PUBLIC TRANSPORT ANALYSIS MODOM

(MObility Demand-Offer Matching)

Corso di: Big Data Architectures

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The need of modal shift

Urban Transition & UN SDGs

- **Global Demographic Surge:** Urban centers face unprecedented density, making infrastructure expansion physically impossible.
- **UN SDG 11.2 Target:** Over 50% of the global urban population currently lacks convenient, equitable access to public transport.
- **The Decarbonization Mandate:** European Green Deal targets require sharp cuts in transport greenhouse gases through modal transfer.

Urban public transportation can be a solution for improving sustainability of citizen mobility need.

Systemic Public Transit Friction

Frequency & Schedule Gaps: Inadequate timetable scheduling forces severe traveller waiting times and route abandonment.

Vehicle Overcrowding: Crushed peak-hour loads degrade comfort and create severe safety and sanitary hazards.

Reliability Degradation: Unpredictable traffic interference causes cascading bus bunching and delay propagation.

The Private Car Trap: Without high-quality transit, travellers default to private motorization, worsening congestion.

The Engineering Challenge

Bridging Service Gaps: Planning authorities lack tools to accurately quantify supply-versus-demand deficits across whole cities.

Multimodal Orchestration: Integrating legacy public transit (bus/tram/rail) with emerging free-floating micro-mobility.

Empirical Decision-Making: Eliminating manual, error-prone surveys in favor of real-time, data-driven simulation engines.

Computational Feasibility: Enabling rapid simulation iterations without days of cluster compute time.

SCDT: From Reactive Counting to Predictive What-If

Legacy Mobility Planning Limitations

Manual Passenger Counts: Stationary observers or manual clipboard tallies provide only isolated, sparse temporal snapshots.

Expensive Household Surveys: High monetary cost, low sample sizes (often <1-2% of population), and severe recall bias.

Privacy & Regulatory Hurdles: GPS tracking and automated license plate recognition (ALPR) face strict GDPR/privacy walls.

Data Fragmentation: Transit operators, shared micromobility providers, and road authorities maintain siloed data lakes.

Reactive Bottleneck: Policy changes are deployed blindly into production; failures take months to observe and correct.

The Smart City Digital Twin (SCDT) Paradigm

Digital Twin Mirroring: A continuous digital representation of physical urban infrastructure, schedules, and citizen flows.

The Snap4City Framework: Open-source, standards-based ecosystem for data ingestion, semantic knowledge graphs, and analytics.

Predictive Decision Support: Evaluating systemic interventions in-silico before committing municipal capital investments.

Rapid What-If Scenarios: Testing service modifications (e.g. line re-routing, fleet sizing, station siting) in minutes.

Closed-Loop Optimization: Coupling simulation metrics directly into AI and Reinforcement Learning optimization engines.

Big Data Inputs

Supply / Offer

- GTFS / NeTEx Feeds: Relational static feeds detailing transit routes, vehicle trips, physical stop coordinates, and arrival times.
- Micromobility Protocols (GBFS / MDS): Standardized APIs tracking free-floating and station-based bike and scooter availability.

Traveler Demand

- Telecom Cellular Presences: Call Detail Records (CDR) and cell tower handovers yielding macro origin-destination matrices.
- Census & Demographic Statistics: Socio-economic strata determining modal preferences and transit dependency rates.
- Modal Split Calibration: national survey data indicating percentage of people using public or alternative transport modalities.

Analytical models for simulations

Analytical models can compute hourly gap indicators by comparing **census demand** vs **GTFS supply**

- Rely on static **algebraic formulations**, matrix normalizations, and network topological shortest paths.
- Execute in **seconds** or **minutes** even across **large metropolitan regions** with low memory overhead.

However:

- Vehicles are treated with **infinite capacity**: cannot model passenger rejection when a bus is full. Thus, fails to compute actual queue lengths, passenger waiting times at stops, and overcrowding distress. Cannot determine whether a line is physically capable of transporting the assigned passenger load.
- Travelers cannot adapt journeys at runtime (**dynamic re-routing**) when encountering delays, full vehicles, or earlier arrivals.
- Produces high-level coverage heatmaps but **fails to deliver decision-grade operational KPIs**.

(Traditional) Agent-Based Simulators

Agent-based simulators are simulation tools that model the **behaviour** and **interactions** of **individual agents** (e.g., vehicles, drivers, or pedestrians) with explicit physics to reproduce and analyse the dynamics of complex transportation systems.

High Parameter Sensitivity: Requires configuring hundreds of micro-parameters: driver reaction time, deceleration limits, pedestrian polite factors, crossroad conflict resolution, signal phase negotiation.

