Modeling individual activity schedules and behavior changes in Covid-19

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Abstract

This paper presents an activity-based model (ABM) adjusted to analyze changes in urban mobility patterns, particularly under the constraints of the COVID-19 pandemic. Centered around Lausanne's population, the model makes use of data from the MATSim database to simulate daily schedules that adapt to various mobility restrictions. By employing a utility function from the OASIS model, the ABM effectively adjusts individual schedules in response to activity limitations, such as altered shopping or leisure habits. This model surpasses existing frameworks like MATSim and OASIS in flexibility and adaptability, catering to the entire urban population and its diverse facilities. The study aims to offer policymakers and urban planners a robust tool for understanding and managing mobility in both pre and post-pandemic contexts.

Contents

1 Introduction

In recent years, a global pandemic has led to significant changes in how populations move and interact, resulting in profound modifications to mobility patterns. The research presented in this paper aims to bridge the gap between epidemiology and mobility to understand these changes, as illustrated in Figure 1. These changes are primarily driven by psychological factors and government-imposed restrictions. The fear of the virus has led individuals to voluntarily alter their daily routines to avoid infection, while governments have implemented various degrees of restrictions to control the spread of COVID-19. Collectively, these factors have reshaped individual mobility within society, with this work focusing on government restrictions.

In response to these challenges, our research introduces an activity-based model integrated into an epidemiological optimization framework. This framework is designed to effectively optimize activity restrictions in both pre- and post-pandemic contexts. The paper presents the Activity-Based Model developed for this purpose.

We aim to generate adaptable schedules under different activity restrictions, allowing for behavioral modifications in response to these restrictions (e.g., increased shopping or dining out when leisure activities are limited). Our framework contrasts with existing models like MATSim[3], which lack flexibility in adapting activities once choices are removed from the set, and OASIS[8], which, although more adaptable, cannot handle the entire population of a city or its numerous facilities. For this reason, we propose an approach that allows us to have control over the parameters, the utility function, and more importantly, over the resolution method and heuristic employed. This solver, written in C language, finds a near-optimum solution by modeling the problem as a shortest path problem.

In summary, the project's objective is to generate schedules for a given population under mobility restrictions, focusing on Lausanne's population and facilities. The data, including individual characteristics and a comprehensive activity network with coordinates for each activity, is sourced from the MATSim data [3] and has been preprocessed in Python for use in the scheduling algorithm. Our model simulates daily schedules by maximizing the utility gain from participating in activities, using the linear utility defined in the OASIS model [7]. This framework presents an Optimization-based Activity Scheduling model with Integrated Simultaneous choice dimensions, generating feasible daily schedules through utility maximization.

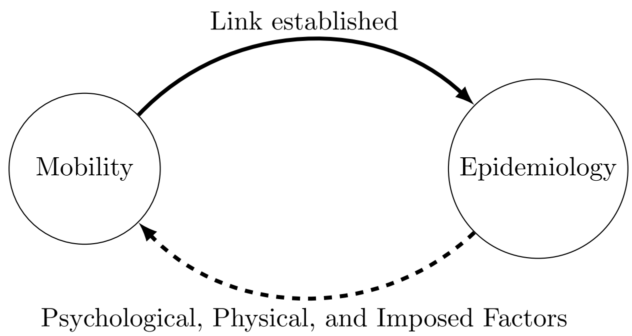

Figure 1: Cycle representing the link between Mobility and Epidemiology. Governments implement constraints to limit spread of COVID-19. Therefore the link from *Epidemiology* to *Mobility* is the objective of the paper.

2 Literature review

Modeling individual activity schedules is crucial for understanding daily mobility behaviors. Since 4 decades, Activity-Based Models (ABMs) rely on a sequence of choices, a restrictive assumption. For this reason, Pougala et al. [7] introduced the OASIS model. This model enables a deeper understanding of trade-offs in activity scheduling decisions by using a simultaneous approach to all choice dimensions: activity participation, scheduling, travel mode, and location. Each individual has preferences that are parameters of a utility function, an econometric utility-based method also explored in other frameworks [10]. The utility is maximized through mixed-integer optimization to simulate realizations of feasible activity schedules. This method provides a profound understanding of the inherent decisions made by an individual planning their day. Indeed, simultaneous evaluations of options can reveal that an individual prefers to shorten the duration of one activity to start the next one earlier.

In their subsequent work, Pougala et al. [8] emphasize the importance of behavioral parameters. They present a procedure to estimate the parameters of the OASIS framework. One option is to sort activities into three flexibility levels: flexible, moderately flexible, and not flexible. The more flexible an activity is, the lower the penalty for varying its start time or duration from the individual's preferences. The framework successfully demonstrates the added value of parameter estimation compared to using literature results and highlights the impact of sampling informative schedules over random ones.

ABMs that focus on maximizing daily utility are either time-discrete or time-continous. Continuous temporal scheduling is closer to real human behavior [5], highlighting the importance of setting a small time interval when dealing with discrete time decisions. High temporal resolution offers more realistic behaviors and resolves scheduling conflicts based on behavioral preferences.

