Modeling the public transport network in Milan: an ABM Approach

Bocconi University

Arturo Mario Bagnara, Davide Nobile, Claudia Sessa and Cecilia Terraneo

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Arturo Mario Bagnara (3188256)	Davide Nobile (3186384)
Claudia Sessa (3042918)	Cecilia Terraneo (3090142)

Abstract
Mobility is one of the key factors for a large city to become a well-developed metropolitan area and simulations in this field have become crucial in understanding cities' issues. This project aims to measure the efficiency of Milan's public transport network, by simulating the flow of individuals through an agent-based model (ABM) and identifying the differences in agents' behavior following shocks and interventions. The choice of an ABM allows to model the complex transportation system in a granular way, as the sum of interactions of the individuals' travel behaviours. Furthermore, it permits to explore how agents interact with the environment, and how, through such interactions, aggregate patterns emerge. This simulator, integrated with other tools, could support decision makers in evaluating changes to the lines and optimizing the network. We show two cases studies in this paper.

Keywords: Mobility, Milan, ABM, Network Model, Simulation

1 Introduction

Urban mobility is a significant component in the development of contemporary societies [1]. Studies in mobility field [2–4] include research on migration, tourism, sustainability, residential and urban daily mobility – the latter being the central interest of this paper. Milan is one of the most avant-garde cities in Italy, with an extensive transportation system that includes a total of 143 routes among metro, tram, bus and filobus, managed by Azienda Trasporti Milanesi (ATM), as well as taxi, car and bike sharing services. Every year, ATM services host around 585 million passengers, spending, on average, 43 min on public transport per day [5].

The efficiency of a transportation system depends both on the regularity of the service (how much the service provided adheres to the planned schedule) and on the extent to which it is suitable for travellers' demand. There are several issues which can arise daily and that are correlated to a wide range of situations: long waiting times at the stops due to spread of means' delays; overcrowded vehicles caused by a limited number of rides; problems caused by changes of the network. Urban daily mobility refers to all the ways in which people change location, which means that it considers the sum of the journeys made, the time it takes to make them and the modes of transport used. The focus of this research is on the public transportation service, and the idea is to simulate the flow of individuals moving on ATM network with an agent-based model (ABM), as to reproduce different realistic scenarios and evaluate how efficient is the network in satisfying the demand.

2 Literature review

2.1 Motivation and the choice of ABM

In order to model the complexity of urban mobility systems it is essential to capture the dynamic behaviour of individuals. However, modelling a metropolis' public transportation system as a whole would involve either creating many variables or making many assumptions, as one should take into account complex large-scale interactions between individuals and the environment. Among the possible types of transport planning models, an ABM allows to represent a system in a more granular though straightforward way, as the sum of interactions of multiple agents which are treated separately [6].

This type of model is characterized by four elements [2] which permit to break a complex problem into smaller modules:

(i) a set of interactive agents and their internal state;
(ii) an environment within which the agents live;
(iii) a set of relationships linking objects and/or agents;
(iv) a set of operators that allow the interaction between the agents and the objects.

By modelling the components instead of the entire system, one can analyse emergent phenomena and interactions. A crucial advantage is the possibility to calibrate the model with real data and test the effects of actual policies that have been implemented in reality, observing different scenarios and supporting policy-makers [7].

2.2 The synthetic population and the activity-based approach

The real population under study can be represented, as accurately as possible, by generating a synthetic population, calibrated on socio-demographic information from census data [8]. Each agent's behaviour and movements can be determined through the assignment of a travel diary [9], a sequence of activities the individual makes in a representative work day, with details such as departure time, origin and destination. This approach is called "activity-based" [10] or "activity-based travel demand model" [6] and it has been adopted in similar works to study mobility systems of different cities. Its main characteristic is that travel decisions are driven by a collection of activities that form an agenda. The activities are scheduled along with the time, location and means of transport used and this activity scheduling can then serve as a module in the agent-based model framework.

