}, a} V_{ab}^3) + \sum_{a=0}^{\mathcal{A}} \sum_{b=0}^{\mathcal{A}} Z_{ab} \cdot \theta_t \cdot \omega_{ab} \quad (2)$$

subject to:

$$\sum_a \sum_b (Z_a^0 \cdot \chi_a^2 + Z_{ab} \cdot \omega_{ab}) = 24 \quad (3)$$

$$\omega_{\text{dawn}} = \omega_{\text{dusk}} = 1 \quad (4)$$

$$\chi_a^2 \geq Z_a^0 \cdot \tau_a^{\min} \quad \forall a \in \mathcal{A} \quad (5)$$

$$\chi_a^2 \leq Z_a^0 \cdot T \quad \forall a \in \mathcal{A} \quad (6)$$

$$Z_{ab} + Z_{ba} \leq 1 \quad \forall a, b \in \mathcal{A}, a \neq b \quad (7)$$

$$Z_{a, \text{dawn}} = Z_{\text{dusk}, a} = 0 \quad \forall a \in \mathcal{A} \quad (8)$$

$$\sum_a Z_{ab} = Z_b^0 \quad \forall b \in \mathcal{A}, b \neq \text{dawn} \quad (9)$$

$$\sum_b Z_{ab} = Z_a^0 \quad \forall a \in \mathcal{A}, a \neq \text{dusk} \quad (10)$$

$$(Z_{ab} - 1) \cdot T \leq \chi_a^1 + \chi_a^2 + Z_{ab} \cdot \omega_{ab} - \chi_b^1 \quad \forall a, b \in \mathcal{A}, a \neq b, \quad (11)$$

$$(1 - Z_{ab}) \cdot T \geq \chi_a^1 + \chi_a^2 + Z_{ab} \cdot \omega_{ab} - \chi_b^1 \quad \forall a, b \in \mathcal{A}, a \neq b \quad (12)$$

$$\chi_a^1 \geq \chi_a^- \quad \forall a \in \mathcal{A} \quad (13)$$

$$\chi_a^1 + \chi_a^2 \leq \chi_a^+ \quad \forall a \in \mathcal{A} \quad (14)$$

$$\sum_{a \in \mathcal{F}_a} Z_a^0 \leq 1 \quad \forall a \in \mathcal{A} \quad (15)$$

$$\varphi_{\text{close}, a} Z_a^0 = 0 \quad \forall \varphi_{\text{close}, a} \in \mathcal{P}, a \in \mathcal{A} \quad (16)$$

$$\varphi_{\text{timeslotstart}, a} \chi_a^1 \geq \varphi_{\text{timeslotstart}, a} t_{\Theta}^1 \quad \forall \varphi_{\text{timeslotstart}, a} \in \mathcal{P}, a \in \mathcal{A} \quad (17)$$

$$\varphi_{\text{timeslotend}, a} (\chi_a^1 + \chi_a^2) \geq \varphi_{\text{timeslotend}, a} t_{\Theta}^2 \quad \forall \varphi_{\text{timeslotend}, a} \in \mathcal{P}, a \in \mathcal{A} \quad (18)$$

$$\varphi_{\text{peakhour}, a} (\chi_a^1 + \chi_a^2) \leq \varphi_{\text{peakhour}, a} (t_{\Theta}^3 + 24 * (1 - Z_2)) \quad \forall \varphi_{\text{peakhour}, a} \in \mathcal{P}, a \in \mathcal{A} \quad (19)$$

¹ χ_n^e includes information such as age, gender, and employment status.

$$\varphi_{\text{peakhour},a} x_a^1 \geq \varphi_{\text{peakhour},a} (t_{\Theta}^4 - 24 * (1 - Z_1)) \quad \forall \varphi_{\text{peakhour},a} \in \mathcal{P}, a \in \mathcal{A} \quad (20)$$

$$\varphi_{\text{peakhour},a} (Z_1 + Z_2 - 1) \geq 0. \quad (21)$$

$$\varphi_{\text{traveltime},a} (Z_{ab} \cdot \omega_{ab}) \leq \varphi_{\text{traveltime},a} t_{\Theta}^5 \quad \forall \varphi_{\text{traveltime},a} \in \mathcal{P}, a \in \mathcal{A} \quad (22)$$

$$\varphi_{\text{curfew}} \tau_{\text{dawn}} \leq \varphi_{\text{curfew}} t_{\Theta}^6 \quad (23)$$