As exact resolution can be computationally intensive when the size of the synthetic population increases or when the number of activities is doubled, Rahman et al. [9] show that heuristics and metaheuristics are viable alternatives. They propose a chance-constrained model and a genetic algorithm-based (GA) memetic algorithm. Usually, a GA starts with a set of random solutions, but here, an initialization is used to acquire good solutions in a reasonable time. If a solution is deemed good, variable neighborhood search is performed. Each chromosome is a sequential activity list. Their method is validated by comparing the results to an exact approach, emphasizing the relevance of using heuristics to schedule a day based on utility maximization, as a heuristic like a GA is computationally efficient, reducing solving time.

The majority of papers assume a static choice. However, life is a dynamic environment where activity duration and resource request/availability are stochastic. Arentze et al. [1] demonstrate the relevance of a dynamic model throughout the days of the week. An individual constantly reconsiders their planning as their needs or daily preferences change. Constraints are also dynamic, including those related to time and resources. Interactions between activities over a 24-hour journey can be linked to daily patterns. Care must be taken to ensure that this does not create bias in predictions of how individuals respond to changes in time use conditions, especially in terms of activity and time allocation choices during a pandemic.

Finally, numerous studies have explored the relationship between mobility and epidemiology, investigating the effects of mobility on the spread of diseases such as COVID-19 ([2], [6]). Concurrently, there are many contributions on estimating and simulating virus propagation effectively based on population mobility ([11], [4]). However, there is a gap in the literature in accurately measuring future changes in mobility during or after an epidemiological event. Relying solely on estimations or historical data limits the accuracy of propagation simulations, potentially leading to severe consequences for populations (Sweden and China are two extreme cases).

3 Activity-Based Model

This section presents the model inputs and outputs, along with a detailed description of assumptions and parameter choices. Figure 2 presents an overview of the model pipeline.

3.1 Input of the model

The input variables consist of the population and the possible facilities in their area. Both are obtained from MATSim real-life schedules for the canton of Vaud

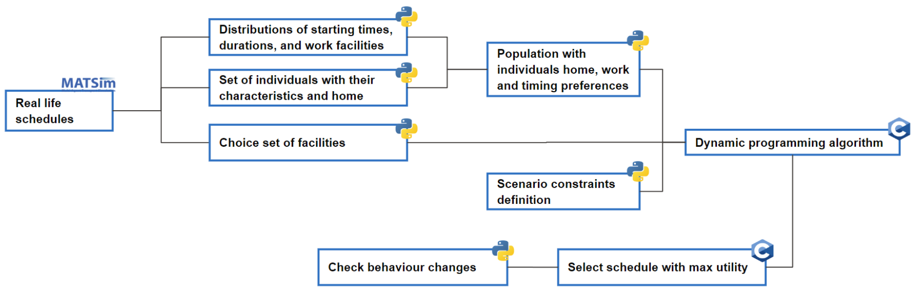

Figure 2: Activity-Based Model processing

id	age	bikeAvailability	carAvail	employed	hasLicense	home_x	home_y	householdIncome	isCarPassenger	...	sex	spRegion	postcode	canton	
1069770	85	FOR_NONE	never	False	no	2569239.0	1190194.0	NaN	False	...	f	3	1580	VD	Av
1103868	85	FOR_NONE	never	False	no	2569239.0	1190194.0	NaN	False	...	f	3	1580	VD	Av
1110921	76	FOR_ALL	always	True	yes	2569193.0	1189751.0	NaN	False	...	m	3	1580	VD	Av
1110922	70	FOR_ALL	never	False	yes	2569193.0	1189751.0	NaN	False	...	f	3	1580	VD	Av
1111181	61	FOR_ALL	always	False	yes	2569340.0	1189900.0	NaN	False	...	f	3	1580	VD	Av

(a) MATSim population

	Unnamed: 0	id	type	facility	link	x	y	start_time	end_time
0	423464	1069770	home	home480932	399007	2569239.0	1190194.0	NaN	09:23:32
1	423465	1069770	shop	168569	244909	2571696.0	1189601.0	09:25:32	09:33:32
2	423466	1069770	home	home480932	399007	2569239.0	1190194.0	09:35:32	09:53:32
3	423467	1069770	leisure	399230	399013	2569430.0	1189314.0	09:56:32	10:23:32
4	423468	1069770	home	home480932	399007	2569239.0	1190194.0	10:26:32	NaN
5	434919	1071953	home	home483115	136934	2551461.0	1166062.0	NaN	15:24:50
6	434920	1071953	shop	556083	28368	2538494.0	1159675.0	15:44:50	16:24:50
7	434921	1071953	home	home483115	136934	2551461.0	1166062.0	16:39:50	NaN

(b) MATSim schedules: 2 examples of real-life individual schedules

(Switzerland). The first file is the population with socio-economic information (Figure 3a), and the second corresponds to their schedules (Figure 3b). There are five facility types: home, work, education, shop, and leisure.

The facility choice set represents the places where everyone will be able to perform an activity. Each facility has the following features:

- *facility id*: facility identifier
- *type*: facility type. Can be either education, shop, or leisure
- *type id*: facility type identifier
- *x, y*: geographic facility coordinates, expressed in meters in the Swiss projection coordinate system. They can be converted to GPS coordinates through the NAVREF tool

Each facility additionally has timing characteristics, representing when it should be used. They are not very restrictive but ensure, for example, that shops are closed during the night:

- *earliest start*: when an activity opens
- *latest start*: when an activity closes
- *max duration*: the maximum duration someone could stay at this facility
- *min duration*: the minimum duration someone should stay at this facility

The opening hours for each facility type in Lausanne are presented in Table 1.