2.3 Previous ABM works on urban mobility

The idea of using an ABM to study individuals' mobility patterns is not new in the field of urban science. In Grignard et al. (2018)[11] , the authors have built an ABM to study the impact of different mobility modes on traffic flow and congestion, with a focus on the city of Cambridge. Another related work is Huynh et al. (2015)[9] , in which authors have simulated land use and transport demand of an urban area of Sydney. As for Milan, several analyses have been conducted concerning the integration of shared mobility services into the public transport network, the latest ones focusing on how to respond to new needs generated by the pandemic, as in Liouta (2021)[12]. Still with respect to the pandemic, in Trucco et al. (2020)[13] authors have adopted a simulation approach to evaluate different unlock strategies for public transportation. No significant work has been published yet which considers the flow of passengers as a determinant of the efficiency of Milan's transport network. This project aims at closing this literature gap.

3 Data description

In order to build our model and make it as close as possible to reality, we have conducted research online to retrieve all the necessary information. The data we have acquired are:

- datasets [14, 15] from Comune di Milano's open data, containing the terminal points and their geographical coordinates, the length and the number of stops for each route of the underground lines and of the surface transit lines respectively;
- datasets [16, 17] from Comune di Milano's open data, containing the AMAT id, the line name and number, the geographical coordinates and the location of all the stops of the metro lines and of the surface transit lines respectively;
- datasets [18, 19] from Comune di Milano's open data, containing the sequence of stops for each route of the underground lines and of the surface transit lines respectively;
- datasets [20, 21] from Comune di Milano's open data, containing the starting time, the ending time, the type of day (weekday, holiday, weekend) for each route of the underground lines and of the surface transit lines respectively;
- dataset [22] from Sistema Statistico Integrato of Milan, on the distribution of resident people in Milan by age and by NIL in 2021;
- dataset [23] from ISTAT, containing the distribution of oriented movements for a specific activity by class age during an ordinary weekday (data refer to 2013). For example, it shows the percentage of people of 15-24 years old that during an ordinary weekday move (use a vehicle) for educational purposes;
- dataset [24] from ISTAT, containing the time spent on a specific activity by class age at a specific time (every 10 minutes) during an ordinary weekday (data refer to 2013). For example, it shows the percentage of people of 15-24 years old that during an ordinary weekday at 9:00 a.m. spend some time in educational activities;
- datasets [25] of GTFS (common format for public transportation schedules and associated geographic information) which we use to design the transit timetables of all the means of transport.

4 The model

Our model has the goal of simulating the mobility of citizens in Milan, exploring the consequences of shocks and interventions that can affect directly the transport network. Specifically, the elements that constitute our model are:

(i) The environment: the public transport network of Milan, including metro, tram, bus and filobus lines.
(ii) The agents: synthetic individuals, constituting the flow of passengers on ATM vehicles.
(iii) The time: the simulation is based on data regarding an ordinary week day, from 5:00 a.m. to 1.00 a.m. of the next day and each step represents 1 minute (for a total of 1200 steps).
(iv) The rules: agents, according to their schedules, move on the network, respecting the timetables and the availability in terms of capacity on the vehicles.

Therefore, our model consists of generating synthetic agents, placing them on the graph representing the transport network of the city of Milan, and letting them move around the city according to their schedules. Individuals interact with each others as they compete to get on the same vehicle with limited capacity. Moreover, they interact with the environment, since they choose the shortest path to their destinations, according to network-specific attributes (i.e. distance between stops, speeds of the vehicles, lines' timetables).

4.1 The environment

The environment on which agents move is a graph representing the public transport network of Milan: each node identifies a stop, while the edges connecting them denote the routes of the different transportation means [18, 19]. In this way, two consecutive stops on the same transport line are joined by an edge. Our graph is a directed multigraph, meaning that all the edges point in a single direction, and between two nodes there may be more than one link of different type. In our specific case, this happens when there are multiple routes that pass through two consecutive stops. The graph has been created in Python, using the NetworkX package which permits to define, manipulate and study the structure and the functions of complex networks. At the end of this process, the final graph contains a total of 4753 nodes and 18470 edges.

