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# A Flexible Approach for Demand-Responsive Public Transport in Rural Areas

Pasqual Martí[1], Jaume Jordán[1], and Vicente Julian[1,2]

[1] Valencian Research Institute for Artificial Intelligence (VRAIN), Universitat Politècnica de València, Camino de Vera s/n, 46022 Valencia, Spain
pasmargi@vrain.upv.es,{jjordan,vinglada}@dsic.upv.es

[2] Valencian Graduate School and Research Network of Artificial Intelligence, Universitat Politècnica de València, Camí de Vera s/n, 46022 Valencia, Spain

**Abstract.** Rural mobility research has been left aside in favor of urban transportation. Rural areas' low demand, the distance among settlements, and an older population on average make conventional public transportation inefficient and costly. This paper assesses the contribution that on-demand mobility has the potential to make to rural areas. First, demand-responsive transportation is described, and the related literature is reviewed to gather existing system configurations. Next, we describe and implement a proposal and test it on a simulation basis. The results show a clear potential of the demand-responsive mobility paradigm to serve rural demand at an acceptable quality of service. Finally, the results are discussed, and the issues of adoption rate and input data scarcity are addressed.

**Keywords:** Demand-responsive, Transportation, Rural mobility, Simulation.

## 1. Introduction

Demand-responsive transportation (DRT) was first developed in the UK in the 1960s as a means of rural transportation [22] with a flexible route and dial-a-ride program. In the past, it has been utilized to provide on-demand transportation services for those who are physically disabled. These early initiatives depended on government money, and if that funding was cut off, they eventually ceased to exist. In fact, funding has always been a major problem in DRT because, typically, a transportation mode's flexibility results in greater operational costs [8,10]. Public transportation companies have rekindled their interest in DRT systems in today's environment of dial-a-ride private transportation [11] (taxi, Uber, Cabify) powered by smartphones and applications. The reason is twofold: On the one hand, the technological advancements in computation and electronics make it possible to solve complex problems such as online vehicle scheduling, routing and detouring in brief computational times. Moreover, the popularization of smartphones has made on-demand mobility more accessible than ever for the newer generations. Finally, the advances in autonomous mobility made demand-responsive transportation more promising. On the other hand, the flexibility and responsiveness of DRT are intuitively good attributes for an environmentally conscious, more sustainable transportation mode that may be able to reduce empty-vehicle displacement, thus reducing energy consumption and greenhouse gas emissions.

The interest of the research community in DRT has been rising in the last few years, although most of the studied and proposed systems are developed for high-density urban areas. In contrast, the application of DRT solutions to rural settlements or areas is less explored. Rural areas count with scattered residents, a low level of transportation demand, and, on average, an older population with respect to urban areas. Its usual transportation methods feature a single line with a mid-to-high capacity vehicle and a low frequency. The lack of quality public transportation is reflected in the usage of individual motorized transport, which is the most popular form of transportation in some rural areas [24]. DRT seems appropriate to fit rural demand and has the potential to cut operating costs while being more sustainable thanks to its on-demand activation. In addition, passenger experience could be improved by lower waiting and riding times.

There are a few works that analyze the potential of DRT for rural mobility. The authors of [6,21] propose the replacement of the traditional transportation services of specific rural areas with a DRT alternative. Both works find a better overall efficiency with DRT compared to the fixed service. Particularly, the results in [6] show a decrease in the amount of traveled kilometers, operational costs, and greenhouse gas emissions per passenger. Other analytical works such as [30,1] focus on the adoption rate of these services among rural inhabitants. Their findings show a potential niche market for DRT transportation and explicit relevant factors that the user takes into account to switch to a new transportation service. Finally, the work in [23] goes over rural DRT services from a customer satisfaction perspective, evidencing a concerning conflict between user expectations and the actual system operation. The authors underscore the importance of the analysis of the rural area and the characterization of its potential customer needs for a successful DRT application. All the research cited above shows that several authors from different contexts find the use of DRT as a potential solution for improved rural mobility. However, there is a noticeable lack of papers that bring more intelligent techniques to rural mobility.

Urban areas have always had a steady flow of quality proposals, such as [16,31], focused on optimizing their processes. However, rural areas find a clear lack of proposals. Specifically, our current research is motivated by the literature gap regarding the application of intelligent techniques for rural DRT services. The main objective of this line of work is the development of practical solutions for dynamic, flexible, reliable, and economically viable rural mobility. Working on such a goal, this paper characterizes DRT systems, assessing each of the challenges their design and implementation implies. Given the specific issues of rural areas, we theorize that the DRT paradigm might be a good fit to provide displacement services to their inhabitants. We prove our hypothesis by describing and implementing a system, which is later tested by simulating its operation in a real rural area. The results show the system achieves a good quality of service over a wide area with a reduced fleet of smaller (with respect to public buses) vehicles. Our work contributes to the rural mobility research field with the introduction of an algorithm that schedules both the static and online operation of the proposed DRT service. In addition, our results show the potential DRT has to modernize and improve rural transportation systems.

This work is an extended version of the paper "Demand-responsive Mobility for Rural Areas: A Review" [19], presented at the $20^{th}$ International Conference on Practical Applications of Agents and Multiagent Systems (PAAMS 2022). The rest of the paper is structured as follows. Section 2 dissects DRT through the review of relevant literature works. Then, Section 3 describes the proposed system, its components, and the algorithms that make it work. Section 4 presents the use case and the simulation results. Section 5 discusses the introduction of DRT to rural areas in accordance with our results. Finally, Section 6 concludes the work and states possible future directions for our research.

## 2. Demand-responsive Transportation Description

A DRT system is composed of a series of subsystems, each in charge of solving one of the many challenges a transportation system involves. These subsystems are highly configurable and can be adapted to the concrete mobility needs of a specific area. Because of that, the variety of DRT services is vast. Nevertheless, all of them deal with a concrete set of issues presented below:

– *Planning of services and scheduling of requests*. Whether it is performed in advance or in real-time after receiving transportation requests, a DRT operator must plan the operation of its fleet according to its resources. Depending on the type of system, such planning may include routing and stop assignment. In addition, in a request-based system, passengers must be assigned to a vehicle (or a concrete line) that will serve them. This assignment implies the rescheduling of the vehicle planning to include new customers while worsening as little worse as possible other passengers' experiences.
– *Optimizing fleet resources*. The goal is to select the appropriate vehicles with a concrete capacity such that the operation of the DRT system yields an acceptable quality of service while being economically viable and sustainable.
– *Demand prediction and estimation* can be a complementary feature of DRT systems used to optimize their operation. Such a feature can be implemented based on historical data or prediction techniques to control future and current demand. Many solutions require the passengers to explicitly state their desire to use the service by issuing a request.
– *Validation* through the definition of appropriated metrics to evaluate and compare different configurations.