$$\varphi_{\text{curfew}} x_{\text{dusk}} \geq \varphi_{\text{curfew}} t_{\Theta}^7 \quad (24)$$

$$\sum_a \sum_b \varphi_{\text{close},a} (Z_{ab} \cdot \omega_{ab} + Z_a^0 \cdot x_a^2 + z_{ba} \cdot \rho_{ba}) \leq \varphi_{\text{close},a} t_{\Theta}^8 \quad \forall \varphi_{\text{close},a} \in \mathcal{P}, a \in \mathcal{A} \quad (25)$$

where:

$$V_a^1 = \theta_a^{\text{early}} \cdot \max(0, \kappa_a - x_a^1 - \Delta_a^{\text{early}}) + \theta_a^{\text{late}} \cdot \max(0, x_a^1 - \kappa_a - \Delta_a^{\text{late}}) \quad (26)$$

$$V_a^2 = \theta_a^{\text{short}} \cdot \max(0, \tau_a - x_a^2 - \Delta_a^{\text{short}}) + \theta_a^{\text{long}} \cdot \max(0, x_a^2 - \tau_a - \Delta_a^{\text{long}}) \quad (27)$$

$$V_{ab}^3 = \theta_t \cdot \omega_{ab} \quad (28)$$

U_0 from Equation (2) is a generic utility for aspects not associated with an activity, χ_a is the utility associated with participating in an activity a during the day, terms V_a^1 and V_a^2 are utility penalties that capture deviations from the preferred starting time and duration, respectively. These terms allow the individual to reorganize by assigning a time window around that preference, depending on the flexibility of the activity. Note that the utility is maximal if $x_a^1 \in [\kappa_a - \Delta_a^{\text{early}}, \kappa_a + \Delta_a^{\text{late}}]$ but decreases with a coefficient θ_a^{early} if the start is earlier, and a parameter θ_a^{late} if later. The same concept applies to durations designated by τ_a . Finally, θ_t represents the penalty due to travel time when going to activity a . Table 1 presents the notation and corresponding description of the variables and parameters.

Table 1: Description of the variables and parameters

| Notation | Description |
|-------------------|--|
| Z_a^0 | binary variable set to 1 if activity a is scheduled during the day, 0 otherwise |
| Z_b^0 | binary variable set to 1 if activity b is scheduled during the day, 0 otherwise |
| Z_{ab} | binary variable set to 1 if activity b follows immediately activity a where $a \neq b$ |
| x_a^1 | discrete variable representing the starting time of activity a |
| x_b^1 | discrete variable representing the starting time of activity b |
| x_a^2 | discrete variable representing the duration of activity a |
| x_{dusk} | discrete variable representing the starting time of the activity at dusk time |
| κ_a | discrete parameter representing the desired starting time of activity a |
| τ_a | discrete parameter representing the desired duration of activity a |
| ω_{ab} | discrete parameter representing the travel time between facilities a and b |
| Δ_a | discrete parameter representing the flexibility level of activity a |
| χ_a | utility associated with participating in an activity during day a |
| θ_t | travel time penalty |
| θ_a | penalty for activity a for starting early, late, being short, or being long |
| t_{Θ}^1 | user-defined time slot to start an activity |
| t_{Θ}^2 | user-defined time slot to end an activity |
| t_{Θ}^3 | user-defined start closing time to avoid peak hours |
| t_{Θ}^4 | user-defined end closing time to avoid peak hours |
| t_{Θ}^5 | user-defined maximum travel time |
| t_{Θ}^6 | user-defined staying at home time |
| t_{Θ}^7 | user-defined starting time of dusk activities |
| t_{Θ}^8 | user-defined maximum allowed time in an activity |