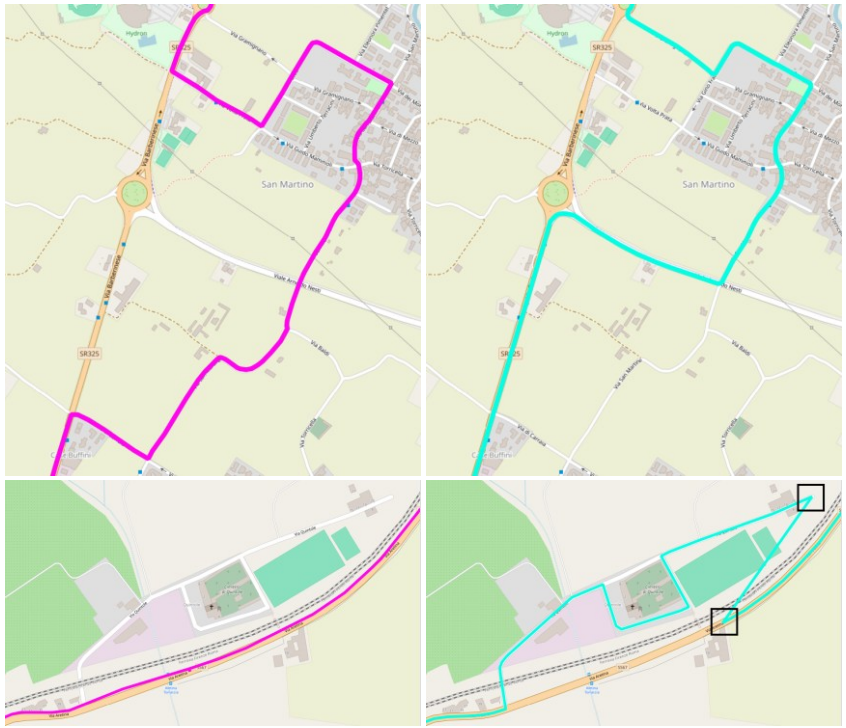
- Default configurations frequently produce unrealistic jamming, phantom gridlocks, or bus stop deadlocks.
- Validating a single metropolitan scenario demands weeks of expert manual tuning and empirical trial runs.

High computational cost: Instantiating 100k+ concurrent active agents causes memory exhaustion and exponential simulation runtimes.

Down-sampling Demand & Short Horizons: Reduce computational costs but destroys real congestion dynamics, queue propagation, and vehicle capacity saturation effects.

Map-Matching Trajectory Fragility

- GTFS encodes bus routes as raw GPS point sequences (shapes.txt) and GPS coordinates suffer from severe multipath noise, sensor drift, and coordinate truncation.
- ABS requires busses to move on specific road segments: a mapping process is required to map the GPS point on road segments.
- Traditional tools exploit closest neighbour assignment and Dijkstra shortest path, and usually produce not accurate mappings.
- This invalidates the simulation and all downstream KPIs



GTFS

Map-matched Trajectory

Multi-Dimensional Benchmark

Method / Simulator	Paradigm	Cost	Multimodal	Sharing	Dynamic Route	Fast Exec. (R15)	Minimal Setup
SimMobility (Adnan et al.)	Micro/Meso ABM	Open	Partial	Yes	Yes	No	No
NetLogo (Wilensky et al.)	General ABM	Open	No	Partial	Partial	No	No
GAMA (Taillandier et al.)	Spatially Explicit ABM	Open	Partial	Partial	Partial	No	No
SUMO (Eclipse / DLR)	Microscopic ABM	Open	Yes	Yes	Partial	No	No
MATSim (Horni, Axhausen)	Activity-Based ABM	Open	Yes	Partial	Yes	No	No
AnyLogic (XJ Technologies)	Multi-Method ($)	Commercial	Partial	Yes	Partial	No	No
PTV Vissim / Aimsun	Micro Traffic ($)	Commercial	Yes	Yes	Yes	No / Variable	No
Analytical (Kaeoruean, Arman)	Matrix / Graph	Research	Partial	No	No	Yes	Partial
Simplified ABM (Nasri et al.)	Queue Network	Research	Partial	No	No	Variable	No
MODOM (Fanfani, Palesi, Nesi)	Asymmetric ABM	Open/S4C	Yes (Bus,Tram,Rail)	Yes (Bikes,Scooters)	Yes (Runtime)	Yes (~4 min)	Yes (Zero Tuning)

MODOM Paradigm

Asymmetric Modelling: Active Vehicles vs Passive Users

- Only public transport vehicles (buses, trams, trains) are modelled as active autonomous agents.
- Travelers are passive entities updated via discrete state transitions at stops. Sharing vehicle are modelled as traveller properties.
- Reduces active agent count from ~120,000 to ~7,500, and delivers full city-wide, full-day simulation in ~4 minutes on consumer desktop hardware.

Decoupled Dynamics: Runtime Adaptation without Re-Routing

- Travelers board any arriving vehicle serving their destination zone rather than rigid static trip IDs.
- Dynamic sharing adoption occurs at runtime via an aging impatience model without global graph re-queries.

Zero-Calibration using direct scheduled execution

- Vehicles progress along GTFS stop schedules directly without explicitly moving on road segment. This eliminates mandatory map-matching during base offer evaluation.
- Answers the core planning question: Can the public transport offer as scheduled satisfy urban demand?