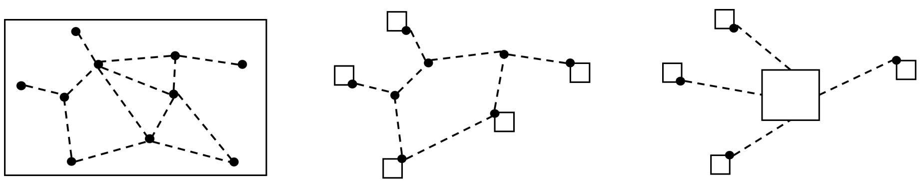
Solutions to the above issues are dependent on the concrete type of DRT system that will be implemented in addition to the modeling and optimization techniques used for that. Following, we describe the different characteristics that a DRT system can have (Section 2.1) and the techniques that have been observed in the literature for their implementation (Section 2.2). Finally, we enumerate the optimization perspectives of the reviewed material (Section 2.3).

### 2.1. System Types

DRT systems have a series of standard elements present in all of them. Different authors apply different labels to those elements. For the current section, we have followed the terminology described in this survey [28].

In a DRT system, a *service* is the departure of a vehicle to serve the transportation requests it has assigned. One service is generally tied to a concrete area or line the transport will follow. In contrast, a *route* is the concrete path the vehicle follows, connecting all the pickups and drop-offs. A route does not necessarily include all existing stops in a line or area. Customers are picked up and dropped off in a predefined set of *stops* within the serviced area or line. Alternatively, a *door-to-door* service can be offered, in which any user-specified location within a particular area may act as a stop. This type of mobility is thought to be *shared*; i.e.: multiple customers are served by the same vehicle. Typical vehicle choices for demand-responsive services include a taxi-like car with a capacity of 4 passengers, vans with 8 to 12 seats, and mini-buses or buses with 16 to 22 seats, respectively.

Many use cases exist for demand-responsive transportation. Specifically, for rural DRT, we find the following: transportation within rural settlements, transportation between rural settlements, and transportation between rural and urban settlements. In practice, these cases can be reduced to two systems: *many-to-many*, with multiple origins and destination locations, and *many-to-one*, where origin and destination locations share a unique pick-up or drop-off point. The last type is usually the so-called feeder line, where flexible transportation service is used to move passengers to another, less accessible service (for instance, communications from rural settlements to an airport). Figure 1 shows a schematic representation of the commented use cases.



**(a)** Within a rural settlement **(b)** Between rural settlements **(c)** Between rural and urban settlements

**Fig. 1.** Observed use cases for rural demand-responsive transportation systems. Boxes indicate rural/urban settlements. Black dots represent stops. Dashed lines represent demand-responsive lines. Pictures (a) and (b) are cases of many-to-many transportation, while (c) represents a many-to-one model

If the customer is required to send a *request* to access transport, then the service is provided *on-demand*. The time between sending a request and the customer's pick up is the *lead time*, and it is used to adapt the fleet operation or *planning* to include such a request. In a stop-based operation, the customer will be assigned a stop from which they will be picked up. On-demand systems can operate based on reservations issued in advance by the users, and in real-time, accepting last-minute bookings. The more complete systems employ a hybrid approach, accepting advanced reservations as well as real-time traveling requests. DRT systems that are not on-demand are also possible. These systems consider current demand or demand predictions for service planning but do not require requests to run.

The period of time for which the DRT service is planned and optimized is referred to as *planning horizon*. The duration of planning horizons is usually a whole day. In addition, the operator may plan for a few hours to adapt to high/low demand periods. According to the influence of the demand data on the service planning, the system will be *fully-*

*flexible* if routes are planned from scratch according to current demand, or *semi-flexible* if a predetermined plan exists but vehicles are allowed to modify it influenced by demand.

### 2.2. Modeling and Optimization Techniques

Once the concrete type of DRT system has been chosen, it must be modeled and tested to check its performance and adjust its attributes. We will discuss below the different steps this involves, citing relevant research and their authors' methods. Please be aware that not every paper cited in this section explores rural DRT.

Most rural DRT works are set in a concrete rural settlement or area. In general, the main transportation network (roads, highways) of the area is mirrored thanks to services like OpenStreetMap (`http://openstreetmap.org`) or OpenSourcingRoutingMachine (OSRM, `http://project-osrm.org`) [9]. Ideally, the actual organization of the area, its types of districts, population, or socio-economic reality, among others, should also be considered. Authors in [15] describe a seven-step analysis method for optimizing any transportation system based on reproducing the features of the currently implemented transport service (that would potentially be replaced) Alternatively, some works employ grid-like modelings of the area where the system will run [5].

Demand modeling is also crucial. Passenger demand has two main aspects: (1) frequency and intensity and (2) shape (location of origin-destination pairs). Demand attributes can be extracted from datasets of different transportation modes and extrapolated, as in [13], where taxi data is used. Moreover, real data of pilot DRT services [26,7] can be reproduced when available. However, the most observed technique is the use of synthetic demand data that can be generated statistically [5], based on socio-demographic information [29], via surveys [15,24,9] or generated in a (semi-)random [27] way according to the properties of the reproduced area (population, age, occupation, vehicle ownership). Finally, if traffic intensity data is available, it is useful to include it in the model, although not as relevant for rural areas with respect to city-centered studies since the former tend to have lower intensity.

The operation of the DRT system requires automated planning and scheduling of vehicle services. At the same time, these tasks need information on the time and traveled kilometers that a concrete detour would imply, which makes routing algorithms also necessary. In addition, since it is common to find online systems that accept real-time requests, the computation time for detours and new request insertions must be kept low. The use of multi-modal planning [9] is common to solve the scheduling of vehicle services. Moreover, some simulation platforms, such as MATSim [2] include their own implementations of the algorithms mentioned above. These implementations usually employ (meta)heuristic techniques [29] that optimize vehicle-passenger assignments (insertion heuristics [4], for instance) or vehicle routing in a short computational time. Besides that, other less exploited techniques, such as automated negotiation, could be used to decide assignments from a decentralized perspective [3].

Finally, to observe the system's dynamics and its operation and adjust its attributes, it is necessary to simulate it. This can be performed through mathematical modeling [15] provided detailed data is available. However, a more popular way of achieving this is through multi-agent simulation (MAS). Among the observed choices, we find NetLogo [25], used in [14], the already mentioned MATSim and even custom simulators [20,9].

### 2.3. Optimization Goals

The main goal of people transportation services is to supply the displacement needs of its users. Ideally, the operation of the service shall be performed by optimizing three factors: (1) the economic viability of the service; (2) the customer's experience (or quality of service); and (3) the sustainability of the service. These three factors are translated into scopes when it comes to transportation research, and thus we can find works that asses one (only operator perspective [18]), or many of them from a multi-objective perspective (passenger and operator perspectives [17]), The optimization of customer experience implies the reduction of passenger travel times, whereas economic viability is ensured by reducing operational costs. Finally, optimizing sustainability requires reducing vehicle traveled kilometers or the total fleet operational time.

