Appendix A - Agent-Based Modelling Framework

The agent-based model (ABM) simulates the daily operations of a DRT-P2 service, employing a fixed-size fleet of low-capacity vehicles. These vehicles are specifically designed to accommodate both passengers and freight with dedicated spaces allocated for each. The model is implemented in the NetLogo development and incorporates three key agent types: vehicles, travellers and virtual stops.

The service area is modelled as a rectangle, with its vertical (L) and horizontal (W) dimensions defined as input parameters. The DRT service operates within a grid street network, assuming no traffic congestion. The connectivity of the street network is controlled by a network density parameter ($\sigma^{net} \in [0,1]$) to emulate sparse road infrastructure.

Passenger pick-up and drop-off operations occur at virtual stops, where parcel deliveries can also be made. The average stop spacing is an input parameter. A higher density of virtual stops in the service area reduces the walking distance for passengers but also decreases the consolidation benefits of shorter routes for the DRT vehicles. In this scenario, customers may need to walk a short distance to collect their parcels (e.g., using a collection and delivery points near the virtual stop).

The total number of travel requests generated during a simulation run is determined by the daily demand Λ (requests/day), while the total number of parcels to be delivered is given by the parameter K (parcels/day). Both are assumed to be uniformly distributed across the service area. The time intervals range from the start service time t_i and the end service time t_f. Passenger demand is modulated by time-dependent profiles, implemented in the model as a set of three hourly vectors covering the 24 hours of the day (**Fig. A1**). These profiles enable a realistic representation of the variation in travel behaviour across the day, particularly in rural and peri-urban areas where commuting patterns emerge.

1. The first profile $\rho(t)$ defines the hourly distribution of demand as a share of the total daily requests.
2. The second profile $\mu(t)$ specifies the proportion of requests classified as "many-to-many" (m:m) trips, i.e., passenger movements entirely within the service area and not involving mass rapid transit (MRT) stations.
3. The remaining fraction of requests is modelled by the third profile $\alpha(t)$ indicating the share of travellers whose destination is a MRT station, i.e., "many-to-one" trip requests (m:1), and the share $1-\alpha(t)$ of travellers whose origin is the MRT station, i.e., "one-to-many" (1:m) trips. This allows the simulation of directionally asymmetric flows such as morning movements toward the station and evening movements away from it.

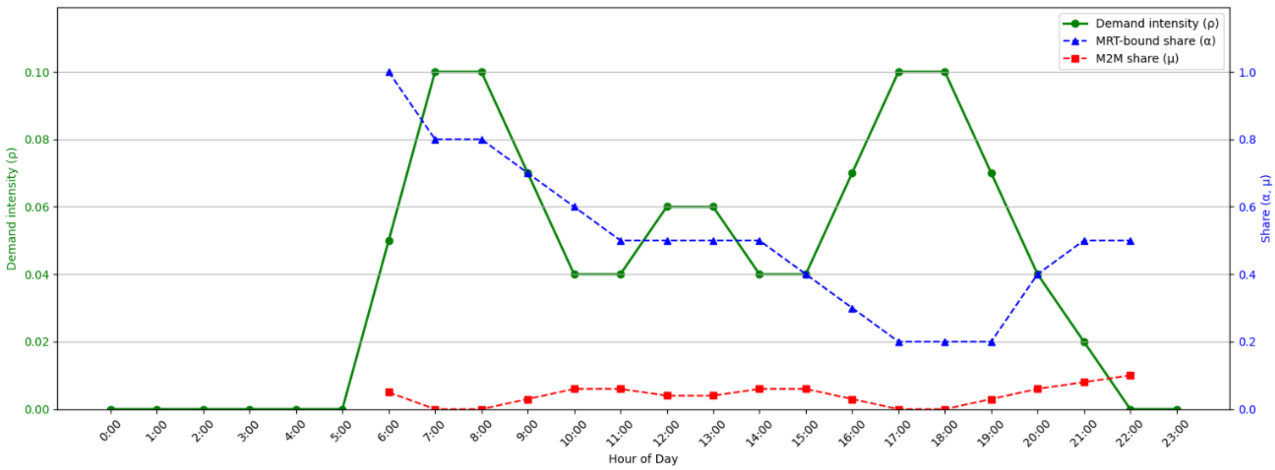

Fig. A1. Hourly travel demand profiles: demand intensity, MRT-bound trip share, and m:m trip share.