Table 1: Opening hours of facilities types

Facility type	Nb of locations	Earliest start	Latest start	Minimum duration	Maximum duration
Home	70 975	—	—	—	—
Work	13 173	05:00	23:00	00:10	12:00
Education	220	06:00	23:00	00:10	10:00
Leisure	6277	06:00	23:00	00:10	10:00
Shops	3177	06:00	23:00	00:10	10:00

The population (139,392 people in Lausanne, planning 5.3 activities every day) is composed of individuals with personal information and timing preferences:

- *id*: individual identifier
- *local*: city of the individual
- *age*
- *employed*: boolean describing the employment status
- *home id*: home identifier
- *home x, home y*: home coordinates, expressed similarly to the coordinates of facilities
- *work id*: work identifier of the individual's workplace
- *work x, work y*: work coordinates, expressed similarly to the coordinates of facilities
- *facility type start*: time of the day representing the preference to start a facility, depending on its type. Facility types are work, education, shop, and leisure, therefore there are four start time preferences
- *facility type duration*: duration representing the preference to stay in a facility, depending on its type. Facility types are the same as above

For our study, the population attributes (work location and timing preferences) are derived from distributions obtained from MATSim. We randomly assign the workplace of each individual across all work facilities, weighted by the number of people initially going to work there, according to MATSim. For timing preferences, we divided the population into 7 sub-populations to represent habits based on individual conditions. The society is first divided into 4 age ranges: below 18, 19 to 35, 36 to 65, and above 66. Each of these ranges, except for the children, is further divided into two groups: workers and non-workers. This division results in useful distributions. For instance, we might examine the distribution of shopping duration for employed people aged between 18 and 35, if necessary. We then iterated over the 4 facility types requiring preferences: work, education, shop, and leisure. For each type, the individual's preferences for starting time and duration are drawn from the two respective distributions for that type. The distributions correspond to the sub-population the individual belongs to.

Finally, the model takes as input the mobility constraints of the simulated scenario. Some examples of restrictions include full or partial closure of a facility type and a curfew.

3.2 Output of the model

The Activity-Based model outputs a schedule for each individual in the population, with scenario restrictions applied. A schedule is a sequence of visiting facilities, specifying a start time and duration for each visit. Therefore, the files created are in .csv format and have the same features as the input files shown in Figure 3a and Figure 3b.

3.3 Model description

This ABM is utility-based. 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 model's time dimension is discrete (5-minute intervals). The variables of our optimization problem are presented in Table 2. Furthermore, directly extracted from the real-life trips (distance, mode of transportation, duration) reported in the MATSim dataset, the average speed of movement in the Lausanne urban area is 15 km/h.
The utility function is:

$$\max_{\omega,z,x,\tau} \quad U_0 + \sum_{a=0}^{A} \omega_a(\gamma_a + V_a^1 + V_a^2) + \sum_{a=0}^{A}\sum_{b=0}^{A} z_{ab} \cdot \theta_t \cdot \rho_{ab} \tag{1}$$

where :

Table 2: Optimization variables and parameters

Parameter	Meaning
w_a	binary variable set to 1 if activity a 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	discrete variable representing the starting time of activity a
τ_a	discrete variable representing the duration of activity a
x_a^*	discrete parameter representing the desired starting time of activity a
τ_a^*	discrete parameter representing the desired duration of activity a
ρ_{ab}	discrete parameter representing the travel time between facilities a and b
Δ_a	discrete parameter representing the flexibility level of activity a (Table 4)

$$V_a^1 = \theta_a^{early} \cdot \max(0, x_a^* - x_a - \Delta_a^{early}) + \theta_a^{late} \cdot \max(0, x_a - x_a^* - \Delta_a^{late}) \quad (2)$$

$$V_a^2 = \theta_a^{short} \cdot \max(0, \tau_a^* - \tau_a - \Delta_a^{short}) + \theta_a^{long} \cdot \max(0, \tau_a - \tau_a^* - \Delta_a^{long}) \quad (3)$$

U_0 is a generic utility for aspects not associated with an activity. γ_a is the utility associated with participating in an activity during day a. Greek letters θ represents various penalty parameters3. 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. The utility is maximal if $x_a \in [x_a - \Delta_a^{early}; x_a + \Delta_a^{late}]$ but decreases with a coefficient θ_a^{early} if the start is earlier (resp. θ_a^{late} if later). The same concept applies to durations designated by τ_a^*. Finally, the last term represents the penalty due to travel time when going to activity a.

The utility function originates from the Optimization-based Activity Scheduling with Integrated Simultaneous Choice Dimensions (OASIS) framework, as presented by Pougala et al. [7]. 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 ($\gamma_{home} = 0$) and no timing desires coming from individuals. The utility parameters are presented in Table 3, and the flexibility profiles in Table 4. Note 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., $\gamma_{education} > \gamma_{work}$. We also observe a high leisure gain. Finally, the travel time penalty θ_t is set to -0.1.