The greatest challenge of demand-responsive transportation systems is finding the equilibrium among the factors above to offer a competitively-priced, economically viable, and flexible mobility alternative to private cars and traditional public transportation. For the case of rural DRT, economic viability is especially difficult, taking into account the relatively low demand.

In this section, DRT research has been dissected by reviewing various works. The enumeration of its many configuration options is crucial to plan the correct system according to the characteristics of the area of application. In addition, knowing how authors model and implement their proposals facilitates future research. Coming up, we introduce a proposal for a dynamic DRT system that aids in improving rural mobility.

## 3. System Proposal

We propose an on-demand, stop-based, many-to-many, and fully-dynamic ride-sharing transportation system to give service to rural areas. A fleet of vehicles provides displacement services with a variable capacity. Each vehicle will follow its own itinerary: the list of stops it will visit during its operation, ordered in time. We assume that users of the system issue travel requests through an application. A travel request indicates the location and time window in a simple manner, such as "Pickup at stop A after 8:30, and dropoff at B by 9:00".

The implementation of our proposal is based on the work in [12]. Our system is managed by a centralized scheduler which allocates each travel request to a vehicle's itinerary. The scheduler has two modes of operation: (1) offline planning of services and (2) online scheduling of incoming travel requests. In offline operation, the scheduler prepares the fleet's itineraries for the following service period (i.e., hours, the following day), finding the optimal allocation of bookings (requests issued in advance). In contrast, during service hours, when the fleet is operating, the scheduler works in online mode, listening to incoming requests and allocating them as they are issued. Figure 2 presents a schematic representation of the scheduler's operation, in which the allocation of a request to an itinerary is referred to as a *trip insertion*.

The scheduler allocates the requests to itineraries such that the system-wide objective function is optimized. Such an objective is the minimization of the fleet's operational time, thus reducing the operational costs of the whole system.

Following, we present the system elements together with their attributes and describe the insertion searching procedure that the scheduler implements.

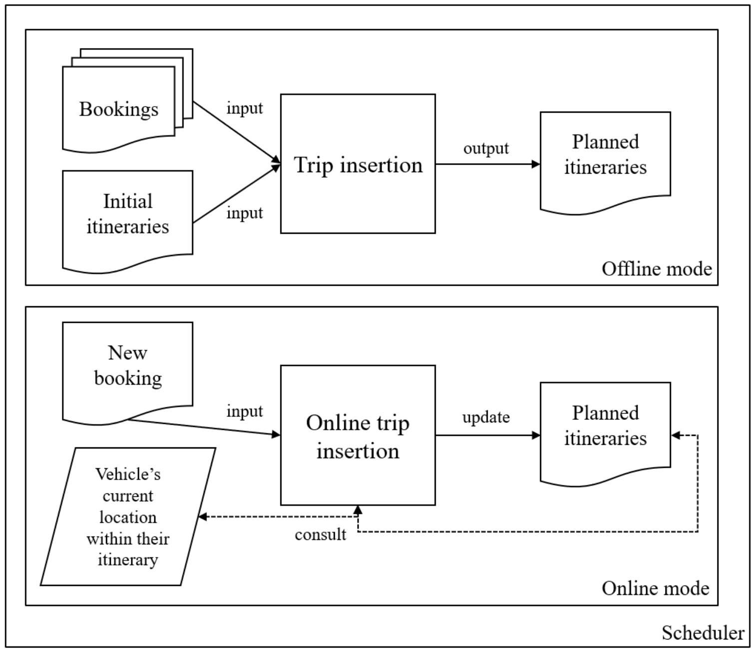



**Fig. 2.** Operation modes of the proposed transportation system scheduler. Offline refers to static planning of services, whereas online mode indicates the real-time allocation of incoming travel requests

### 3.1. Definitions

Before describing the request allocation algorithm, it is necessary to define the system's elements. This section briefly enumerates those elements and attributes, giving important notions to understand our implementation. The time units employed in the following formulation are minutes, as these better serve the purposes of our experimentation.

**Itineraries.** The fleet is managed by the scheduler, a centralized entity with updated information about each vehicle's itinerary, capacity, and location. An itinerary is equivalent to the vehicle it represents. An itinerary is mainly characterized by its stop list, an ordered list of stops that the vehicle will visit, including the time of arrival to and departure from each of them. Even though an itinerary has additional attributes, we underscore that when the text mentions the insertion of an element in an itinerary, it is referring to the itinerary's stop list, as it can be deduced. The attributes of an itinerary $I$ are:

- $veh_I$: Vehicle represented by itinerary $I$.
- $cap_I$: Capacity of $veh_I$.
- $I$'s stop list: List of stops of the itinerary; it has at least two stops.
  - $S_I^{start}$: Stop where $veh_I$ begins its shift, including location and time window.
  - $S_I^{end}$: Stop where $veh_I$ ends its shift, including location and time window.
- $next_I$: Next stop of $veh_I$ within $I$'s stop list.

– $cost_I$: Total amount of time that $veh_I$ will spend driving to complete the itinerary.

At the beginning of the operation, an itinerary per fleet vehicle is created. The stop list in those itineraries only contains the stop where its vehicle begins its shift and, subsequently, the stop at which finishes it. As travel requests are assigned to vehicles, the stop list of the vehicle's itinerary is updated, inserting new stops in visiting order. Because of that, the stop list represents the route the vehicle will follow to complete its itinerary.

**Trip.** The scheduler receives travel requests from the system customers. The request is the explicit petition for displacement. Such a petition describes the displacement in what we call a trip. A trip indicates the need for a certain number of passengers to move from its origin stop to its destination stop. Accepting a request implies that the trip it defines has been inserted in an itinerary, and thus its customers will be serviced. The attributes of a trip $t$ are:

– $npass_t$: Number of passengers traveling as a group on the trip.
– $S_{OR(t)}$: Pickup stop with location and time window.
– $S_{DEST(t)}$: Drop-off stop with location and time window.
– $I_{(t)}$: Itinerary to which the trip is assigned if any. $I_{(t)} \neq \emptyset$ implies $S_{OR(t)}, S_{DEST(t)} \in$ $I_{(t)}$'s stop list.

The time window associated with stop $S_{OR(t)}$ defines the earliest and latest possible times at which the customers can be picked up. Similarly, $S_{DEST(t)}$'s time window defines the earliest and latest drop-off time for the customers. For further clarification on a stop's time window, please refer to the definition of Stops. The wider the time window of a request, the more flexibility the system has to allocate its trip.