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RESEARCH ARTICLE

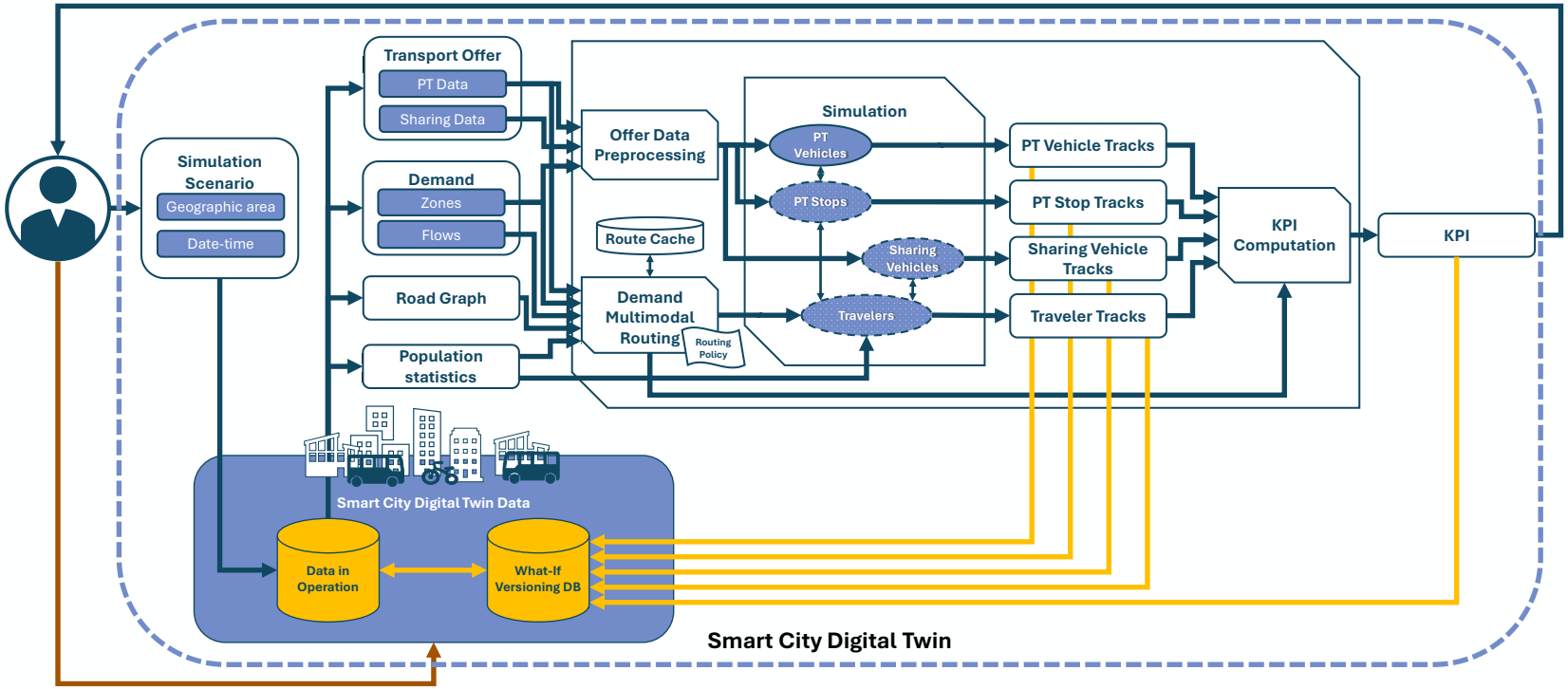
Data-Driven Mobility Demand-Versus-Offer Matching by Dynamic Integration of Public and Sharing Services

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ABSTRACT A systematic transition toward more sustainable transport solutions, included among the Sustainable Development Goals of the United Nations, is one of the main challenge modern cities must face. Increasing the usage of public transport and alternative mobility, like sharing services and micro-mobility, has been indicated as the most promising strategy since it can provide wide accessibility, reduce traffic congestion and consequently contain environmental impacts. Nevertheless, the citizen behavior shift toward such solutions in place of private motor mobility is hampered by several factors, among which quality of service emerge as one of the most relevant. To support decision makers in what-if analysis, tactical and strategic planning for improving of transport services, we present MODOM (MObility Demand-Offer Matching), a lightweight agent-based simulator that takes into account public transportation offer and sharing/micro-mobility solutions to evaluate the match with respect to the city users' demand. MODOM supports dynamic updates of people's travel plans to react to specific conditions and produces rich, decision-grade KPIs. The simulator runs city-scale scenarios in few minutes, avoids time-consuming configurations, and is integrated with a Smart City Digital Twin for rapid what-if analysis, Snap4City. When needed for tactical planning, measured traffic can be injected by altering public transport timetables. Several experiments demonstrate that MODOM solves current simulator shortcomings and provides detailed simulation results to support decision-making processes.

INDEX TERMS Mobility offer demand matching, public transport, sharing mobility, micro-mobility, simulation software.

Snap4City integration



Offer data preprocessing

MODOM parses GTFS disjoint text tables into a compact JSON structures.

- Stops, vehicles, and schedules are mapped directly to corresponding origin-destination zones.
- Enables instant spatial indexing: vehicles query stop waiting lists in O(1) time without spatial geometric intersections.
- GTFS modelling time is around 50 minutes for full Florence offer — nearly 6x faster than SUMO (over 5 hours) since no map-matching is required.