To compute the distances and better visualize the network, all the stops are placed in space using their real geographic coordinates [16, 17]. We assign to each stop, using web-scraping techniques since no complete source was available, the Nucleo d'Identità Locale (NIL) it belongs to, among the 89 NILs in which Milan's area is divided. This will allow us to exploit, when generating the agents, demographic data at a more granular level and make the population synthesis more accurate.

So far, our nodes are connected only through the existing transport lines. However, in reality, people usually move among stops of different lines when

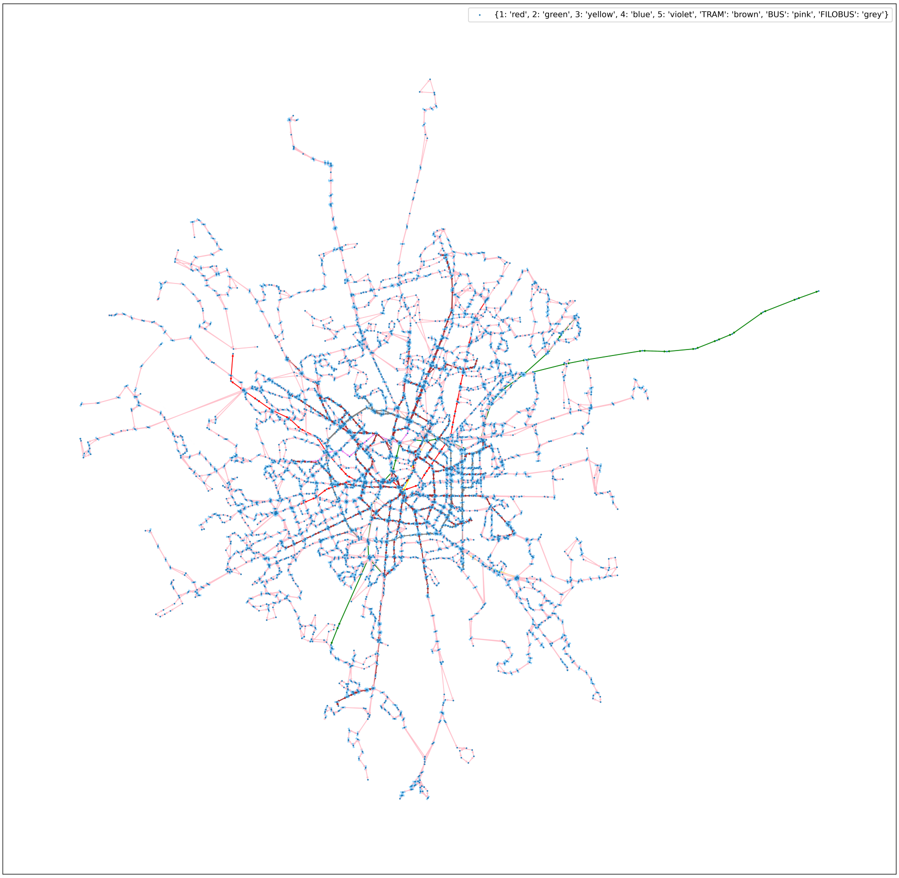

Fig. 1: The network.

they are close to each other, for example on the opposite side of the road. In order to allow agents to move in a more realistic way, we have decided to connect stops that are less than 200 meters away from each other with an edge that represents a walking path. The final network is shown in figure 1.

During the graph generation process, we have also assigned several attributes to both the nodes and the edges. First of all, each node is characterised by a unique id, which corresponds to the official AMAT id, and a dictionary that contains the number of points of interests which are at most 500 meters away from the stop. In particular, the points of interest and their location have been retrieved using OpenStreetMap data [26]. The source provides several classes of categories, but, as explained more in details in section 4.2, only four of these classes have been selected: food, leisure, school and office. Secondly, each edge is identified by the id of the two nodes that it connects and the specific line of the mean of transport (eg. 11497, 11500, TRAM12). Its attributes are: transport mode, total capacity, weight, next edges, waiting list and passengers list. The total capacity [27–30] and the weight depend on the transport mode. Specifically, the weight can be considered as the traveling time between two stops, which is computed dividing the distance between stops by the average commercial speed of the vehicle [31]. Next edges is a list which, in most cases, refers to the following edge on the same line. However, there are cases in which forks require a single edge to have two “next edges”. Additionally, foot edges do not have “next edges”. Finally, the waiting list and the passengers list allow to identify the travellers that are waiting for and boarding the vehicle.