**Stops.** A stop represents a physical location within the transportation service infrastructure where customers can board or lay off a vehicle. In our problem formulation, a stop must be part of a trip or an itinerary. Stops have a time window associated with them. The time window indicates to the scheduler the period of time a stop must be serviced, understanding the service of a stop as the service of the passengers associated with it.When part of a trip, a stop $S$ has the following attributes:

– $t_S^{start}$: Soonest time at which the stop can be visited by a vehicle. Start of the time window.
– $t_S^{end}$: Latest time at which the stop can be visited by a vehicle. End of the time window.
– $t_S^{serv}$: Time employed by a vehicle for passenger pick-up and drop-off at the stop.

In addition, when a stop $S$ is part of the stop list of itinerary $I$, it has the following attributes, which come in handy to check the feasibility of trip insertions. As a reminder, $veh_I$ indicates the vehicle that follows itinerary $I$.

– $t_S^{arrival}$: Time at which $veh_I$ arrives to $S$.
– $t_S^{departure}$: Time at which $veh_I$ departs from $S$.
– $w_S^{serv}$: Service window at $S$, indicating the time taken by passengers boarding or laying off $veh_I$ in $S$.

- $w_S^{wait}$: Waiting window at $S$, during which $veh_I$ waits in $S$ until the departure time.
- $npass_S$: Number of passengers boarded in the $veh_I$ on departure from $S$.

Given the above attributes, the time window of a stop is defined as follows:

$$t_S^{start} \leq t_S^{arrival}, [w_S^{serv}], [w_S^{wait}], t_S^{departure} \leq t_S^{end}$$

The vehicle visiting a stop can arrive to it at time $t_S^{start}$ as the soonest. Then, the service interval $[w_S^{serv}]$ begins, in which passengers are going on or off the vehicle. Following, the vehicle may wait at the stop for a defined waiting interval $[w_S^{wait}]$. At the end of such a waiting period, the vehicle departs from the stop, which may be at time $t_S^{end}$ at the latest.

The particular arrival and departure times to a stop are determined according to a dispatching strategy. A dispatching strategy defines the use of the so-called slack time, the period of time during which the vehicle does not yet need to leave the stop where it is stationary (represented by $w_S^{wait}$ in our formulation). A general dispatching strategy would be departing the current stop as soon as possible, providing the earliest possible service to those customers of the following stop. In contrast, other strategies force the vehicle to wait at its current stop as much as possible, hoping new requests will be issued and thus having more stationary vehicles to assign them to. For this work, we make use of a hybrid strategy. Vehicles will depart from a stop to ensure the earliest feasible service to the following stop. When the vehicle has slack time, it waits at a stop to maximize the chance of inserting an incoming request.

**Insertions.** An insertion indicates the feasibility of allocating the trip of a request to a particular itinerary. Moreover, it indicates the positions within the itinerary's stop list where each trip stop will be inserted. The scheduler looks for all feasible insertions of a trip and implements the best one.

Given a trip $t$, its insertion in an itinerary $I$ implies finding appropriate spots within $I$'s stop list to visit $t$'s $S_{OR(t)}$ and $S_{DEST(t)}$. The visit to $S_{DEST(t)}$ must be subsequent (but not necessarily directly after) to that of $S_{OR(t)}$. A trip insertion will always increase the itinerary's duration ($cost_I$).

We define a trip insertion $\pi_{ij}$ with the following attributes:

- $I_{(\pi)}$: Itinerary in which the trip will be inserted.
- $i$: Position within $I$'s stop list where $S_{OR}$ will be inserted.
- $j$: Position within $I$'s stop list where $S_{DEST}$ will be inserted.
- $\Delta_{ij}$: Time increment incurred by inserting $\pi$ in $I$.

Let us have insertion $\pi_{ij}$ that allocates trip $t = \langle S_{OR}, S_{DEST}\rangle$ to itinerary $I = [S_I^{start}, S_1, \ldots, S_n, S_I^{end}]$. The insertion implies creating two new connections in the itinerary: $(S_{i-1} \rightarrow S_{OR})$ and $(S_{j-1} \rightarrow S_{DEST})$, finally obtaining $I = [S_I^{start}, S_1, \ldots, S_{i-1}, S_{OR}, \ldots, S_{j-1}, S_{DEST}, \ldots, S_n, S_I^{end}]$. Keep in mind that we could have $S_{j-1} = S_{OR}$, as the destination stop could be visited immediately after the origin stop.

The implementation of a trip insertion modifies the planned operation of the vehicle to whose itinerary the trip is allocated. Such a modification may occur during the reservation-based operation of the system or in real-time while the vehicle is already in service. In the former case, the time windows associated with each stop in the vehicle's itinerary are updated taking into account the visit to the inserted trip stops. In the latter case, time windows are adjusted in the same manner, but the vehicle may need to change its route to reflect the changes in its itinerary's stop list. Such a change of route, however, will not break the time window of any already scheduled stop, as that is taken into account by our scheduling algorithm (see Insertion feasibility checks, under Section 3.2 for further details).

**Cost computation & Objective function.** As commented on the definition of an itinerary, its cost is equivalent to the time the vehicle it represents spends traveling throughout its list of stops. Given an itinerary $I$ with stop list = $[S_0, S_1, \ldots, S_{n-1}, S_n]$, its $cost_I$ would be computed by adding the traveling time between every two consecutive stops in its stop list. Let us assume a function $travelTime(x, y)$, which, given service stops $x$ and $y$, returns the time taken by a fleet vehicle to travel from $x$ to $y$ in minutes. For an itinerary $I$ with $n$ stops in its stop list, the cost would be computed as shown in Equation 1.

$$cost_I = \sum_{i=0}^{n-1} travelTime(S_i, S_{i+1}), \ \ \forall\, S \in I \tag{1}$$

Given a fleet $F$ of vehicles, the system's objective function is to minimize the total vehicle travel time or distance. This implies direct benefits for both passengers (shorter trips) and the service provider (less operational costs). Such an objective is achieved by the way in which requests are allocated to vehicles. These allocations are done with the insertion search procedure, which works by iteratively finding the best possible insertion for each of the pending requests and implementing it. The search for the best insertion is guided by the cost increment $\Delta$ that each feasible insertion may incur to an itinerary's cost $cost_I$. Therefore, the system's objective function can also be described as the minimization of the sum of the cost of each itinerary, as represented by Equation 2.

$$min(\sum cost_I), \ \ \forall\, I \in F \tag{2}$$

### 3.2. Insertion Search Procedures

An insertion search procedure is the action of finding the best position within an itinerary to allocate a request's trip. In other words, the best moment to visit the trip's origin stop and the same for the destination. Our system implements two insertion search procedures, each for an operation mode (online, offline). Following, both procedures are briefly described, together with the system constraints that ensure the consistency of itineraries as trips are inserted.

**Offline insertion search.** The offline insertion procedure allocates all bookings to the initially empty itineraries of the fleet. The bookings' trips are inserted one by one, according to issuing time, in the best possible itinerary, i.e., the one that minimizes operational time.