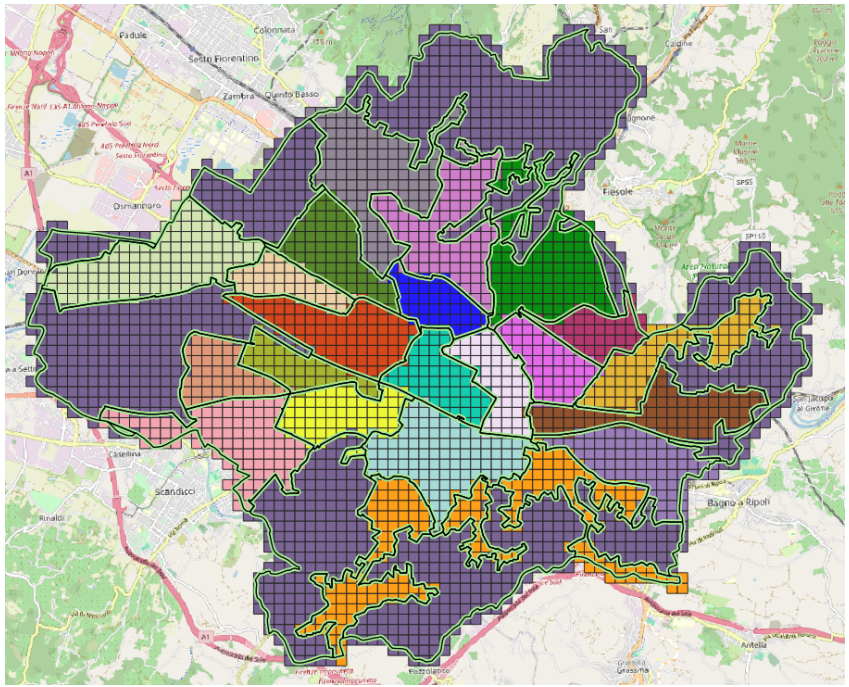
Demand data preprocessing

Telecom ODMs in Italy are legally aggregated over **coarse census polygons** to preserve privacy.

The entire historic centre of Florence is covered by only 3 massive census zones. Peripheral census areas form irregular, concave, or donut-like shapes with centroids in unpopulated fields.

MODOM remaps the ODM flows on a uniform Military Grid Reference System (MGRS) grid of 200m x 200m cells:

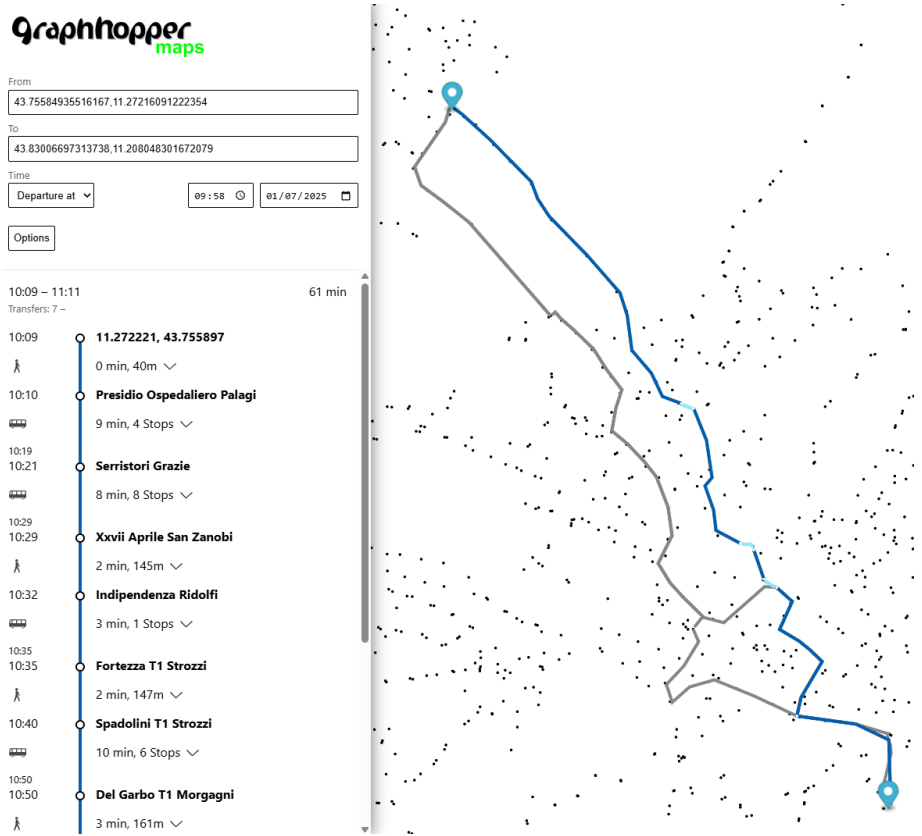
- Exploits mobile phone GPS presence distributions provided by telecom operators at 200m tile resolution.
- Each census area polygon is partitioned into its intersecting set of MGRS tiles.
- ODM flow are partitioned into the 200m-cell grid giving more weight to the most populated cells



Distributed Multimodal Routing

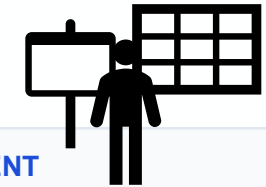
Employs local embedded GraphHopper routing engine instances on 4-thread execution parallel

- Compute multi-modal routes for 120,033 commuters in 4,073 seconds (averaging ~34 milliseconds per plan).
- Recent optimization further reduced times to around 6 ms per plan



Active Vehicle Agents vs. Passive Commuters





ACTIVE ENTITY MODELING

Public Transport Vehicles ($A = \{a_i\}$)

- Buses, trams, and trains are modelled as **autonomous**, **active agents**.
- Each agent a_i has a **state** including:
  - its ordered sequence of stops $\sigma_{a_i} = \{s_{a_i}\}$
  - the scheduled departing time from each stop $\tau_{a_i} = \{t_{a_i}\}$
  - its maximum capacity $\kappa_{a_i}^{MAX}$
  - its current onboard-list κ_{a_i} (with $|\kappa_{a_i}| \leq \kappa_{a_i}^{MAX}$)
- Each agent perform two **discrete schedule actions at each stop**: drop-off rule and pick-up rule.