Equation (3) constrains the total time of a schedule to match a 24-hour time-horizon. Equations (8) and (12) ensure that each schedule begins and ends with dummy home activities, symbolizing dawn and dusk. Equations (9) and (10) enforce the consistency of activity durations, requiring them to be longer than a minimum duration but shorter than the time horizon, and nullify the duration if an activity is absent from the schedule. Equation (11) stipulates that two distinct activities, a and b , can follow each other only

once, and an activity cannot follow itself. Equations (13)–(14) mandate that each activity has exactly one predecessor and successor, implying that:

$$Z_{ab} = 1 \Leftrightarrow Z_a^0 = 1 \quad \text{and} \quad Z_b^0 = 1.$$

Equations (15) and (16) ensure time consistency between consecutive activities: $Z_{ab} = 1 \Rightarrow x_b^1 = x_a^1 + x_a^2 + \omega_{ab}$. This prevents activities from overlapping, whether they are immediately consecutive or not. Constraints (17) and (18) specify that activities must occur within defined time windows. Lastly, Equation (19) limits to only one facility per activity \mathcal{F}_a . Equations (16)–(25) are activated by the binary parameter $\varphi_{\text{restriction},a}$ which takes the value of 1 if a certain restriction is activated for activity a , and 0 otherwise. It modifies the constraints dynamically, allowing the model to adapt to different policy scenarios. $\varphi_{\text{restriction},a}$ integrates the following model constraints:

- **Closure of Activities:** When $\varphi_{\text{close},a}$ is activated (i.e., set to 1), it enforces the closure constraints, effectively setting $Z_a^0 = 0$ for the closed activities, as seen in Equation (16). The activities can also be closed for a specific slot of time, by activating $\varphi_{\text{timeslotsstart},a}$ which defines the time slot to start an activity at time t_{Θ}^1 (Equation (17)), and $\varphi_{\text{timeslotend}}$ which defines the time slot when an activity ends at time t_{Θ}^2 (Equation (18)).
- **Peak Hours:** The $\varphi_{\text{peakhour},a}$ parameter controls whether the peak hour constraints are active. If set, it influences the scheduling of activities to avoid peak hours, from t_{Θ}^3 to t_{Θ}^4 , as reflected in Equations (19) – (21).
- **Travel-Time Restriction:** $\varphi_{\text{traveltime},a}$ activates the travel time constraints, ensuring that the duration of travel between activities a and b does not exceed a predefined limit t_{Θ}^5 , as per Equation (22).
- **Curfew Constraint:** Similarly, φ_{curfew} governs the enforcement of curfew-related constraints, affecting the allowed times for the start and end of activities, one to prevent people leaving their home before a certain hour t_{Θ}^6 (see Equation (23)), and another to force them to be back at home at a given time t_{Θ}^7 (see Equation (24)).
- **Outside Time Limit:** In the case of $\varphi_{\text{outsidelimit}}$, it restricts the total duration of certain activities like leisure and shopping, aligning with Equation (25) which ensures that the travel time to go to the activities t_{Θ}^8 is respected.

Model Parameters As already mentioned, the utility function originates from the OASIS framework (Pougala et al., 2022). Thus, we are adopting the utility parameters from their literature, as well as the flexibility levels they estimated for each facility type. Our approach differs from OASIS in that we do not consider budget constraints, mode of transportation variables, and there is no random term in the objective function. Home has no associated utility ($\chi_{\text{home}} = 0$) and no timing desires coming from individuals. For information regarding the utility parameters and the flexibility profiles, please refer to (Pougala et al., 2022)².

Computational Complexity Since the goal of the ABM is to be included in an epidemiological activity-based model, the facility choice set needs to match the population size. This need arises from the fact a limited number of facilities can result in overcrowding, thereby escalating the virus transmission, whereas an excessively large number of facilities can spread out the gatherings, consequently reducing the virus spread. The problem with increasing the number of facilities is that the execution time is affected by the choice set size, growing exponentially with more options. In fact, solving model (2)–(25) with commercial solvers is slow and the model is intractable even for small instances with a few activities. To address this problem, we make the assumption that an individual only considers the closest facilities to them. This assumption is restrictive but does not impact the ABM results, since there is no benefit in traveling further to do an activity that could have been done closer. The number of nearby facilities to work and home is user-defined. In addition, we use an advanced dynamic programming algorithm to solve the problem, by representing model (2)–(25) in a network allowing us to reduce computation complexity, as discussed in the following paragraph.

²Note that utility parameters have been evaluated on a student population. Consequently, even an adult in active life has more gain to go to an education-related facility, i.e., $\chi_{\text{education}} > \chi_{\text{work}}$.