The search works as follows: While there are non-allocated requests, the scheduler selects the next request and extracts its trip $t$. Given $t$, with origin stop $S_{OR}$ and destination stop $S_{DEST}$, we want to obtain all feasible insertions of that trip within all itineraries of the fleet. Algorithm 1 receives the $S_{OR}$, $S_{DEST}$, and an itinerary $I$ with $N$ stops. Then,

**Algorithm 1:** Search for feasible insertions within an itinerary $I$

**Data:** $S_{OR}$, $S_{DEST}$, $I$
**Result:** All feasible insertions of $S_{OR}$, $S_{DEST}$ in $I$

```
found ← [] ;                      /* List to store feasible insertions */
n ← 0 ;  /* Pointer to first stop, N = number of stops in I */
while n < N do
    R ← I[n] ;                            /* Select stop in position n */
    if (R → S_OR) is feasible then
        i ← n + 1 ;                          /* Position to insert S_OR */
        I' ← I.insert(S_OR, i), recalculate time constraints;
        m ← i ;                                      /* Pointer to S_OR */
        while m < N do
            R ← I[m] ;
            if (R → S_DEST) is feasible then
                j ← m + 1 ;                /* Position to insert S_DEST */
                I'' ← I'.insert(S_DEST, j), recalculate time constraints;
                Δ_ij ← cost_I'' − cost_I ;          /* Increase in duration */
                found ← found + (π_ij, Δ_ij);
            else
                m ← m + 1 ;                            /* Go to next stop */
            end
        end
    else
        n ← n + 1 ;                                    /* Go to next stop */
    end
end
return found ;
```

it returns all feasible insertions found for trip $t$ in $I$. This is done for all itineraries of the fleet, and all the returned insertions are ordered according to their time increment $\Delta$. The scheduler then implements the insertion with a lower $\Delta$. The request is rejected if the procedure does not find any feasible insertion.

As it can be seen, Algorithm 1 tries to insert $S_{OR}$ in every possible position within $I$. Once a feasible position is found for $S_{OR}$, it is inserted in a copy of $I$, and the time windows of other stops are updated, thus creating itinerary $I'$. Then, the process tries to insert $S_{DEST}$ in the position of all stops subsequent to $S_{OR}$ in $I'$. Once a feasible position is found for $S_{DEST}$, it is inserted in a copy of $I'$, and the time windows of other stops are updated, thus creating itinerary $I''$. We have found a feasible insertion at this point, so the algorithm computes its time increment (comparing $I''$ and $I$'s costs) and stores it before continuing the exploration. Please note that $I'$ and $I''$ are simply auxiliary itineraries; thus, neither $I$ nor the stops in $t$ are modified by the search algorithm. The described procedure constitutes a complete exploration of the possible insertions, allowing the scheduler to implement the optimal one.

**Online insertion search.** The online insertion procedure works similarly to the offline one but considers the current position of the vehicles within their itineraries. Therefore, given a trip $t$ and an itinerary $I$ being considered for its insertion, assuming $veh_I$ is traveling the connection $(R \rightarrow next_I)$, Algorithm 1 only explores positions within $[next_I, S_I^{end}[$ for the insertion of the trip's origin and destination stops.

If the trip's origin stop were to be scheduled in $next_I$'s position, we would have an immediate request, which implies the rerouting of $veh_I$, changing its following stop from $next_I$ to $S_{OR}$.

**Insertion feasibility checks.** For the system to work correctly, all itineraries must be consistent. This consistency is enforced through time and capacity constraints.

Let $S$ be a stop in an itinerary $I$. Let $veh_I$ be the vehicle represented by itinerary $I$, with a capacity of $cap_I$. Let $npass_S$ be the number of passengers on board $veh_I$ on departure from $S$. The capacity constraint states that: $npass_S \leq cap_I, \forall S \in I$. Simply put, the number of passengers on departure from any of the stops of an itinerary can be, at most, the capacity of the vehicle following such an itinerary.

Concerning time constraints, the system implements the following:

- All passengers must be picked up within the time window specified by their request's start time and the maximum waiting time.
- All passengers must get to their destination before their request's end time.
- All stops must have service windows contained within their arrival and departure.
- All stops must be reached within their time window.

An insertion will be *feasible* if the insertion of its trip in its itinerary does not violate any of the above constraints. The developed insertion search procedure returns only feasible insertions. Because of that, the insertion of a trip in an itinerary will never cause any inconsistencies or constraint violations.

**Computational complexity.** The presented insertion search procedures perform an exhaustive analysis of every possible position in which to allocate a trip within all the fleet's itineraries. This procedure composes a subproblem of the resolution of the whole DRT service, which will be solved once all travel requests have been dealt with.

Regarding the trip insertion search procedure, its computational complexity depends on the number of stops that the itinerary being explored contains. Such a number of stops, in addition, is generally incremented every time a trip is inserted in the itinerary. This causes the search for trip insertion at the beginning of the operation to be less complex than towards its end. Assuming an itinerary has $n$ stops, the complexity of the search is of $\mathcal{O}(n^2)$, as the algorithm checks each feasible position for the trip's origin stop and, for each of these positions, explores all feasible positions for the destination stop, using two nested loops. In practice, the actual search for an insertion is less costly, as the many restrictions that a feasible insertion has to preserve facilitate early discarding of invalid positions within the stop list.

When it comes to the complexity of solving the scenario, we must take into account that the aforementioned search is performed for every travel request (trip) and every vehicle (itinerary) in the fleet. Thus, the computational complexity of allocating $T$ trips within $I$ itineraries is of $\mathcal{O}(T \times I \times n^2)$.

As it can be understood, the service schedules travel requests iteratively according to their issuance time, following a FIFO logic. This way of operating is mandatory in the online scheduling of requests, as future demand is unknown. Because of that, the resolution of the proposed DRT service is performed greedily and is sensitive to the order in which requests are fed to the scheduler. To palliate this, improvement procedures could be implemented, which considered global cost optimizations over a solved scenario.

## 4. Experimental Results

This section tests the proposed system's potential to satisfy rural mobility demand. For that, we defined simulations that reproduce the system's operation over a concrete rural area. Following, the rural area where the simulations are set is described. Then, the results of various simulations are presented, showing the evolution of the overall service quality of the system according to demand intensity and fleet size.