[1]F: Flexible (60m), MF: Moderately Flexible (30m), NF: Not Flexible (10m)

Table 3: Utility parameters from OASIS

Parameter	Parameter estimation	Parameter	Parameter estimation
γ_{work}	13.1	$\gamma_{shopping}$	10.5
θ^{early}_{work}	-0.619	$\theta^{early}_{shopping}$	-1.01
θ^{late}_{work}	-0.338	$\theta^{late}_{shopping}$	-0.858
θ^{long}_{work}	-1.22	$\theta^{long}_{shopping}$	-0.683
θ^{short}_{work}	-0.932	$\theta^{short}_{shopping}$	-1.81
$\gamma_{education}$	18.7	$\gamma_{leisure}$	8.74
$\theta^{early}_{education}$	-1.35	$\theta^{early}_{leisure}$	-0.0996
$\theta^{late}_{education}$	-1.63	$\theta^{late}_{leisure}$	-0.239
$\theta^{long}_{education}$	-1.14	$\theta^{long}_{leisure}$	-0.08
$\theta^{short}_{education}$	-1.75	$\theta^{short}_{leisure}$	-0.101

Table 4: Flexibility profiles of activities

Activity	Category	Flexibility profile[1]	
		Start	Duration
Work	Mandatory	Early: NF	Short: NF
Education		Late: MF	Long: NF
Shopping	Discretionary	Late: MF	Long: F
Leisure			

The implemented constraints for a valid schedule are the following:

$$\sum_a \sum_b (\omega_a \cdot \tau_a + z_{ab} \cdot \rho_{ab}) = T \tag{4}$$

$$\omega_{\text{dawn}} = \omega_{\text{dusk}} = 1 \tag{5}$$

$$\tau_a \geq \omega_a \cdot \tau_a^{\text{min}} \qquad \forall a \in \mathcal{A} \tag{6}$$

$$\tau_a \leq \omega_a \cdot T \qquad \forall a \in \mathcal{A} \tag{7}$$

$$z_{ab} + z_{ba} \leq 1 \qquad \forall a, b \in \mathcal{A}, a \neq b \tag{8}$$

$$z_{a,\text{dawn}} = z_{\text{dusk},a} = 0 \qquad \forall a \in \mathcal{A} \tag{9}$$

$$\sum_a z_{ab} = \omega_b \qquad \forall b \in \mathcal{A}, b \neq \text{dawn} \tag{10}$$

$$\sum_b z_{ab} = \omega_a \qquad \forall a \in \mathcal{A}, a \neq \text{dusk} \tag{11}$$

$$(z_{ab} - 1) \cdot T \leq x_a + \tau_a + z_{ab} \cdot \rho_{ab} - x_b \qquad \forall a, b \in \mathcal{A}, a \neq b, \tag{12}$$

$$(1 - z_{ab}) \cdot T \geq x_a + \tau_a + z_{ab} \cdot \rho_{ab} - x_b \qquad \forall a, b \in \mathcal{A}, a \neq b \tag{13}$$

$$x_a \geq \gamma_a^- \qquad \forall a \in \mathcal{A} \tag{14}$$

$$x_a + \tau_a \leq \gamma_a^+ \qquad \forall a \in \mathcal{A} \tag{15}$$

$$\sum_{a \in G_k} \omega_a \leq 1 \qquad k = 0, \ldots, 4 \tag{16}$$

Equation (4) constrains the total time of a schedule to equal the time-horizon, here 24 hours. Equations (5) and (9) ensure that each schedule begins and ends with the dummy home activities, dawn and dusk. Equations (6) and (7) enforce consistency of the activity duration by requiring the activity to last longer than the minimal duration but shorter than the time horizon. The second equation also ensures that the duration is null if an activity does not take place in the schedule. Equation (8) ensures that two activities, a and b, can only follow each other once and that an activity cannot follow itself. Equations (10)–(11) state that each activity has exactly one predecessor and successor. This implies that $z_{ab} = 1 \Leftrightarrow w_a = 1$ and $w_b = 1$ (the same if $z_{ab} = 0$). Equations (12) and (13) enforce time consistency between two consecutive activities: $z_{ab} = 1 \Rightarrow x_b = x_a + \tau_a + \rho_{ab}$. Due to the cascading effect, activities are prevented from overlapping with one another, regardless of whether they are immediately consecutive or not. The activities should take place within time windows as represented by constraints (14) and (15). Finally, equation (16) limits to only one activity per group of activity G_k.

The choice set of facilities needs to be proportional to the population considered. If the number of facilities is too small, everyone will meet in the same few facilities, artificially increasing the virus spread. Conversely, a too large choice set will dilute people's aggregation, resulting in a lighter propagation. However, the execution time is highly dependent on the size of the facility choice set. Indeed, it increases exponentially when new possibilities are offered to everyone. A trade-off between the execution speed and the total number of facilities could be stated as follows: an individual only considers the closest facilities to him/her. This assumption is restrictive but does not impact the ABM results. There is no benefit in traveling further to do an activity that could have been done closer. At the beginning of an iteration over an individual, the model computes the minimal distance between the home-facility and work-facility. The facilities are then sorted in ascending order based on this calculation, and only the first 15 are chosen. This selection is also proportional to the facility type: if the choice set has 50% of shop-related facilities, then the individual choice set will have 50% of shop-related facilities. The number of 15 has been determined experimentally. It provides at least 2 choices for each facility type and those possible locations can be either close to their home or their work. For example, shops represent 35% of the total facilities. With this stratified sampling method, there will be at least $0.35 \times 15 = 5.25$ shop facilities in an individual's facility choice set (the same applies to education and leisure facilities, which are 15% and 50% of the total facilities, respectively). Among those 5 shops, 3 could be near his/her home, and 2 near his/her work location.