By combining these profiles, the model simulates realistic temporal and spatial heterogeneity in demand, capturing both the commuting-driven directionality and background local mobility. Such granularity is essential to assess the robustness of the DRT-P2 service under peak loads and varying user types Within multimodal trip chains, a set of MRT stations serves as either the destination for first-mile trips or the origin for last-mile trips. In the first case we refer to these as “drop-off passengers,” in the second case, as “pick-up passengers.” Demand profiles of **Fig. A1** show that the morning peak hours (7:00-9:00 A.M.) are characterized by a high percentage of travellers wanting to be transported to MRT stations (i.e., $\alpha = 0.8$), while the evening peak hours (5:00-7:00 P.M.) are characterized by a high percentage of travellers wanting to be picked-up from MRT stations (i.e., $\alpha = 0.2$). This scenario is typical of residential and rural areas gravitating around the transit system. It is assumed that the share of m:m trips is low (i.e., $\mu \leq 0.1$) and is higher when ρ is lower.

Delivery operation start at $t_i^{del} > t_i$ and end at $t_f^{del} < t_f$. It is assumed that all parcels are collected early in the morning based on the requests received on the previous day(s), prior to the start of the DRT service, and transported to a collection and delivery point (CDP), such as a parcel locker or a small delivery hub, located at the PT station, by a freight carrier. Throughout the day, passenger requests are processed by updating vehicles’ routes and schedules. When making a travel request, travellers require time windows including the earliest pick-up time (t^{ep}) and latest drop-off time (t^{ld}). In contrast, parcel deliveries can be inserted into the vehicle route schedule when the vehicle is approaching the departure time from the terminal for the new trip. **Fig. A2** provides a representation of the potential operations within the integrated DRT-P2 service.

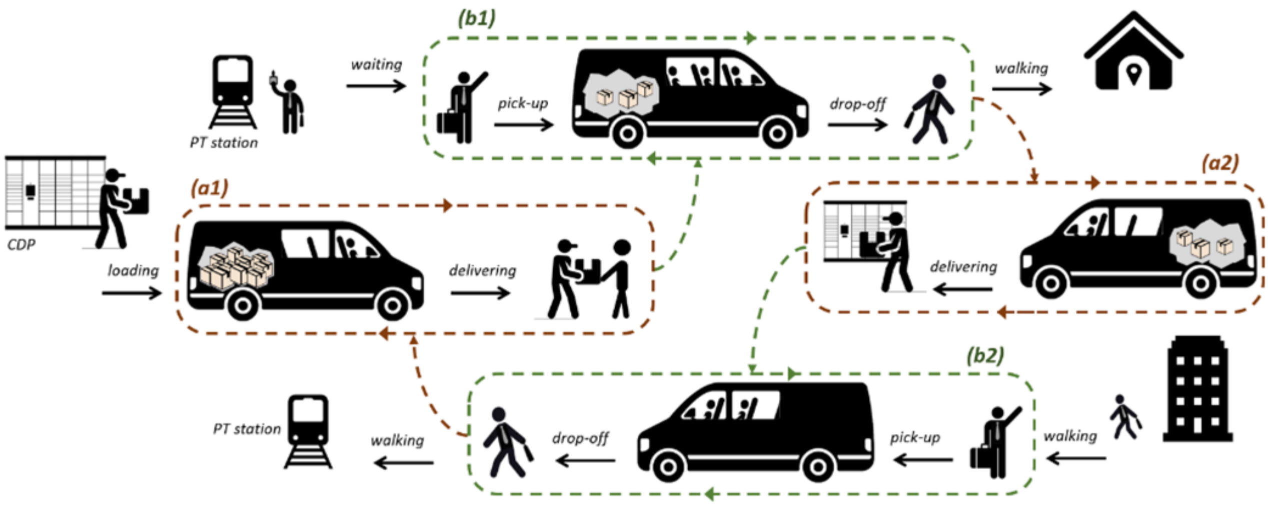

Fig. A2. Potential operations within the integrated DRT-P2 service: (a1) collecting parcels at the PT terminal station; (b1) serving pick-up passengers; (a2) delivering parcels; (b2) accommodating drop-off passengers.