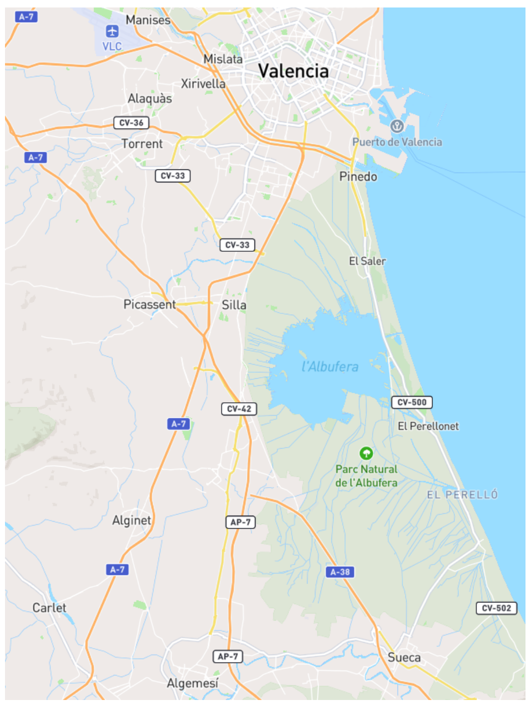



**Fig. 3.** Rural sub-area chosen for the deployment of the proposed system. The area features many small-to-medium-sized settlements. The northern part of the area shows the city of Valencia, Spain

### 4.1. Rural Use Case Description

A rural sub-area of the region of Valencia, Spain, was chosen for the deployment of the demand-responsive service. For that, we departed from the existing public interurban bus service of the Valencian Community, which connects many rural settlements between them and with the region's main cities. The dataset[3], publicly accessible thanks to the Generalitat Valenciana (`https://linkshortner.net/kkvFj`, accessed on December $15^{th}$, 2022), contains information on the different transportation lines, routes and stops the service offered. Specifically, it describes 722 lines with a total of 4562 stops. From those, only the elements lying inside the area shown in Figure 3 were kept. That amounted to 88 lines and 341 stops, shown in Figure 4. Since we propose dynamic DRT, the bus lines effectively disappeared, as now vehicles move freely between the stops scheduled in their itinerary. The existing stops, however, were clustered so that any two stops were at least 500 meters apart. With this, the final distribution of 99 stops that can be seen in Figure 5 (left) is obtained. With fewer stops and longer distances between them, a better representation of interurban displacement is achieved.

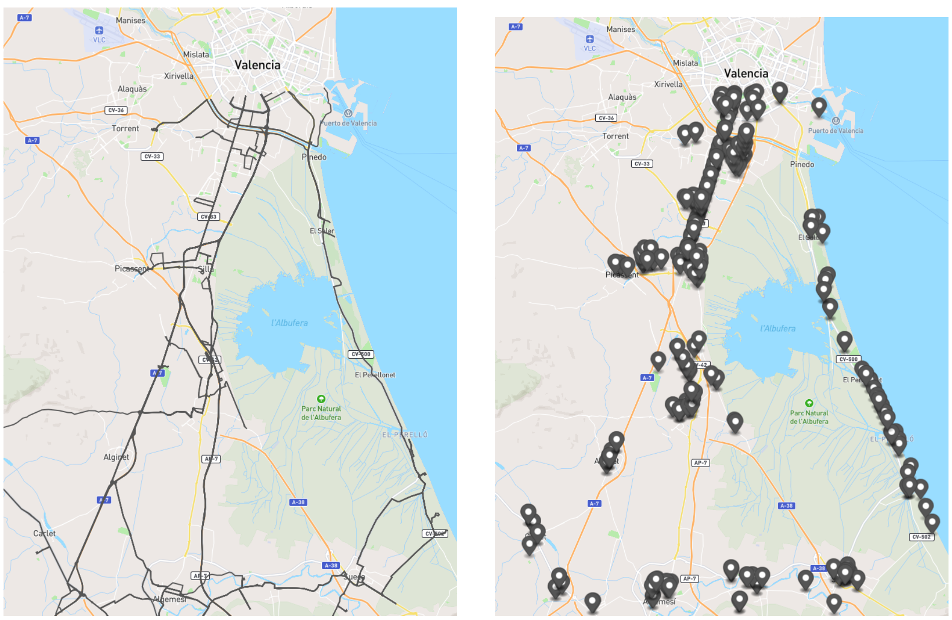



**Fig. 4.** Bus lines (left) and stops (right) the public interurban bus service defines in the assessed rural area

The deployment area features mainly small-to-medium-sized towns located in rural contexts. It can also be noticed how the urban density increases in the northern part of the area, which is closer to the city of Valencia. Our proposal aims to provide on-demand transportation to citizens of the shown settlements, such as Alginet, Algemesí, Silla, Picassent, and El Saler, to mention a few. Figure 5 (right) shows a close-up in which the location of stops can be better appreciated. Specifically, it shows the town of Sueca and many smaller settlements nearby.

[3] https://dadesobertes.gva.es/va/dataset/gtfs-itineraris-horaris-transport-public-interurba-autobus-comunitat-valenciana

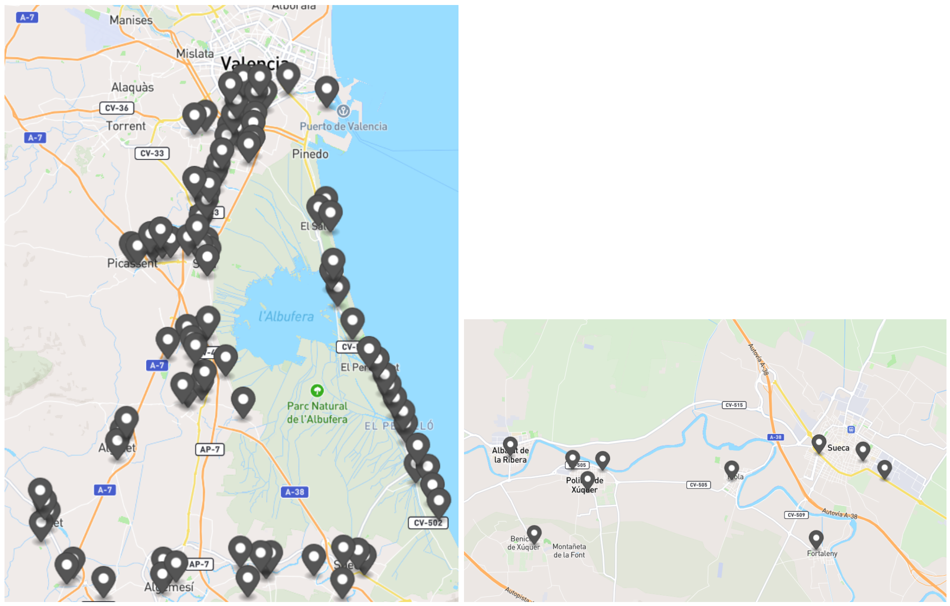



**Fig. 5.** Final distribution of 99 stops over the chosen deployment area (left). All stops are at least 500 meters apart. The image on the right shows a close-up view of small settlements in the southeastern part of the area, near the town of Sueca

With respect to the displacement demand, the dataset did not provide usage data. To the best of our knowledge, there is no publicly available usage data for interurban displacement within the chosen region. Rural transportation demand has a lower intensity than that of a city, and given the service area, it tends to be widely distributed in space. With that in mind, a synthetic demand generator was employed to feed data to the simulations.