4.2 The agents

The creation of the synthetic population that is used for the simulation proceeds through different steps, as summarised in the algorithm 1 below.

First of all, for each agent we draw an age class (among the following: 15-24, 25-44, 45-64, 65+) based on the distribution of inhabitants of Milan. Then, we draw a NIL for the agent’s house from the distribution of the NILs conditional on the chosen age group [22]. After this, we draw uniformly at random, from the stops in the selected NIL, a precise node which represents the agent’s home.

At this point, for each of the five possible activities (education, work, leisure time, self-care [1] and housework) we decide whether the agent will or not perform it during the day, by drawing from a Bernoulli with parameter equal to the probability that the agent carries it out in an ordinary weekday conditional on the agent’s age class. This probability comes from a distribution constructed from the data provided by ISTAT [23] regarding how people spend their time within an average weekday. Therefore, each agent can have a variable number of activities to carry out, ranging from 1 to 5. We have realized that, on average, around 20% of the initially generated agents do not have any planned activity in their schedule and, therefore, we have decided to discard them. Consequently, for each activity selected for the agent, we assign the location (i.e., the specific node in the network) with probability proportional to the number of facilities corresponding to that task nearby each node [26]. Among the possible categories proposed by OpenStreetMap, we only take into consideration the ones that match the ISTAT activities (eg. schools, universities, etc. for education; offices, co-working place, etc. for work; cinema, gyms, etc. for leisure time; restaurants, bars, etc. for eat/sleep). When the activity “housework” is selected, we assign as destination the agent’s house node. We now assign a departure time for each scheduled activity by drawing a 10-minutes time slot from the distribution of oriented movements over time conditional on the specific activity [24], which has to be performed approximately 40 minutes after the departure (40 minutes being the average traveling time). To allow for minute-by-minute departure times, we also include a randomization term that adds or removes at most 5 minutes from the picked time. Finally, if the last

[1] ISTAT actually provides a category that includes eat, sleep and other self-care. However, given the time horizon we consider (5:00 a.m to 1:00 a.m), we assume that “sleep” can be neglected.

destination of the agent is not "home", we compute a critical time at which we let the agent depart again to go back home (time of the last activity + 40 min + average duration of last activity [24] + noise in the [-10 min, +10 min] interval). We assume that, if this critical time is after 10:30 p.m. the agent prefers not to use public transports to go back home, as the timetables are not favourable later in the evening.

Algorithm 1 Agents' generation

Require: $n \geq 0$
  for each agent $i = 1, ..., n$ **do**:
    $age\_class \sim Multinomial(p_l)$ ▷ p_l = P(age class l) for $l = 1, ..., 4$
    $nil \sim Multinomial(q_{jl})$ ▷ q_j = P(nil j | age_class) for $j = 1, ..., 89$
    $home \sim Uniform(k)$ ▷ $k = \frac{1}{|\{s : s \in nil\}|}$
    for each activity a = 1, ..., 5 **do**:
      $u \sim Bernoulli(f_a)$ ▷ f_a = P(a | age_class)
      if $u = 1$ **then**:
        $destination \sim Multinomial(g_s)$
        ▷ $g_s = \frac{\text{\# amenities of type a close to node s}}{\text{total \# of amenities of type a}}$
        $departure\_time \sim Multinomial(r_t)$
        ▷ r_t = P(travel time | a) + U(-5, 5)
      end if
    end for
  end for

At this point, for each agent we have: a unique id, the age group, the starting point (node on the network) and a schedule of activities (from 1 to 5 activities, with the related destination and the time at which the agent has to start the journey to get there), as shown in the table 1 below.