Each vehicle $v \in \mathcal{V}$ has an associated daily schedule, consisting of a series of trips. Denoting $m \in \{1,2,\dots,M\}$ as the position of a generic trip in the daily schedule of vehicle v, each trip $trip^{(v,m)} \in \mathcal{T}^v$ can be identified by a unique pair (v,m). The structure behind each trip schedule consists of a sequence of 6-tuples $n = (s_n, t_n, e_n, l_n, p_n, q_n)$, where: s_n is the stop at the n-th position of the stop sequence, with $n \in \{0,1,\dots,N^{(v,m)}\}$; t_n is the estimated vehicle arrival time at s_n (t_0 represents the departure time from the terminal); e_n is the earliest vehicle arrival time at s_n ($e_n \leq t_n$); l_n is the latest vehicle arrival time at s_n ($l_n \geq t_n$); p_n is the expected number of onboard passengers and q_n is the expected parcel load in m^3. The departure time of each trip is based on the calculation of the maximum vehicle cycle time $\mathcal{C}_v$, which is inspired by the analytical approach of Quadrifoglio and Li[1] (2009). Specifically, it is computed as:

$$\mathcal{C}_v = \frac{2 \cdot L}{v} + \left(\frac{\bar{N}_{pax}}{6} + \frac{2}{3}\right) \cdot \frac{W}{N_{ter} \cdot v} + \bar{N}_{pax} \cdot \left(\tau_s + \tau_p\right) + \tau_t \tag{1}$$

[1] Quadrifoglio, L., Li, X.: A methodology to derive the critical demand density for designing and operating feeder transit services. Transportation Research Part B: Methodological, 43(10), 922-935 (2009).

$$\overline{N}_{pax} = \min\left(C_{pax},\ \Lambda \cdot \max \rho(t) \cdot \frac{\mathcal{C}_{\mathcal{v}}}{N_{veh}/N_{ter}}\right) \quad (2)$$

In Equation (**1**), $\overline{N}_{pax}$ represents the expected number of passengers of the trip; v is the vehicle cruising speed; τ_s, τ_p, and τ_t are the extra times for pick-up/drop-off operations, for any additional boarding/alighting passenger and for the (minimum) idle time at terminal, respectively. $\overline{N}_{pax}$ is determined in Equation (**2**) as the minimum between the vehicle passenger capacity C_{pax}, and the maximum number of travel requests that can arise during $\mathcal{C}_{\mathcal{v}}$, considering the peak-hour demand and the number of vehicles serving one terminal (N_{veh}/N_{ter}). The headway between two subsequent departures from the terminal is derived by dividing $\mathcal{C}_{\mathcal{v}}$ by the number of DRT vehicles serving that terminal. This approach aims to schedule deliveries to minimize passenger delays, preferably utilizing idle times in the trip schedule. **Fig. A3** illustrates the simulation process though traveller and vehicle state charts.