The model implementation can be found on this GitHub. Find more information in the README.md file. The solver is written in C language and is called for a given scenario and individual via the Python Ctypes package. It maximizes utility by minimizing a shortest path problem ($\max U = \min -U$). The nodes are facilities, and edges have a cost associated with them. This cost is the sum of the preferred duration deviation penalty term of the previous activity, gain to do this activity, penalty if its start deviates from the preferred timing, and penalty associated with the travel time between the two facilities. Edges are also time-constrained. As we do not want to simulate all possible schedules with decisions every 5 minutes, we evaluate at each timestamp which schedules could lead to the best utility at the end of the day. To do this, we eliminate schedules that are dominated by at least one other schedule according to the following dominance rules. S1 dominates S2 if:

1. the two incomplete schedules are compared at the same completion level, i.e., at the same advancement in the day
2. they have performed the same activities. E.g., if S1 is leisure, then shop, then work, all three activities can also be included in S2
3. the utility of S1 is higher than S2

The logic behind this is that, at equal footing (i.e., same amount of time and activities to do), S2 will never catch up to the utility level of S1.

3.4 Mobility restriction policies

In order to analyze the impact of activity restrictions on mobility, we introduce new convex constraints that reflect the various interventions implemented by governments during the Covid-19 pandemic. These constraints aim to regulate activity choices and scheduling in line with observed behaviors.
These constraints can be activated or deactivated based on user preferences. We will implement two types of constraints:

1. to close all similar facilities:

$$\omega_{activity} = 0$$

2. to limit opening hours of all similar facilities:

$$x_{\text{activity}} \geq t_1 \tag{17}$$

$$x_{\text{activity}} + \tau_{\text{activity}} \leq t_2 \tag{18}$$

   where t_1 and t_2 are user-defined time slots. By utilizing these constraints, the model can ensure that activities are scheduled to start and end within specific time ranges.

We define 7 different mobility restrictions scenarios:

1. No restrictions:
   At the beginning of the pandemic, the population exhibited normal behavior. Indeed, only a few individuals had already understood the risk.

2. Outing limitations:
   During the pandemic, governments worldwide implemented measures to close down certain establishments such as cinemas, restaurants, and bars to prevent gatherings. The opening hours of stores may have been restricted as well. The constraint set is:

$$\omega_{\text{leisure}} = 0 \tag{19}$$
$$x_{\text{leisure}} \geq 8\text{am} \tag{20}$$
$$x_{\text{leisure}} + \tau_{\text{leisure}} \leq 12\text{am} \tag{21}$$

3. Early curfew:
   To limit non-essential interactions while still allowing freedom of movement, many countries chose to set up a curfew:

$$x_{\text{activity}} + \tau_{\text{activity}} \leq 5\text{pm}, \quad \forall \text{ activity} \tag{22}$$

4. Economy preservation:
   Governments may also have wanted to maintain a healthy economy. People were authorized to work on-site, but no other activities were allowed:

$$\omega_{\text{education}} = \omega_{\text{shop}} = \omega_{\text{leisure}} = 0 \tag{23}$$

5. Essential needs:
   Another, more realistic solution is to open the stores in addition to the workplaces:

$$\omega_{\text{education}} = \omega_{\text{leisure}} = 0 \tag{24}$$

6. Work-education balance:
   A way to reduce human interaction is to create a trade-off between the active population and children going to school:

$$x_{\text{work}} \geq 8\text{am} \tag{25}$$
$$x_{\text{work}} + \tau_{\text{work}} \leq 12\text{am} \tag{26}$$
$$x_{\text{education}} \geq 1\text{pm} \tag{27}$$
$$x_{\text{education}} + \tau_{\text{education}} \leq 5\text{pm} \tag{28}$$

7. Leisure facilities closure:
   Again, we could reduce human interactions by closing non-essential activities, i.e., all leisure-related facilities such as cinemas, bars, restaurants, theaters, and bowling alleys:

$$\omega_{\text{leisure}} = 0 \tag{29}$$

Table 5 shows a summary of the scenarios.

Table 5: Summary of different scenarios implemented

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

4 Results and discussion

This section presents the results of the model for each policy. The discussion is based on both qualitative and quantitative interpretations, thanks to precise insights extracted from the outputs.

4.1 Execution

As mentioned earlier, the average speed in an urban center such as Lausanne has been set at 15 km/h. The facility choice set was composed of 14,000 facilities (excluding work and home locations, which means that we assume that an individual do not choose neither his/her work nor his/her home locations). The 15 closest facilities were pre-filtered for each individual. The population size was 4,000 people. Further details about simulation performances are summarized in Table 6.