Table 1: Example of agent's generation

The agent		The schedule		
Features	Data	Activity	Destination	Departure time
Unique id	7548	1) Education	V.le Bligny, 19	7:30
Age	15-24	2) Work	Duomo M3	14:15
Starting point	Corvetto M3	3) Leisure	Moscova	19:25

The final step to complete the synthesis of the population is to assign to each agent the list of edges that form the shortest path to reach their destinations (Example in table 2 below). Specifically, the shortest path is calculated through the Dijkstra algorithm, using as weight the traveling time of each edge. However, not all nodes are taken into account in this process. In fact, the shortest path is computed on the subgraph of the edges constituting the lines that are active in a limited time window around the departure time. In this way, the agent can only select routes that are available at the time of their departure. Lastly, since we are working on a multigraph, it may be the case that two stops are linked by two different means of transport. In this case, the agent includes in the shortest path the edges that minimize the number of changes of transport method needed.

Table 2: Example of shortest path

Id AMAT	Edge	Vehicle
966 - 988	Corvetto - Brenta	Metro 3
988 - 942	Brenta - Lodi T.I.B.B.	Metro 3
942 - 924	Lodi T.I.B.B. - Porta Romana	Metro 3
924 - 11773	Porta Romana - V.le Sabotino	On foot
11773 - 11772	V.le Sabotino - V.le Sabotino, 15	Tram 9
11772 - 11767	V.le Sabotino, 15 - V.le Sabotino, 1	Tram 9
11767 - 11753	V.le Sabotino, 1 - V.le Bligny, 39	Tram 9
11753 - 11471	V.le Bligny, 39 - V.le Bligny, 19	Tram 9

5 The simulation

For the sake of the simulation, each agent is characterized by a state, which can take four possible values: busy, waiting, traveling and finished. Busy agents are those that are currently in one of the facilities and do not have to travel. Waiting agents are the ones that are waiting at a stop in order to get on a vehicle. Traveling agents are situated on edges and they are moving to their next destination. Finally, finished agents are those that have already completed all the journeys in their daily schedule.

Each iteration represents one minute. At each minute, we activate agents within groups in random order, to avoid always giving the first-mover advantage to the same individual. We first consider the set of "busy" agents, and, if their schedule contains the current minute, meaning they have to depart, they start their daily trip by becoming "waiting". Otherwise, they remain "busy" at their current position. We then loop over the "traveling" agents: looking at their path, they evaluate whether they have to get off their means of transport and disembark if that is the case. Clearly, they can only do so if the vehicle has crossed the edge and reached the next stop. Edges in the graph can be either active or inactive at any given time step. An edge is active at minute t if there's a vehicle that is passing at the starting node of the edge and can embark passengers, based on data about the transit timetables for all the means of transport [25]. "Waiting" agents are the last to act. Each of them looks at the next edge in their path and, if it is active and there's space on the vehicle, they get on board. If that is not the case, they stay on the stop waiting.

We simulate 20 hours, from 5:00 a.m. to 1:00 a.m. of the next day, and let agents move on the network to reach all the destinations in their schedule.

Once agents complete all of their tasks, their state changes to “finished” and they are no longer considered in the following iterations. It can happen that agents are scheduled to depart for an activity very late in the night, when rides are less frequent, so they fail to complete their journey, and their state never becomes ”finished”. We assume that they will use alternative ways, not covered in our model, to proceed.

During the simulation, we collect measures and statistics which help us evaluating the state of the system and the effects of shocks and interventions. In particular, we are interested in:

- total waiting time and total waiting time per trip;
- total traveling time and total traveling time per trip;
- percentage of traveling and waiting agents at each time step;
- total number of vehicle changes;
- total number of minutes each edge reaches its full capacity;
- total number of times an agent travels on foot;
- total number of passengers on each vehicle during the day;
- total number of agents passing on each node and each edge;
- maximum number of simultaneous agents on an edge;
- distance-adjusted per trip time distribution.