Dynamic programming algorithm The problem can be described as an elementary shortest path problem with resource constraints which is a common sub-problem for the solution of vehicle routing problems. The method used to solve this variant of the shortest path problem is usually a dynamic programming method, also known as labeling algorithms (e.g., (Torres, Gendreau, & Rei, 2022a, 2022b)). To describe the Dynamic Programming algorithm, we first discretize the time into 288 intervals for every 5 minutes. We define a state using a label $\mathcal{L} = (a, U, t, x_a^3, u, \mathcal{R})$, where a is the current activity, U is the total utility collected including the current activity, t is the time interval, x_a^3 is the duration of the activity, u is the cumulative cost, and \mathcal{R} is the set of activities that cannot be reached either because they have been completed or are mutually exclusive with completed activities.

The algorithm starts with an initial label that represents the start of the day. In each iteration, it explores all possible activities, creating new labels with updated states. Resources are extended through resource extension functions which keep track and update resource consumption. To extend a label \mathcal{L}_k to a new activity a_j , we first check if the extension is feasible, ensuring that no constraints (such as time or budget) are violated and a_j is not in \mathcal{U}_j . If feasible, we create a new label \mathcal{L}_j with updated resource states.

4 RESULTS

Tested Scenarios and Computational Complexity We explore seven different scenarios, each representing a different imposed NPI, as detailed by Table 2. The first scenario, "No restrictions," represents a baseline with all sectors operating normally. "Outing limitations" imposes time restrictions on shopping and leisure, leaving education and work unaffected. The "Early curfew" scenario introduces a curfew at 5 PM without impacting sector operations. "Economy preservation" proposes to close leisure, shopping, and education sectors, but allows working activity. The "Essential needs" scenario restricts leisure and education while keeping other sectors operational. "Work-education balance" adjusts operating hours for the education and work sectors to facilitate a balance, and finally, "Leisure facilities closure" specifically targets leisure activities for closure, with other sectors remaining operational. The model efficiently manages a facility choice set of 86,207 with a population of 100,000, achieving an average execution time as detailed in Table 3. These results show the model's computational robustness.

| Tested Scenarios | Closure | | | | Constraints |
|----------------------------|---------|----------------|---------------|----------------|-------------|
| | Leisure | Shopping | Education | Work | Curfew |
| No restrictions | | | | | |
| Outing limitations | x | from 8 to 12am | | | |
| Early curfew | | | | | 5pm |
| Economy preservation | x | x | x | | |
| Essential needs | x | | x | | |
| Work-education balance | | | from 1 to 5pm | from 8 to 12am | |
| Leisure facilities closure | x | | | | |

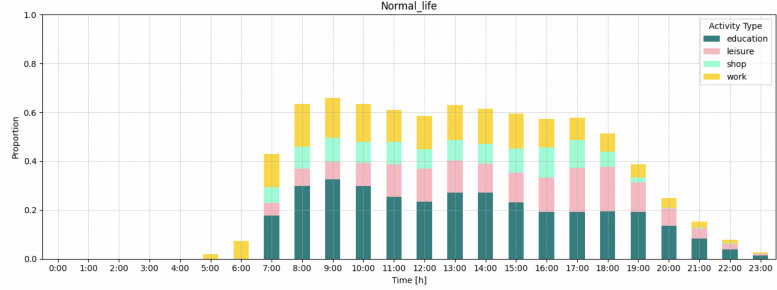
Table 2: Tested scenarios, each one considering different NPIs as input to the ABM.

| | Execution time [h:mm:ss] | individuals/second | second/individuals |
|----------------------------|--------------------------|--------------------|--------------------|
| No restrictions | 1:40:35 | 16.57 | 0.06 |
| Outing limitations | 24:9 | 69.01 | 0.014 |
| Early curfew | 1:38:53 | 16.85 | 0.059 |
| Economy preservation | 2:55 | 570.13 | 0.0018 |
| Essential needs | 39:11 | 42.54 | 0.024 |
| Work-education balance | 1:18:09 | 21.33 | 0.047 |
| Leisure facilities closure | 38:45 | 43:01 | 0.023 |

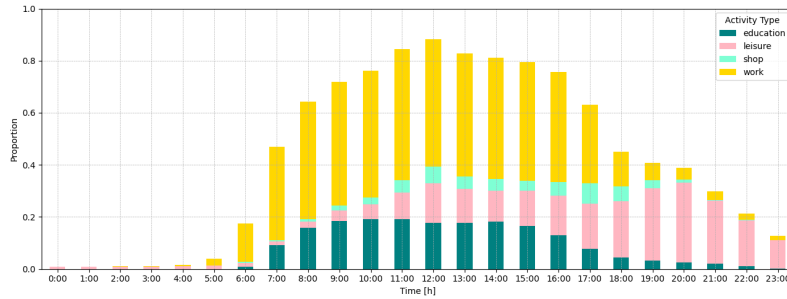
Table 3: Execution details, for each tested scenario (to be filled new values).