Table 6: Execution details

	Execution time [mm:ss]	people/second	second/people
No restrictions	08:29	7.86	0.127
Outing limitations	02:32	25.69	0.038
Early curfew	06:45	9.87	0.101
Economy preservation	00:11	363.6	0.001
Essential needs	03:39	18.25	0.055
Work-education balance	06:07	10.89	0.092
Leisure facilities closure	03:23	19.66	0.051

4.2 Mobility restriction policies impact

We will first make some general observations about our simulations before examining in detail how individuals adapt to a set of mobility restrictions. Table 7 presents material for an objective comparison between different scenarios. There are two performance indicators presented: duration, which is the average time someone spends performing an activity, and frequency, which is the fraction of schedules in which an activity is included. More precisely, it is calculated as the number of people performing a given activity over the total number of people performing at least one activity. Some relevant insights from the results are:

- The more people are restricted, the less they deviate from their preferences. Here, the so-called deviation from preferences refers to the cumulative sum, across all activities done during the day, of the total deviation between the effective starting time and their ideal preference for starting time. These time deltas are then added to calculate the total deviation of an individual from his/her timing preferences. The same method can be applied to activity durations. This may seem counter-intuitive because one might expect people to adapt their schedules more. However, they engage in fewer activities, which mechanically results in less deviation. Also, individuals tend to deviate from their preferences even without constraints as they attempt to fit the maximum number of activities into their day. Without any restrictions, this is when they can most adapt to perform more activities and maximize their utility.

- In the scenario with a curfew at 5pm, 1% of people stay at home all day. In the economy preservation scenario, this number increases to 21%. In other scenarios, almost no one stays at home all day. In real life, a significant fraction of people do so. This could indicate that our model is too flexible for individuals. However, even with less flexibility, everyone would go outside at least once a day. Therefore, the issue lies not only in the flexibility afforded to individuals but also in the utility function. Remember that we adopted the assumption from the OASIS framework that staying at home has no associated utility gain. The fraction of people staying at home when only work is permitted (21%) is a consequence of the assumption that children cannot work

Table 7: Frequency and mean duration of activities

	Work	Education	Shop	Leisure
No restrictions	Frequency: 0.50	Frequency: 0.94	Frequency: 0.86	Frequency: 0.91
	Duration: 02:34	Duration: 02:55	Duration: 00:16	Duration: 00:44
Outing limitations	Frequency: 0.50	Frequency: 0.94	Frequency: 0.36	
	Duration: 03:02	Duration: 03:00	Duration: 00:16	
Early curfew	Frequency: 0.39	Frequency: 0.60	Frequency: 0.80	Frequency: 0.71
	Duration: 02:30	Duration: 02:41	Duration: 00:19	Duration: 00:43
Economy preservation	Frequency: 1.00			
	Duration: 04:08			
Essential needs	Frequency: 0.75		Frequency: 0.87	
	Duration: 04:03		Duration: 00:19	
Work-education balance	Frequency: 0.13	Frequency: 0.16	Frequency: 0.98	Frequency: 0.94
	Duration: 01:28	Duration: 01:53	Duration: 00:21	Duration: 00:53
Leisure facilities closure	Frequency: 0.50	Frequency: 0.92	Frequency: 0.86	
	Duration: 03:03	Duration: 02:57	Duration: 00:19	
MATSim	Frequency: 0.51	Frequency: 0.14	Frequency: 0.42	Frequency: 0.52
	Duration: 05:28	Duration: 03:52	Duration: 00:32	Duration: 01:53

Our framework also allows for the examination of individual planning (Figure 4), which can be informative in some cases. Each rectangle correspond to a schedule, and there are 7 schedules corresponding to the 7 scenarios. Each activity has a color assigned (blue=home ; green=education ; yellow=work ; turquoise=shopping ; pink = leisure). We can observe at the individual scale how someone is reorganizing his/her planning, giving up an activty to do it remotely for example. However, we are now focusing on population schedule trends. In the following images, yellow corresponds to work, dark green to education, turquoise to shopping, and pink to leisure.

1. No restrictions:
   This scenario depicts the typical movements of our population on a normal day and serves as a reference for subsequent policies. The participation rate for all activity types is high, except for work, which could be further compared to other facilities. Work and education both last between 2.5 and 3 hours. People usually shop quickly, perhaps for their meals. Finally, more time is dedicated to leisure, as this type of activity takes, on average, 44 minutes during the day, which is consistent with going have a drink or play bowling.

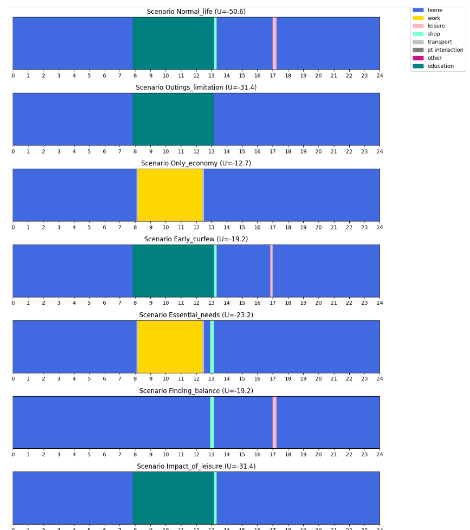

Figure 4: Schedule reorganisation of an individual.