6 Experiments

We perform two experiments to test the functioning of our model, reproducing two separate case studies. Each of the experiments is made up of two main phases:

- a pre-experiment phase, in which agents are generated and the simulation is conducted on the original network (without interventions);
- a post-experiment phase, in which the same agents are used but the paths for the simulation are changed to account for the network modifications.

For each experiment, we generate 10 groups of 25,000 agents, of which around 20,000 have non-empty paths, each one taking, on average, 8 different vehicles during the day. Counting each time an agent takes a different vehicle as a separate passenger, we get to a total of 160,000 passengers per simulation. Since the total number of daily travelers on all the transport network of Milan is 1,590,000 [32], we get that each agent represents 10 real individuals. We run 10 separate simulations per each phase of each experiment and we then average the results in order to account for the stochasticity in the population synthesis.

6.1 Experiment 1: Suspension of metro stop Duomo

The first use case that we consider refers to the situation in which the metro stops of “Duomo” are closed and, therefore, cannot be reached directly through the use of the metro. This intervention is usually implemented in Milan when big events are organized in Piazza Duomo, one of the main squares of the city. Indeed, in order to preserve public security and reduce the affluence to that stop that could be overcrowded, ATM temporarily interrupts the possibility to get out of the Metro 1 and Metro 3 in Duomo, allowing direct connections between the immediately previous and subsequent stops of the metro line.

The first phase of the experiment consists of generating the agents and letting them travel on the original network. There are no changes to be considered in the graph, since it reflects an ordinary week day, with all the means of transport working according to their timetables.

The second phase of the experiment is conducted on the same 10 groups of agents generated before, but on a new graph reflecting the shock: the metro stops in Piazza Duomo are now only reachable by foot and the edges on the Metro 1 line and on the Metro 3 line that reach Duomo stop (San Babila-Duomo, Cordusio-Duomo and Missori-Duomo, Montenapoleone-Duomo) in both directions have been substituted by direct edges between the border stops of San Babila - Cordusio and Missori - Montenapoleone. The main consequence is that the agents are characterised by the same schedules (i.e. the same activities and the same stops to be reached), but, having to move on a new graph, a different shortest path is computed to get to their destinations.

When analysing the results of this experiment, it should be noted that, unlike in the case of a real event, we did not implement an increase in the number of people directed to Duomo. This allowed us to consider the same agents before and after the shock, to interpret the impacts of the intervention as causal effects as much as possible.

If we take into consideration all agents, we cannot observe any significant change in metrics such as the average traveling and waiting time (figure 2). This suggests a resilience of the system to this particular shock. On the other hand, when looking more specifically at agents that have to either change vehicle or carry out an activity in one of the Duomo stops, the intervention does produce some noteworthy effects. In particular, the average waiting time and the average traveling time increase from 57.13 to 61.38 minutes and from 79.63 to 84.89 respectively. This subset of agent is also affected in terms of vehicle changes: they need to take on average one additional means of transport after the intervention. Another remarkable result is how the alteration in the Metro 1 and 3 routes is reflected in a different usage of other means. In particular, figure 3 shows how the lines that experienced an increase in the number of daily passengers (tram 16 by 235%, tram 12 by 22.5% and tram 19.9%) all have stops in proximity to Duomo and therefore constitute an alternative way to reach this location. On the contrary, the passengers of Metro 1 and 3, directly touched by the intervention, drop by 8.4% 11.7% respectively. These numbers become even more insightful when considering that, in absolute terms, the average number of passengers decreases by 7883.6 and 6388.6.

Lastly, while before the intervention Duomo stops are among the top fifteen most trafficked nodes, after the intervention they are not present in the top ranking. Note that the agents' schedules do not change, which means that the

(a) Transport network pre-experiment 1. (b) Transport network post-experiment 1.

Fig. 2: Changes in the traffic on Milan's transport network

Fig. 3: Lines whose average number of passengers increase and decrease after the shock.

number of people that need to reach Duomo in order to carry out an activity also remains unchanged. This implies that, for numerous agents, Duomo stops are key linking nodes and not simply destinations, as confirmed by the fact that they are among the nodes with the highest betweenness centrality in the network.