The demand generator receives geolocated population information of the service area to create demand according to it. The more population nearby a stop, the more probable it is to be selected as the trip's origin. The destination stop of the request, however, is chosen randomly among all stops, considering a configurable minimum trip distance. Longer trip distances favor the reproduction of interurban displacements. In addition, each request can have between 1 and 5 passengers with respect to given probabilities (less probable the more people). The demand is uniformly distributed throughout the service hours of the system. The end of a request's time window (the time at which the passengers need to be at their destination) is computed according to a chosen maximum waiting time (at a stop to be serviced) and the direct travel time between origin and destination. The direct travel time is multiplied by a configurable factor. The higher this factor, the wider the time window, and thus the more flexibility the system has to serve the request.

### 4.2. Service Quality Assessment

The proposed system has been tested through many 14-hour services (07:00 AM to 09:00 PM) simulations with different amounts of vehicles and travel requests. Inspired by the reviewed literature, a fleet of 10 vans, each with a capacity for eight people, was fixed for the first round of experiments. The vans were deployed from a warehouse in Valencia (the northern part of the service area) at 06:00 AM, an hour before the first requests could be scheduled. Similarly, the drivers had to end their shift at the warehouse no later than 10:00 PM.

With regard to the demand, a total number of travel requests was specified and then generated as described above in Section 4.1. The demand is divided into 50% of bookings (scheduled before the system's operation) and another 50% of real-time requests. Each request could have either 1, 2, 3, 4, or 5 passengers with a probability of 0.6, 0.15, 0.125, 0.1, and 0.025, respectively. Finally, a minimum trip distance of 2,000 meters and a maximum waiting time of 15 minutes were chosen. It must be noted that the different probabilities that influence demand generation determine the importance of the subsequent results. For the purposes of demonstrating the proposed algorithm's operation, those probabilities defined above have been used. We remark that the results presented below are dependent on the specific demand generation. Nevertheless, their assessment can give insights to guide future work in this field.

With the fixed fleet of 10 vans, we explored the system's service quality as the number of requests increased. Service quality is defined as the percentage of accepted requests with respect to the total number of requests. In addition, the time that passengers wait for a vehicle to pick them up is included as an additional measurement of service quality. As commented above, for a request to be accepted, their passengers must be picked up before a wait of 15 minutes. Nevertheless, waiting times closer to such a maximum indicate worse passenger experiences. Because of that, our results reflect the average waiting time of all accepted passengers, together with its standard deviation. Table 1 shows our first results. The running time of the most complex simulation was 30 seconds, being executed in a machine running Windows 11 with an Intel Core i7-10750H CPU at 2.60GHz and 16GB of memory.

The system maintained near-perfect service quality in runs with 100 to 300 requests (rows 1 to 5). As it can be seen in the last column, given a particular fleet, the system tries to schedule trips so that all vehicles are employed. Only in the first run, with 100 requests, a vehicle is unused. With 350 requests, the system maintains an acceptable service quality with 84.29% of scheduled requests. From 400 requests on, the service quality decays, lowering to 70% with 450 requests and 62.8% with 500 requests. These last three runs present an unacceptable quality of service ($< 80\%$) based on similar works of the literature. With regards to the average waiting times, results show how these increase proportionally to the number of requests. The standard deviation, however, is kept around 5 minutes throughout all executions. This fact reflects the high variability among each of the individual waiting times, which in turn is motivated by the differences among the generated trips. The obtained average times indicate that most of the passengers are picked up relatively soon after the issuance of their travel requests.

**Fleet size.** After the initial experimentation, the fleet was varied by adding or subtracting a few vehicles. Once again, the aim was to observe service quality and vehicle usage

**Table 1.** Service quality evolution with increasing demand and a fixed fleet of 10 vehicles

| Requests | req/hour | Vehicles | Capacity | Service quality (%) | Avg. pax wait (min) | Fleet usage |
|---|---|---|---|---|---|---|
| 100 | ∼8 | 10 | 8 | 100.00 | 3.5 ± 5.0 | 9/10 |
| 150 | ∼11 | 10 | 8 | 99.33 | 4.4 ± 5.2 | 10/10 |
| 200 | ∼15 | 10 | 8 | 99.00 | 4.3 ± 5.1 | 10/10 |
| 250 | ∼18 | 10 | 8 | 96.00 | 4.8 ± 5.0 | 10/10 |
| 300 | ∼22 | 10 | 8 | 89.67 | 5.0 ± 4.9 | 10/10 |
| 350 | ∼25 | 10 | 8 | 84.29 | 5.5 ± 5.3 | 10/10 |
| 400 | ∼29 | 10 | 8 | 74.75 | 6.1 ± 5.2 | 10/10 |
| 450 | ∼33 | 10 | 8 | 70.00 | 6.2 ± 5.1 | 10/10 |
| 500 | ∼36 | 10 | 8 | 62.80 | 6.5 ± 5.3 | 10/10 |

evolution. For these tests, the number of requests increased from 200 to 500 in 50 request intervals. Table 2 presents all the runs. The results indicate that reducing the fleet also reduces the amount of demand the system can appropriately manage, as can be expected. Similarly, with a more significant fleet, the quality of service is preserved above the 70% margin for higher intensities of demand. Even in runs with a more extensive fleet, the system achieves a uniform division of requests among vehicles, employing all of them. The pattern of evolution of passenger waiting times is observed to be the same as in the previous experimentation, having standard deviations approaching 5 minutes across all the tested parameter combinations.

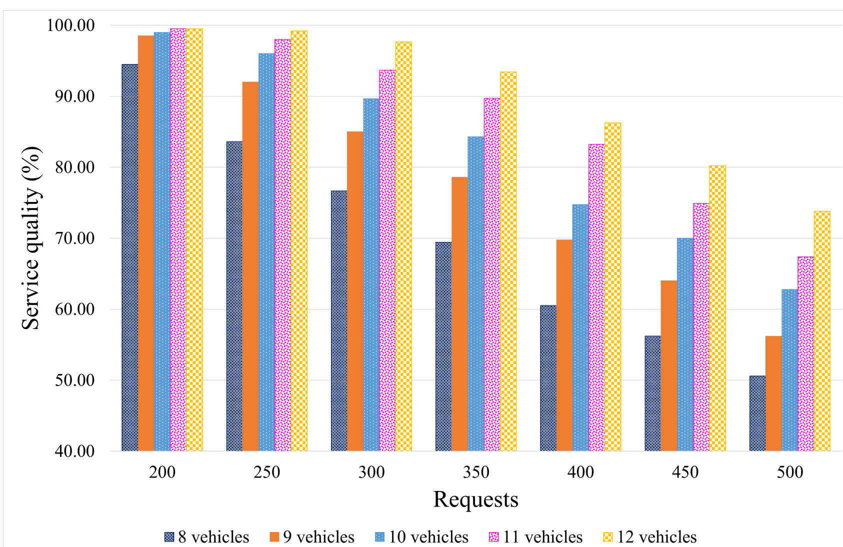



**Fig. 6.** Visualization of service quality according to various number of requests and fleet sizes

**Table 2.** Service quality evolution with different fleets ranging from 8 to 12 vehicles and various demand intensities