PASSIVE ENTITY MODELING: ENVIRONMENT

Zones $Z = \{z_h\}$, Travelers $C = \{c_k\}$, and Stops $S = \{s_m\}$

- Commuters are associated to
  - starting and ending zones $\{z_{c_k}^o, z_{c_k}^d\} \in Z$
  - departure time $t_{c_k}^o$,
  - walking speed v_{c_k}
  - travel plan ρ_{c_k}.
- A travel plan can be composed by **one or more legs** ($\rho_{c_k} = [\varphi_{c_k}^0, \dots, \varphi_{c_k}^N]$), described with starting ($z_{c_k}^{n\uparrow}$) and arrival ($z_{c_k}^{n\downarrow}$) zones, travel modality ($\mu_{c_k}^n$), leg duration ($\delta_{c_k}^n$), and the pick-up ($s_{c_k}^{n\uparrow}$) stop
- Stops are subsumed into the zone they belong with a function $\mathcal{F}: S \to Z$.

Simulation step: Entering/Exiting rules



At each **discrete time** tick t, vehicles whose scheduled start time matches ($t^S_{a_i} = t$) are dynamically spawned into the simulation at their starting stop $s^S_{a_i}$ with an empty on-board list ($\kappa_{a_i} = \emptyset$).

Vehicles exit the simulation when reaching their final stop $s^E_{a_i}$ at time $t^E_{a_i}$, after dropping off residual onboard passengers

Travelers enter the simulation at their departing time $t^o_{c_k}$ and are added into their departing zone $z^o_{c_k}$.



They immediately start walking toward the boarding stop of their first travel leg ($s^{n\uparrow}_{c_k}$): the walking leg duration ($\delta^n_{c_k}$) is progressively decreased as the simulation goes on. Only when $\delta^n_{c_k} = 0$, a traveller is enqueued in the waiting list of its departing stop ($\lambda_{s^{n+1\uparrow}_{c_k}}$), removed from the zone, and its new travel leg is activated.

This action represent the **walking rule**, and it is repeated whenever a passenger has a walking leg (even between successive trips on PT)

Simulation step: Boarding and Alighting rules

When a PT vehicle reach a stop (i.e., simulation time $t = t_{a_i}^n \in \tau_{a_i}$) two rules are executed:

ALIGHTING MECHANICS

Passenger Drop-Off



Scans onboard passenger list κ_{a_i}

- If passenger **drop-off zone matches current stop zone**, it is removed from vehicle onboard list

Then each passenger is handled as

- If passenger has reached its final destination, it exits the simulation;
- otherwise, the **passenger travel leg is updated** with the next one and:
  - if it is a **walking leg**, the passenger is added to walking list of the zone (activating the **walking rule**)
  - if it is a **PT ride leg**, the passenger is enqueued to its next bus stop waiting list

BOARDING CONSTRAINTS

Capacity-Constrained Pick-Up



Scans waiting queue at current stop:

- if traveller next drop-off zone lies along downstream vehicle stops, the **traveller boards the vehicle**.
  - the traveller is removed from the stop waiting list and added to the vehicle passenger list κ_{a_i}
- **Hard capacity bound**: boarding is permitted ONLY if $|\kappa_{a_i}| \leq \kappa_{a_i}^{MAX}$.
- If vehicle is fully occupied, remaining travellers continue waiting; a ***Miss* event is formally recorded in system KPIs**.

Decoupled Line Selection

In conventional simulators, commuters are **strictly bound to a single static trip ID** from routing initialization.

- If the assigned bus is delayed, full, or cancelled, the commuter remains stranded at the platform **indefinitely**. Even if an alternative parallel bus arrives with free capacity serving the same destination, the agent cannot board.
- To solve this problem a **new routing computation** is required!

MODOM **decouples commuter travel plans from specific carrier IDs**, binding travellers to destination zones.

- Boarding Rule permits boarding any passing transit vehicle whose downstream route intersects the traveller next destination zone.
- Travelers opportunistically board whichever carrier arrives first with available seats (lowest headway capture), **emulating human behaviour** (passengers take the first available service heading in their direction)
  - Absorbs line delays and local capacity shocks dynamically without triggering costly global Dijkstra re-computations.
  - Provides a realistic evaluation of public transit corridor redundancy and multi-line network capacity.

Extension to Sharing and Private micro-mobility

Introduces **free-floating sharing vehicle** set $Sh = \{sh_q\}$ into the spatial simulation environment

Each sharing vehicle sh_q is modeled with:

- its location z_{sh_q} (the zone where it is placed)
- its status $\gamma_{sh_q} = \{free, inUse\}$
- its typical velocity v_{sh_q}
- a vehicle specific distance friction ϱ_{sh_q} (the higher, the less the vehicle can be used for long journey)

Additionally, **traveler model must be augmented** including

- the possibility to own **private micro-mobility vehicles** (m_{c_k})
- a **propensity** parameter to use sharing vehicle (base value $\eta^0_{c_k}$ and current value η_{c_k}, with $\eta_{c_k} \geq \eta^0_{c_k}$

In practice, travelers using micro-mobility have their speed increased when covering walking legs.

Commuter Impatience: Sigmoid-Based Sharing Adoption Model

When a traveler start a walking legs and there is a sharing vehicle available in its zone, the **traveler propensity to get the sharing vehicle is evaluated**.