Model Validation To validate our model, we compared it with MATSim which shows similar trends but with reduced activity durations, suggesting a more conservative approach to mobility (Figure 2). The

overall pattern, as shown in Figure 2b, aligns with our results (Figure 2a), underscoring our model’s validity. However, MATSim shows slightly higher activity frequencies, and individuals in MATSim rarely stay home all day. Our model also tends to shorten activity durations, given our flexibility feature allowing individuals to end activities earlier. Also, it is worth remembering that our model stratifies the population into seven groups. This stratification ensures realistic activity scheduling; for instance, it prevents unlikely scenarios such as children or elderly individuals going to work, or unemployed people engaging in work-related activities, which can sometimes occur in MATSim. These differences, while notable, confirm our model’s robustness and its utility in predicting behavioral changes in various scenarios.



(a) Output of the mobility restriction model for the baseline scenario.



(b) Output of MATSim.

Figure 2: Model comparison with MATSim.

Behavioral Adaptations The most important feature of the proposed ABM is that it allows the individual to make changes to their schedule when an NPI is introduced. This reveals varied individual and population responses to different mobility restriction scenarios. To provide an overview of these rescheduling choices, we present the share of population (S) performing each activity and mean duration (D) for the scenarios tested in Table 4. By comparing "Leisure facilities closure" with the "No restriction" scenario,

| | Work | | Education | | Shop | | Leisure | |
|----------------------------|------|-------|-----------|-------|------|-------|---------|-------|
| | S | D | S | D | S | D | S | D |
| No restrictions | 50% | 02:34 | 94% | 02:55 | 86% | 00:16 | 91% | 00:44 |
| Outing limitations | 50% | 03:02 | 94% | 03:00 | 36% | 00:16 | - | - |
| Early curfew | 39% | 02:30 | 60% | 02:41 | 80% | 00:19 | 71% | 00:43 |
| Economy preservation | 100% | 04:08 | - | - | - | - | - | - |
| Essential needs | 75% | 04:03 | - | - | 87% | 00:19 | - | - |
| Work-education balance | 13% | 01:28 | 16% | 01:53 | 98% | 00:21 | 94% | 00:53 |
| Leisure facilities closure | 50% | 03:03 | 92% | 02:57 | 86% | 00:19 | - | - |
| MATSim | 51% | 05:28 | 14% | 03:52 | 42% | 00:32 | 52% | 01:53 |

Table 4: Share of population (S) performing the activity and mean duration (D).

we can directly observe the importance of modeling the rescheduling of activities. Indeed, when the closing of leisure facilities is imposed, the model outputs an increased activity in work and shop activities. In particular, average working time increases by 30 minutes and shop by a few minutes. This deviation in

the participation of the population to different activities can affect the epidemiological model linked to the ABM. This is because the epidemiological model considers contacts in activities as the cause of infections. If the mean duration of "shop" increases, the amount of contacts also increases, causing the "Leisure facilities closure" NPI to be less effective. This modification is not considered in models like MATSim that instead focus on the change of mean of transportation from one activity to the other.

5 CONCLUSIONS

The paper presents an ABM that models individual responses to NPIs. The model, built upon the foundation set by the OASIS model, incorporates possible NPIs imposed on the population, allowing for the study of larger populations and facility numbers. A key aspect of our study is the validation of our model against existing standards, particularly MATSim. By comparing our results in a "No restriction" scenario with those of MATSim, we show the robustness and reliability of our approach. Furthermore, our study provides information on how people adjust their activities when faced with specific restrictions. When usual activities are limited or shut down, we see an increase in other types of activities. Understanding this shift in behavior is crucial for studying diseases, as it alters the patterns of how people interact, influenced by health guidelines, and therefore it directly impacts the spreading. Future work considers the integration of a latent class inside the utility function that captures the memory of the fear of individuals, as a function of their socioeconomic characteristics, and the integration of the developed ABM inside the epidemiological tool developed in (Cortes Balcells et al., 2023), to study how better modeling of people scheduling impacts the Pareto frontier of the optimal NPIs to be imposed.

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