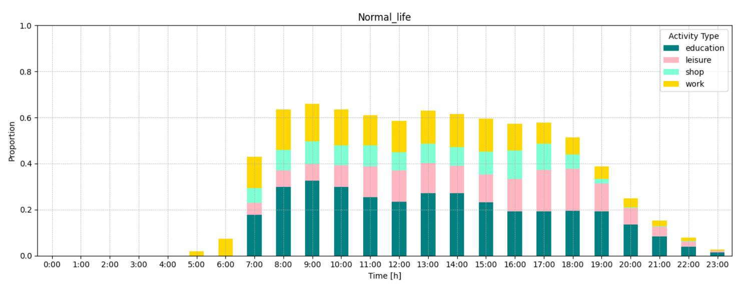

Figure 5: No restrictions

2. Outing limitations:
   When the shops are open only in the morning, we notice that people organize themselves to go early, before long-duration activities such as work and education. They could be buying their lunch and starting their workday a bit later than usual. For the rest of the day, they can spend a longer time at work (2h34). This efficiently reduces the number of people aggregating in the afternoon. Indeed, it makes sense because people go to the cinema or have parties in the late afternoon or at the start of the night.

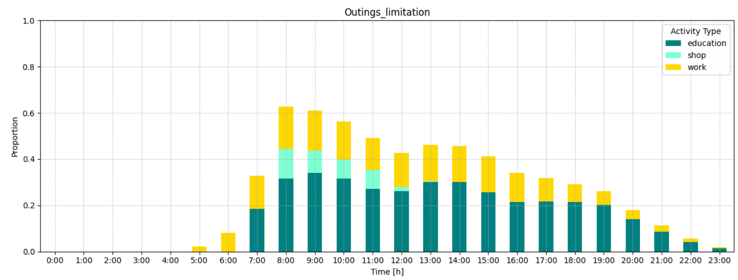

Figure 6: Outing limitations

3. Early curfew:

Many governments imposed a curfew during the Covid-19 pandemic,

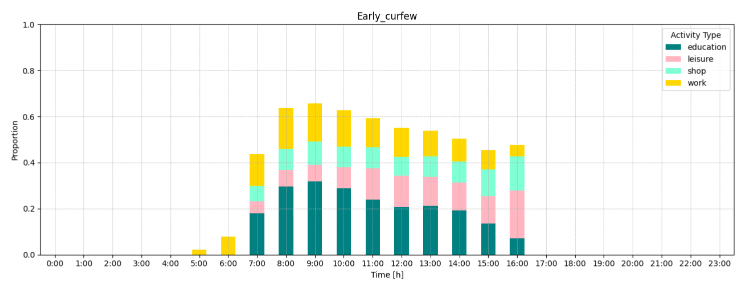

Figure 7: Early curfew

assuming that late activities mostly involve people going to bars or other non-essential activities. Our results show that it does not reduce the proportion of people outside until 2 pm. After that, people avoid starting long-duration activities (such as work and education) because they would have to go home midway. Remote work is preferred. We also notice that people reorganize to go shopping and enjoy some leisure in the last hour before the curfew (4 to 5 pm), possibly buying their dinner or trying to enjoy the rest of their day. Shopping and leisure, the shorter and more flexible activities, are the most recurrent across the population (Table 7).

4. Economy preservation:
   Having no other choice to maximize their utility, and without time restric-

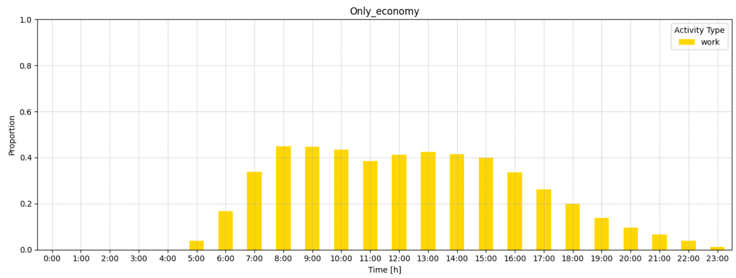

Figure 8: Economy preservation

tions, everyone except children goes to work. The proportion of people outside is greatly reduced. In that scenario, virus propagation would be much more predictable as the clusters are work locations that are easily identified.

5. Essential needs:
   This policy is a more realistic variant of the previous one. People need

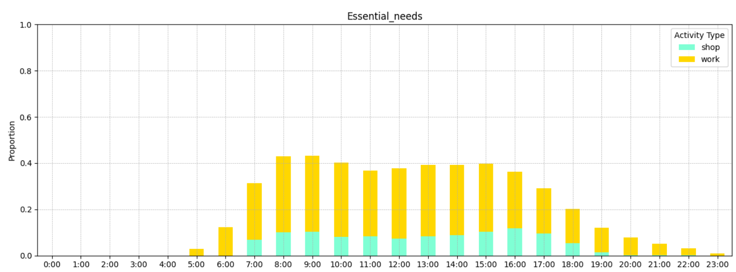

Figure 9: Essential needs

to get essentials. We notice that the reduction in people's aggregation is still efficient. The proportion of people going to work remains high (0.75).

6. Work-education balance:
   This policy imposes restrictive time constraints on longer activities, which results in them becoming much less popular (0.13 for work, 0.16 for education). However, this could be a credible way to find a trade-off between younger and older generations. It also limits the prolonged duration of virus transmission. Indeed, shopping and leisure, which are preferred, last respectively 21 minutes and 53 minutes.