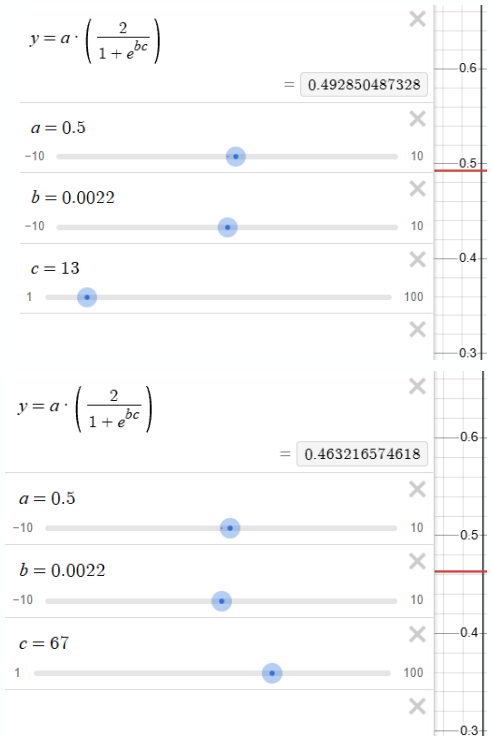
A sharing vehicle is taken if

$$x \leq \eta \frac{2}{1 + e^{\varrho d}}$$

- $x \sim \mathcal{U}(0,1)$ is a random variable sampled from a uniform distribution in [0,1]
- η is the traveler propensity in using sharing vehicles
- ϱ is the vehicle distance-friction parameter
- d is the distance to be covered (the higher d, the lower the result)

While waiting at a public transit stop, **traveler propensity increments** every minute: $\eta = \eta + \alpha$

- Aging parameter α models **growing traveler frustration and impatience** during prolonged bus delays. As waiting time accumulates, commuters spontaneously abandon the stop queue and seize nearby sharing vehicles!



https://www.desmos.com/calculator

Private Micromobility Logic

Traveler profile encodes private vehicle ownership m_{c_k} with operating velocity v_{m_k}

If OD distance is less than a threshold **traveler covers the entire trip using their private vehicle**.

- Travel plan is collapsed into a **single autonomous alternative leg**
- Completely bypasses public transit network, relieving pressure on congested urban bus corridors.

Otherwise, engine **inspects the modality of the non-walking leg**:

- If is tram or train, since vehicle onboarding rules permit carrying private micromobility aboard, all walking are converted to alternative leg: traveller rides to tram/train station, boards, and rides egress leg.
- If it has to take a bus, since private vehicle cannot be brought aboard, traveller drops its vehicle and uses standard transit.

New rule to handle sharing micro-mobility

Zone Walking Vehicle Pickup: Triggered when a pedestrian enters a new zone during a walking leg (for example when entering the simulation or after alighting from a PT vehicle).

- Searches zone for free sharing vehicle in the zone
- Its sharing propensity is evaluated, and if the test is passed, the vehicle is seized ($\gamma_{sh_q} = inUse$) and travel leg converted to alternative.

Stop Waiting Impatience: Triggered for all commuters waiting in a stop queue:

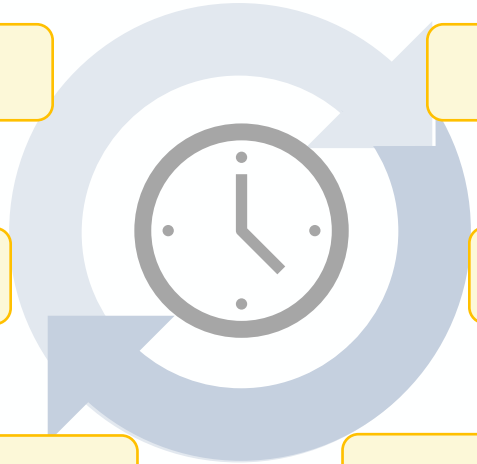
- Increments propensity: $\eta = \eta + \alpha$
- searches surrounding MGRS zone for free sharing vehicles.
- If propensity check is passed the commuter departs stop queue and rides sharing vehicle.

Vehicle Release & Propensity Reset: Updates walking rule considering alternative legs. When leg duration reaches zero ($\delta_{c_k}^n = 0$):

- If vehicle was sharing, the vehicle is released in arrival zone and traveler propensity is reset to baseline
- Then, commuter boards connecting train or exits simulation.

Rule sequence

1. Vehicle and Travelers Entering rules
2. Walking rule
3. Stop Waiting Impatience rule
4. Alt Vehicle Release rule
5. Drop-off rule
6. Pick-up rule
7. Exiting rule



Traffic Flow Injection

Traditional ABMs simulate traffic jams by **generating thousands of individual private cars**, exploding compute time.

MODOM incorporates real-world traffic by directly **altering GTFS departure and arrival schedules** (`stop_times.txt`).

Given measured **road speeds** from sensor loops or navigator apps (Google Maps, TomTom, HERE) along road set it computes altered traversal time between consecutive stops based on empirical velocity time series.

- Processes road segments incrementally: arrival time at segment i determines lookup timestamp for segment i+1.
- If average speed is not directly recorded, speeds are derived from flow and density via Greenshields or Underwood models.
- Do not affect preferential lanes (detected from OSM data)

Preserves the core lightweight ABM architecture: zero additional agent threads required to simulate traffic jams, still allowing planners to test extreme congestion scenarios in seconds.

Traffic injection requires map-matching of bus routes!

Experimental setup

- Full working day: Thursday 1st July 2025, from 04:00 AM to 02:30 AM next day (service end).
- Metropolitan Florence partitioned into **4,624** regular 200m x 200m MGRS grid cells.
- 228 sequential 5-minute ODMs generated from 05:00 AM to 23:55 PM, modelling **121,862** daily trips.
- **6,326** active bus runs, **750** tram rides (lines T1, T2), and **427** suburban train runs (total PT fleet = 7,503).
- Sharing fleet: **2,000** free-floating bicycles and **1,000** electric scooters across **181** base parking stations.