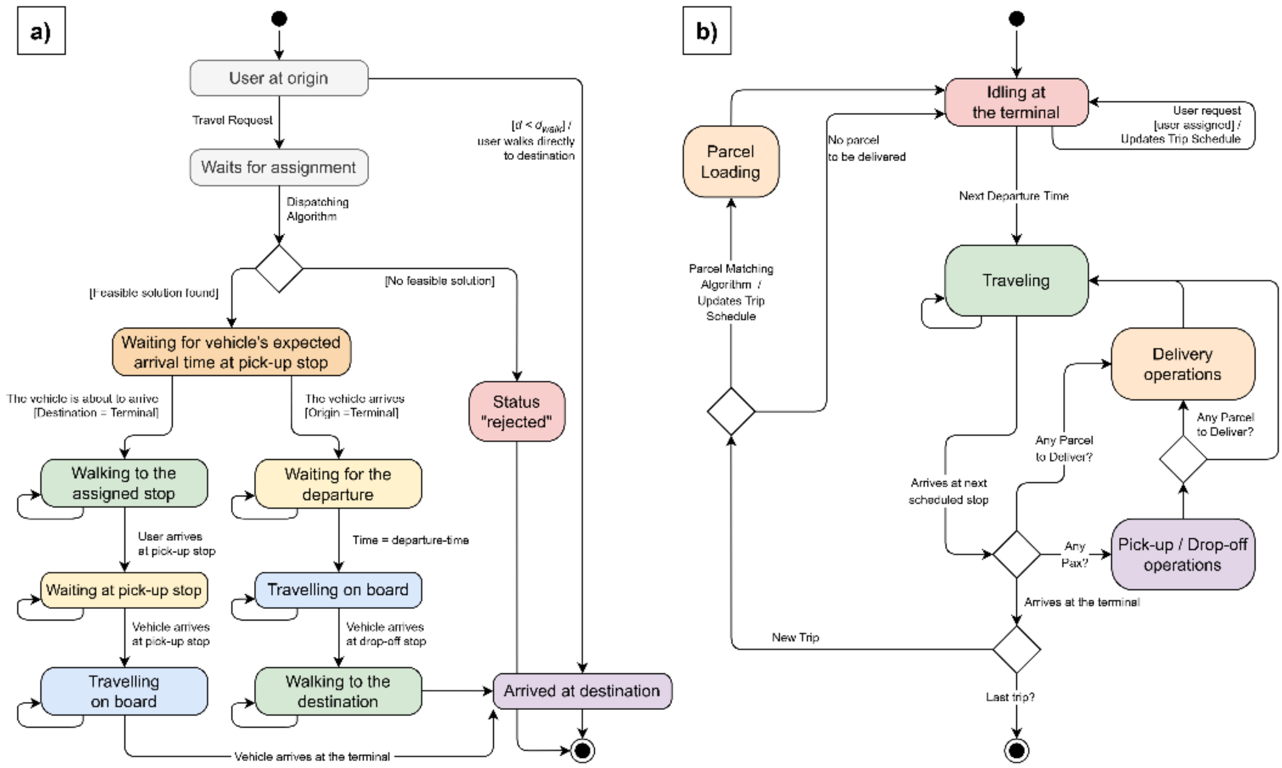

Fig. A3. State charts for travellers (a) and vehicles (b).

Each $trip^{(\mathcal{v},m)}$ is dynamically constructed by processing travel requests through a matching algorithm, utilizing an insertion heuristic approach, as in Calabrò et al.[2] (2022). This algorithm explores possible trip chain combinations between vehicle trips, candidate pick-up stops s^{PU} (for drop-off passengers), and candidate drop-off stops s^{DO} (for drop-off passengers). These stops can either be already included in the trip schedule or need to be inserted. If the distance from origin to destination is below the distance threshold d_{wk}, travellers walk without using the DRT. The matching algorithm considers time-window and capacity constraints, as follows:

$$t\left(s_i^{PU}, \mathcal{v}, m\right) \geq t_i^{ep} \quad (3)$$

$$t\left(s_i^{DO}, \mathcal{v}, m\right) \leq t_i^{ld} \quad (4)$$

[2] Calabrò, G., Le Pira, M., Giuffrida, N., Inturri, G., Ignaccolo, M., Correia, G. H. D. A.: Fixed-Route vs. Demand-Responsive Transport Feeder Services: An Exploratory Study Using an Agent-Based Model. Journal of Advanced Transportation, 2022(1), 8382754 (2022)

$$e_n \leq t_n \leq l_n, \forall n \in trip^{(v,m)} \tag{5}$$

$$p_n \leq C_{pax}, \forall n \in trip^{(v,m)} \tag{6}$$

$$q_n \leq C_{prc}, \forall n \in trip^{(v,m)} \tag{7}$$

Equation (**3**) ensures that the arrival time at the pick-up stop occurs before the earliest pick-up time for travel request i. Equation (**4**) guarantees that the vehicle reaches the drop-off stop no later than the latest drop-off time. Equation (**5**) ensures that the arrival time at each scheduled stop s_n is within the earliest and latest arrival times, which may be updated due to new travel requests. Equations (**6**) and (**7**) ensure compliance with passenger and parcel capacity constraints, respectively.