7. Leisure facilities closure:
   The idea of closing leisure-related facilities is to shut down the less es-

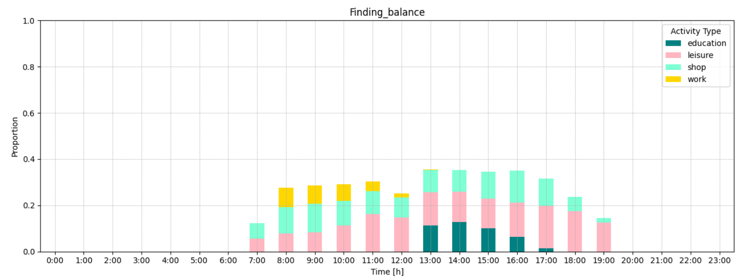

Figure 10: Work-education balance

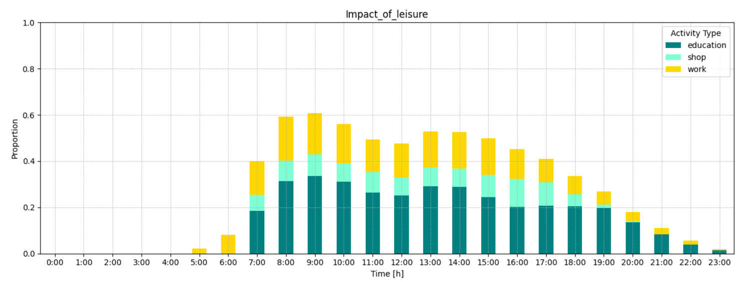

Figure 11: Leisure facilities closure

sential services first. However, since shopping is also a short and flexible activity, people may substitute one for the other. Therefore, this policy does not seem very efficient.

8. Comparison to MATSim:
To validate our model, we compared our results with those from MATSim. Initially, we observed that the distribution of the population across activities differs significantly, likely due to the distinct utility parameters in our model. Furthermore, the general pattern seen in Figure 12 resembles ours, indicating a positive aspect of our model. However, the frequency bars for MATSim are marginally higher (with the largest difference being +0.15). Upon examining the schedules more closely, we found that individuals who stay at home all day (homebodies) are rare in MATSim, where people visit an average of 5.3 facilities each day. This frequency is considerably higher than in our model, where an individual can participate in a maximum of four distinct activities (repeating the same activity is not allowed). Additionally, Table 7 suggests that our model tends to shorten the duration of activities. This phenomenon could be attributed to the flexibility we allowed in activity duration, enabling individuals to end activities earlier without penalty (thus reducing the incentive to prolong participation). Overall, despite some differences which are largely explainable, the global results appear credible and demonstrate the ro-

bustness of our model. This credibility lends confidence to the subsequent simulations of various scenarios, which are instrumental in anticipating behavioral changes.

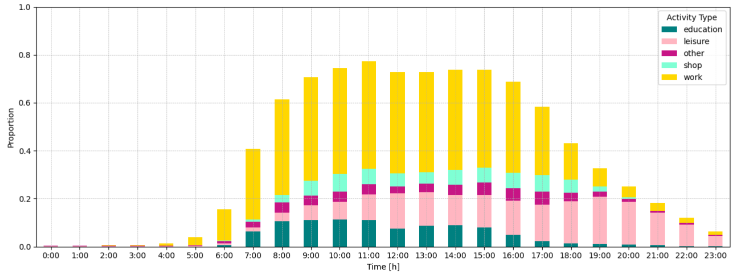

Figure 12: Matsim schedules data

5 Conclusions

The research successfully demonstrates the model's ability to simulate individual daily schedules under various mobility restrictions, showing how people adapt their behaviors in response to policies like curfews, economy preservation, and leisure facilities closure. The model, creating an population from the MATSim database and a linear utility function from the OASIS model, surpasses existing frameworks in adaptability. Therefore, the flexibility added by developing it from scratch allows us to build upon a probabilistic epidemiology model.

The analysis provides valuable insights into how different policies impact daily life. For instance, curfews led to a shift in earlier activity timings, and the closure of leisure facilities did not significantly affect people's ability to engage in other short, flexible activities. These findings highlight the importance of considering human behavior's adaptability in policy-making.

While the model is an advanced tool, it has limitations. The assumption that staying at home has no utility gain might have led to an underestimation of people staying indoors. Furthermore, the flexibility levels associated with the activities could be too generous, as they create a shift toward earlier and shorter activities, and do not fully capture the reluctance of some individuals to leave their homes, even without restrictions. The assumption of people's behavior could be relaxed. Many reasons could lead someone to go to a farther facility. This assumption was coherent with the shape of our utility function.

Indeed, the utility function could be refined to more accurately reflect the complexities of human decision-making, especially under varying pandemic conditions. Including psychological variables, such as fear or risk perception, might provide a more comprehensive understanding of mobility patterns. Moreover, utility parameters could be re-estimated too.

Incorporating more detailed demographic data could allow for more nuanced simulations, particularly in understanding how different segments of the population respond to mobility restrictions. Extending the model to simulate longer periods could help understand long-term behavioral changes and policy impacts. Indeed, daily schedules are interdependent throughout a week. Moreover, modes of transportation would have been an interesting feature to add to our model. However, as predicted travels are usually shorts, it did not seems essential to do at first. Finally, validating the model's predictions with actual mobility data from the pandemic could strengthen its credibility.

In conclusion, this project provides an efficient Activity-Based Model for understanding and simulating mobility under pandemic conditions. However, further refinements and expansions of the model are necessary for it to become an even more robust tool for policymakers.

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