Comprehensive KPI

- **Unmet demand**: total number of people that have not reached their destination within the simulation time
- **Number of Misses**: how many times a traveller has been unable to take the vehicle due to overcrowding conditions
- **Mean Travel Time (MTT) ratio**: ration between the simulated travel time and the one estimated by routing
- **Avg ride/wait/walking/sharing times**: measures the time spent in seconds by travelers on some PT vehicle/waiting at a bus stop/walking/on sharing vehicles
- **Sharing Rides**: number of usages of sharing vehicles

What-If Phase 1: Bus Fleet Downsizing and Multimodal Rail/Tram

BASELINE EXPERIMENT (E0)

Large Bus Fleet (Cap = 85)

- Full bus service with standard 85-passenger capacity; trams, trains, and sharing disabled.
- Unmet Demand = 35 passengers; Misses = 278; MTT Ratio = 1.128; Avg Wait Time = 428.55 s (~7 min).
- Demonstrates that planned GTFS bus service with full-sized vehicles is well-sized to satisfy baseline urban demand.

CAPACITY STRESS (E1)

Downsized Minibuses (Cap = 35)

- Bus capacity reduced to 35 passengers (simulating smaller minibuses suited for Florence historic alleys).
- Unmet Demand explodes to 9,832 passengers; Misses surge to 350,805; Avg Wait Time leaps to 1,251.56 s (~21 min).
- Severe vehicle saturation triggers compounding stop queues and systemic network breakdown.

MULTIMODAL RESCUE (E2)

Adding Trams & Commuter Trains

- Maintains 35-passenger minibuses but activates high-capacity rail infrastructure: 750 trams (cap 278) and 427 trains (cap 1,000).
- Unmet Demand collapses from 9,832 to 1,215 (87.6% recovery); Misses plunge from 350,805 to 85,968.
- Proves the indispensable role of fixed-guideway mass transit in absorbing corridor demand overflows.

What-If Phase 2: Sharing Penetration, Demographic Aging & Station Siting

SHARING ADOPTION (E3–E6)

Propensity Shifts & Stop Aging

• E3 introduces 2,000 bikes and 1,000 scooters: unmet demand drops to 1,082; misses drop to 77,374; 7,040 sharing trips.

• Progressively shifting population into high-propensity classes (E4–E6) expands sharing rides to 20,979.

• Unmet demand drops to 927; stop wait times fall from 734s to 675s; MTT Ratio improves from 1.304 to 1.202.

SPATIAL LAYOUT (E7)

Bivariate Gaussian Dispersion

• Expands sharing stations from 181 to 500, placing stations via Bivariate Gaussian distribution cantered downtown (sigma = 5km).

• Performance severely degrades sharing rides drop from 7,040 to 5,030; unmet demand worsens from 1,082 to 1,126.

• Naive geographic clustering places stations in unpopulated hills while starving outer transit hubs.

PRESENCE-WEIGHTED (E8)

Cellular Demand-Driven Siting

• Expands to 500 stations using telecom mobile phone presences at 09:00 AM to weight unserved suburban zones.

• Restores performance: sharing rides recover to 6,920; unmet demand improves to 1,067 (besting E3).

• Proves that data-driven station siting is vastly more critical than simply purchasing additional fleet vehicles.

What-If Phase 3: Traffic injection

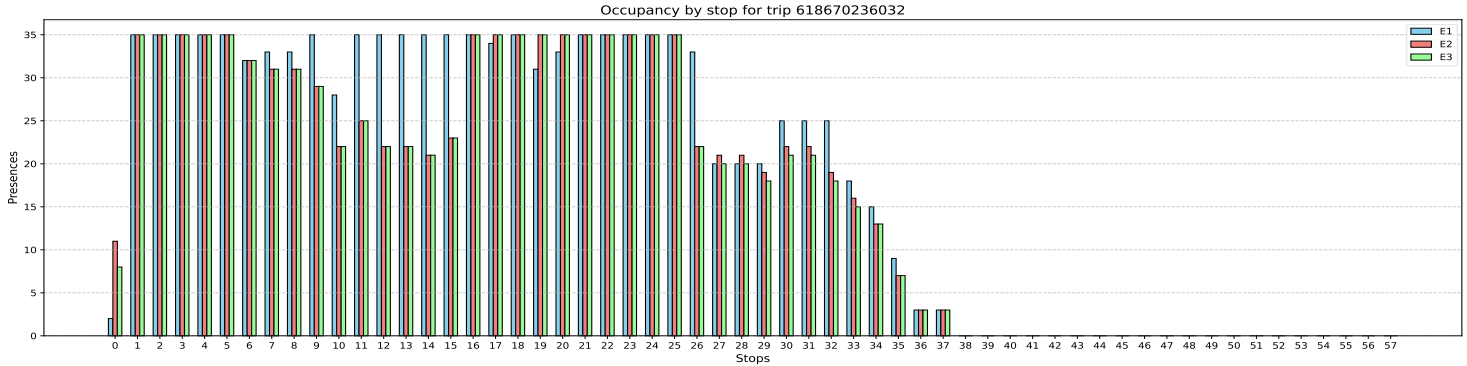
Injects real-world navigator speed time-series (02/07/2024) across the Florence road network.