6.2 Experiment 2: The addition of the new Metro 4

The second use case that we consider regards the introduction of the Metro 4 (blue line) in the transport system. The construction has started in 2012 and it has been estimated that the Metro 4 should be completely operative within the end of 2023. The route comprehends 21 stops, and it aims to connect the western side of Milan, from San Cristoforo, to Linate Airport. The blue line will cross the Metro 1 in San Babila and Metro 2 in Sant'Ambrogio. Our model

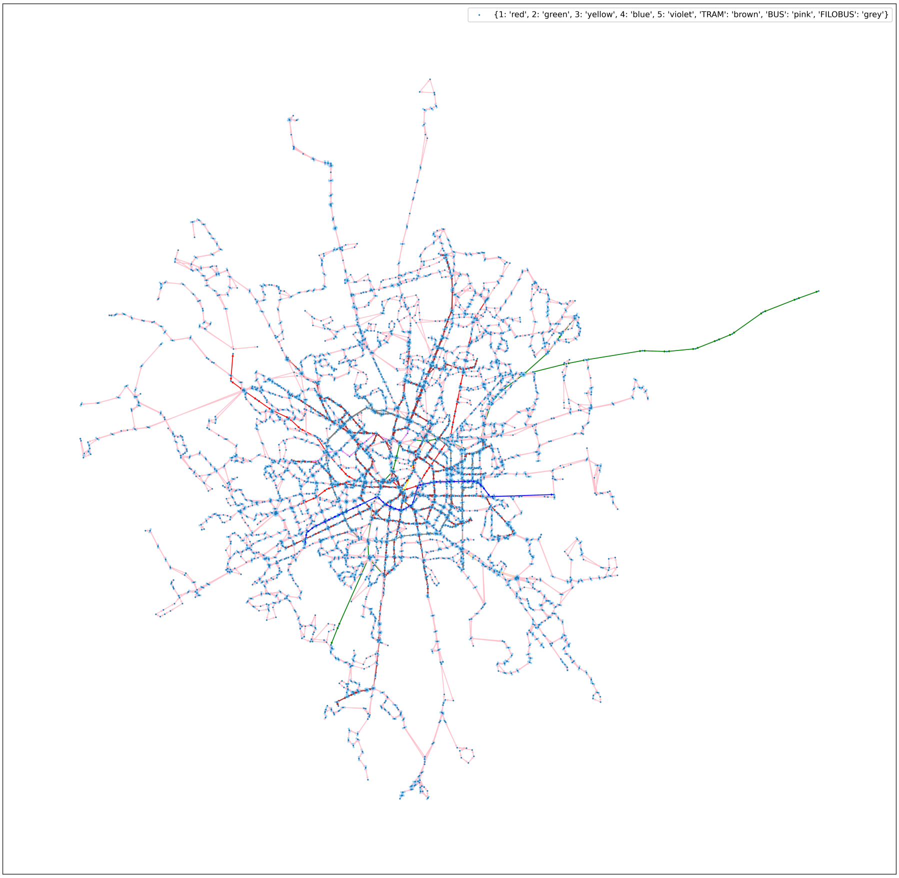

Fig. 4: Network after the introduction of Metro 4.

allows us to anticipate how the use of public vehicles will change, understanding whether the introduction of the Metro 4 has effective consequences on the mobility plan.

For the first part (pre-experiment) we apply changes to the original network in order to insert the nodes characterising the new stops. The new network is represented in 4. Using the geographical coordinates, we place the new nodes in space, create new walking edges that connect them to the closest stops, and assign the number of reachable facilities to each stop. In this way, when the schedules are created at the beginning of the simulation, we allow for the possibility to have as house or destination also the stops of Metro 4. These nodes, however, are reachable only through the already existing means of transport or by foot edges during the first phase of the experiment.