The best solution (i) among the feasible trip chains found by the matching algorithm is the one minimizing the cost function (Equation **8**), which is defined as the sum of the cost $\chi_i^{request}$ for inserting the new travel request, the additional cost χ_i^{delay} due to delays for already scheduled passengers and the cost to the operator $\chi_i^{operator}$ resulting from any additional travel time.

$$\chi_i = \chi_i^{request} + \chi_i^{delay} + \chi_i^{operator} \tag{8}$$

$$\chi_i^{request} = \left(w_{wk} \cdot \Delta t_i^{wk} + w_{wt} \cdot \Delta t_i^{wt} + w_{rd} \cdot \left(\Delta t_i^{rd} - \Delta t_i^{sp}\right)\right) \cdot VoT \tag{9}$$

$$\chi_i^{delay} = \sum_{j \in \mathcal{D}^i} \left(w_{wt} \cdot \Delta t_j^{wt} + w_{rd} \cdot \Delta t_j^{rd}\right) \cdot VoT \tag{10}$$

$$\chi_i^{operator} = \left(w_{op} \cdot \Delta t_i^{trip}\right) \cdot c_d / v \tag{11}$$

In Equation (**9**), Δt_i^{wk} is the walking time required to reach the pick-up stop from the origin (or the destination from the drop-off stop) at speed v_{wk}; Δt_i^{wt} is the waiting time at the pick-up stop; Δt_i^{rd} is the expected ride time on board the assigned vehicle; Δt_i^{sp} is the ride time needed from the pick-up to the drop-off stop travelling along the shortest path without intermediate stops; VoT is the traveller Value of Time (in €/h).

In Equation (**10**), Δt_j^{wt} and Δt_j^{rd} are the extra waiting and ride times, respectively, for the j-th already scheduled passenger who experiences a delay due to the insertion of i.

In Equation (**11**), Δt_i^{trip} is the additional vehicle trip time and c_d is the distance-related cost coefficient (in €/km). The time-related cost coefficient c_h (in €/h), which accounts for driver costs and fixed costs, is not included in the cost function since these costs are independent from any modifications to the trip schedule. Finally, w_{wk}, w_{wt}, w_{rd} are the weight coefficients for traveller walking time, waiting time, and ride time, respectively, while w_{op} is the weight coefficient for the additional trip time incurred by the transport operator.

At the end of each vehicle trip, when vehicles return to the terminal, if there are parcels still to be delivered, the matching algorithm is used to find the best feasible insertions of parcel deliveries into the next trip schedule. Unlike a travel request, in this case $\chi_i^{request} = 0$ and Equation (**8**) only include the cost for delayed passengers and for the vehicle extra trip time due to the parcel delivery operations. In this case, an additional condition is imposed for the insertion: the cost of the i-th insertion must be less than the expected average parcel delivery cost, as shown in Equation (**12**). This cost is calculated as the sum of the expected hourly costs and distance costs incurred by conventional deliveries made by couriers ($c_h \cdot t^{VRP} + c_d \cdot d^{VRP}$), divided by the total number of parcels to be delivered K. The time needed for conventional deliveries is computed using an analytical approach to the associated vehicle routing problem (VRP), considering the total travel distance d^{VRP} and the time τ_d spent in delivery operations (in seconds) multiplied by the total number of parcels to be delivered.

$$\chi_i < \overline{\chi^{prc}} = \frac{(c_h \cdot t^{VRP} + c_d \cdot d^{VRP})}{N^{prc}} \tag{12}$$

$$t^{VRP} = \frac{d^{VRP}}{v} + \frac{K \cdot \tau_d}{3600} \tag{13}$$

The d^{VRP} of Equation (**13**) can be approximated by the square root of the product of the size of the service area and the number of deliveries, i.e., $\sqrt{L \cdot W \cdot N^{prc}}$, following the continuous approximation approach reported by Ansari et al.[3] (2018).

Appendix B - Acronyms and abbreviations

ABM	Agent-Based Model
CDP	Collection and Delivery Point
DRT	Demand Responsive Transport
DRT-P2	Demand Responsive Transport for Passengers and Parcels
MRT	Mass Rapid Transit
PU/DO	Pick-up/Drop-off
VRP	Vehicle Routing Problem

[3] Ansari, S., Başdere, M., Li, X., Ouyang, Y., Smilowitz, K.: Advancements in continuous approximation models for logistics and transportation systems: 1996–2016. Transportation Research Part B: Methodological, 107, 229-252 (2018)