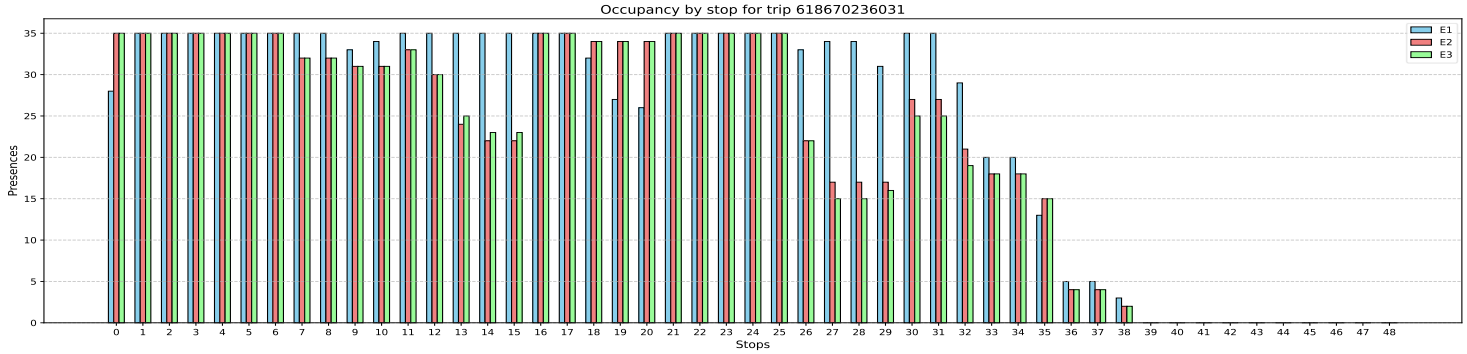
Average commuter waiting time increases by 143.8 seconds (from 717.48s in E3 to 861.28s in E9).

Unmet demand increases from 1,082 to 1,177 commuters; ride durations contract due to missed downstream transfers.

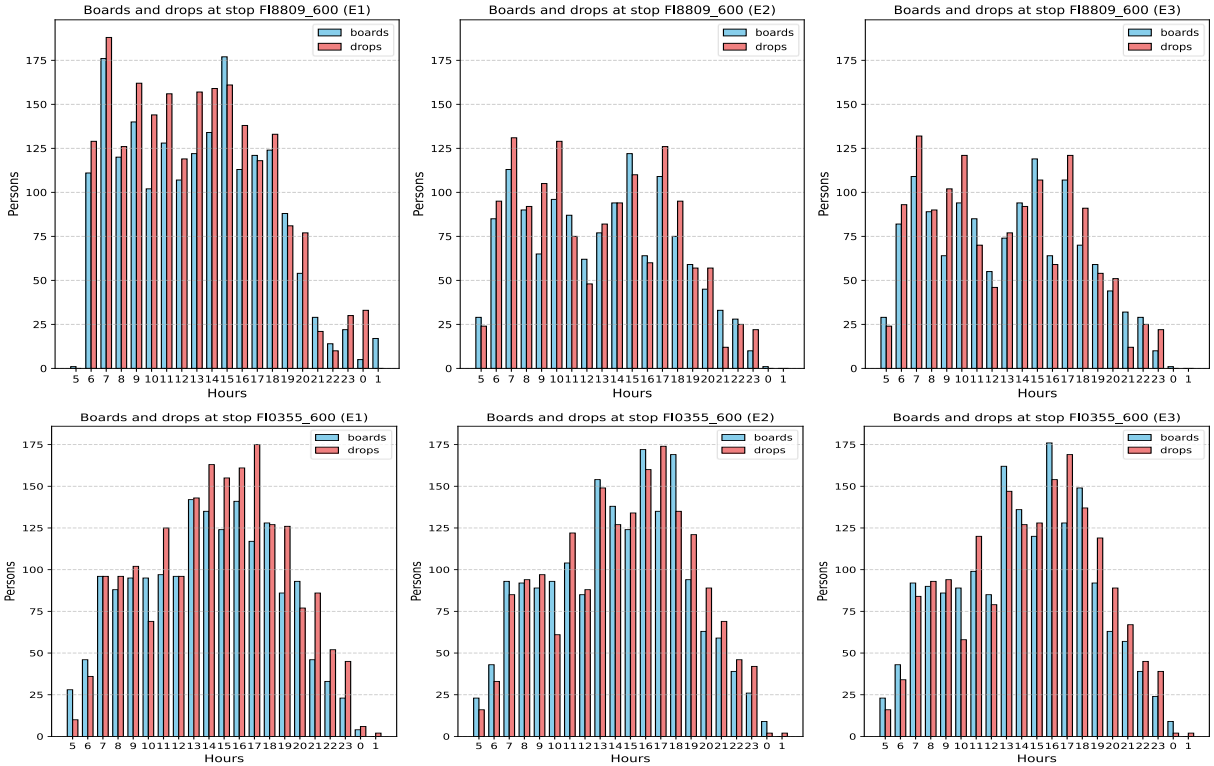
ID	Unmet demand (#persons)	Misses (#)	MTT Ratio	Avg Ride Time (s)	Avg Walk Time (s)	Avg Wait Time (s)	Avg Sharing Time (s)	Avg Private Micro mobility Time (s)	Number of Public Transport Legs (#)	Sharing Rides (#)	Private Micro mobility Usage (#)
E3	1082	77374	1.259	807.73	707.71	717.48	188.56	265.57	153420	7040	3522
E9	1177	77417	1.275	729.45	706.52	861.28	193.51	270.61	152777	7260	3508

Evolution of vehicle occupancy stop by stop





Pick-ups and drop-offs from vehicles



Beslan T1 Fortezza

Leopardi Gramsci