In the second phase (post-experiment) we add the Metro 4 edges connecting the new stops. In this way we simulate the complete functioning of the Metro 4. To do so, we make an assumption regarding the timetable of the new line,

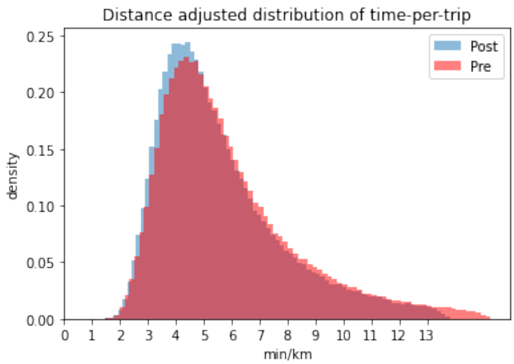

Fig. 5: Distance-adjusted distributions of time-per-trip in experiment 2.

since it is not yet available. Among the other Metro lines, the Metro 5 is most similar to the Metro 4, when it comes to the technology and number of stops. Therefore, we consider the timetables of the terminal stations of Metro 5 and rearrange them for the Metro 4. Specifically, we assume that the rides of the Metro 4 and those of the Metro 5 start from the respective terminals at the same time, and then the Metro 4 vehicles reach the following stops in a number of minutes proportional to the length of the edges. After the introduction of this changes to the network, the simulation is run in order to check the alteration of the system.

From the results of the simulation, it is possible to observe the impact of the intervention from different perspectives. First of all, the new Metro 4 line joins the other metros as one of the most used means of transport. Additionally, we observe a modest reduction in both the average waiting and traveling times experienced by the agents. In particular, the average waiting time and the average traveling time decrease from 53.13 to 50.4 minutes and from 37.27 to 33.61 respectively. This suggests that the new metro is likely to make the whole system more efficient. The same outcome is observable also through the analysis of the distributions of time-per-destination adjusted for the distance of the trip pre and post the shock, as shown in figure 5: after the intervention is seems to be slightly more skewed to the right, implying that agents manage to traverse the network more rapidly.

We then focused on the effects of the changes to the network on the usage of previously existing lines, as represented in figure 6. Specifically, some of them, such as the buses 73 and 45, experience a great decrease in the average number of passengers during the day, meaning that they are probably substituted by the newly activated metro 4, which, in fact, lies in the neighborhood of their routes. On the other hand, the introduction of Metro 4 incentivises the agents to use other lines, like buses 65 and 351, which result to host a higher number of passengers on average. Finally, we checked the 15 most crowded stops before and after the experiment: both "San Babila" and "S. Ambrogio", which are

(a) Transport network pre-experiment 2. (b) Transport network post-experiment 2.

Fig. 6: Changes in the traffic on Milan's transport network.

the stops that the new line shares with Metro 1 and Metro 2 respectively, are among those and experience an increase in traffic.

7 Conclusion and discussion

In this paper, we have presented an Agent-Based Model (ABM) to reproduce the flow of individuals moving on Milan's transport network. In order to be able to perform simulations, we have generated a synthetic population representing the share of the residents in Milan who travel using public transport means. We have also performed two experiments to demonstrate the usability of our tool. Our model has proved to be effective in studying in a controlled framework the consequences of measures that have already been taken in reality by public authorities, and in anticipating the effects of future alterations to the transportation network. From the obtained results, it is clear how this model can support the analysis of interdependencies between the vehicles that constitute the system. This, for example, would allow policy makers to consider possible changes to the frequency of rides when expecting a shock similar to the ones we have investigated.

The presented model could be further improved in several directions. In particular, at the current state, it is strongly relying on the data and strategy used to synthesize the population. Results could be made more reliable by using more granular data both at the geographic and demographic level, and more precise information regarding traveling behavior of individuals in Milan. Moreover, one could take into account also the share of travelers who are not living in the city (such as tourists and commuters), about whom data collection is more challenging.

Even with the aforementioned limitations, the proposed model presents notable advantages. Firstly, it is easily replicable and extendable to other types of shocks. It can also be applied to different systems by modifying the underlying network and the data fed to the population generating process. Lastly, this model could be extended to account for additional means of transport, such as private and shared surface vehicles, and to assess, together with the efficiency of the network, also its environmental impact.

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