| Requests | req/hour | Vehicles | Capacity | Service quality (%) | Avg. pax wait (min) | Fleet usage |
|---|---|---|---|---|---|---|
| 200 | ∼15 | 8 | 8 | 94.50 | 4.2 ± 5.0 | 8/8 |
| 250 | ∼18 | 8 | 8 | 83.60 | 5.5 ± 5.1 | 8/8 |
| 300 | ∼22 | 8 | 8 | 76.67 | 6.3 ± 5.2 | 8/8 |
| 350 | ∼25 | 8 | 8 | 69.43 | 5.9 ± 5.3 | 8/8 |
| 400 | ∼29 | 8 | 8 | 60.50 | 6.4 ± 5.1 | 8/8 |
| 450 | ∼33 | 8 | 8 | 56.22 | 6.5 ± 5.2 | 8/8 |
| 500 | ∼36 | 8 | 8 | 50.60 | 6.9 ± 5.3 | 8/8 |
| 200 | ∼15 | 9 | 8 | 98.50 | 4.5 ± 5.3 | 9/9 |
| 250 | ∼18 | 9 | 8 | 92.00 | 4.8 ± 4.9 | 9/9 |
| 300 | ∼22 | 9 | 8 | 85.00 | 5.2 ± 4.9 | 9/9 |
| 350 | ∼25 | 9 | 8 | 78.57 | 5.9 ± 5.3 | 9/9 |
| 400 | ∼29 | 9 | 8 | 69.75 | 6.2 ± 5.0 | 9/9 |
| 450 | ∼33 | 9 | 8 | 64.00 | 6.5 ± 5.1 | 9/9 |
| 500 | ∼36 | 9 | 8 | 56.20 | 6.5 ± 5.2 | 9/9 |
| 200 | ∼15 | 11 | 8 | 99.50 | 4.2 ± 5.1 | 11/11 |
| 250 | ∼18 | 11 | 8 | 98.00 | 4.7 ± 5.1 | 11/11 |
| 300 | ∼22 | 11 | 8 | 93.67 | 4.4 ± 4.9 | 11/11 |
| 350 | ∼25 | 11 | 8 | 89.71 | 5.1 ± 5.1 | 11/11 |
| 400 | ∼29 | 11 | 8 | 83.25 | 5.6 ± 5.0 | 11/11 |
| 450 | ∼33 | 11 | 8 | 74.89 | 6.0 ± 5.0 | 11/11 |
| 500 | ∼36 | 11 | 8 | 67.40 | 7.0 ± 5.3 | 11/11 |
| 200 | ∼15 | 12 | 8 | 99.50 | 4.2 ± 5.1 | 12/12 |
| 250 | ∼18 | 12 | 8 | 99.20 | 4.3 ± 4.9 | 12/12 |
| 300 | ∼22 | 12 | 8 | 97.67 | 4.3 ± 4.8 | 12/12 |
| 350 | ∼25 | 12 | 8 | 93.43 | 4.9 ± 5.1 | 12/12 |
| 400 | ∼29 | 12 | 8 | 86.25 | 5.4 ± 5.0 | 12/12 |
| 450 | ∼33 | 12 | 8 | 80.22 | 6.1 ± 5.2 | 12/12 |
| 500 | ∼36 | 12 | 8 | 73.80 | 6.4 ± 5.3 | 12/12 |

The graph on Figure 6 visually represents the results of Tables 1 and 2, showing the evolution of the service quality provided by fleets of various vehicles with respect to an increasing number of requests. Table 3 summarizes all results, showing the lower bounds of acceptable service quality found for each combination of demand and fleet size.

**Table 3.** Lower bound of acceptable service quality found for all combinations of demand intensity and fleet sizes

| Requests | req/hour | Vehicles | Capacity | Service quality (%) | Avg. pax wait (min) | Fleet usage |
|---|---|---|---|---|---|---|
| 250 | $\sim$18 | 8 | 8 | 83.60 | $5.5 \pm 5.1$ | 8/8 |
| 300 | $\sim$22 | 9 | 8 | 85.00 | $5.2 \pm 4.9$ | 9/9 |
| 350 | $\sim$25 | 10 | 8 | 84.29 | $5.5 \pm 5.3$ | 10/10 |
| 400 | $\sim$29 | 11 | 8 | 83.25 | $5.6 \pm 5.0$ | 11/11 |
| 450 | $\sim$33 | 12 | 8 | 80.22 | $6.1 \pm 5.2$ | 12/12 |

**Vehicle capacity.** The final parameter that was assessed was vehicle capacity. The above simulations were run with fleets of 8 to 12 vehicles but changing their capacity to that of a minibus, ranging from 16 to 22 passengers. The results in terms of quality of service, however, were very similar to what has been presented so far. This indicates that, given the shape of the generated demand, vehicle capacity was not a bottleneck of the system, and rejected requests were motivated by time window incompatibilities and not because of capacity constraints. We must acknowledge, however, that the conclusions drawn from this study of vehicle capacity are only applicable to the specific generated demand. From a general perspective, varying the capacity of fleet vehicles could have a great impact on the system's performance, which is what motivated this final experimentation.

## 5. Discussion

Given the results summarized in Section 4.2, we can conclude that dynamic DRT is a good fit for the synthetically generated rural mobility demand. The inefficiency of traditional interurban public mobility options in rural contexts comes from the shape of its demand. Vehicles with a high occupancy ratio, scheduled in periodic lines, tend to drive mostly empty, therefore being costly to maintain for public transport providers. The proposed system tackles these problems by ensuring maximum fleet usage, taking advantage of every present vehicle. In addition, this behavior eases the consideration of adding new vehicles to the fleet, as the fleet administrator has the certainty that it will be exploited and thus not a waste of resources.

With regard to the economic viability of the system, having a smaller fleet of smaller vehicles implies lower maintenance and salary expenses. Furthermore, if autonomous mobility becomes feasible in the future, economic expenses would lower even more due to the avoidance of driver salaries. Our experimentation has not explicitly considered the service's environmental impact. Nevertheless, the proposed system has features which indirectly contribute to a better sustainability. On the one hand, the objective function reduced vehicle travel time which, in turn, would reduce any type of emissions stemming from the fleet. In addition, we assess a reduction of such a fleet, achieving a similar level of service quality while cutting costs. Finally, it is worth mentioning that the environment is better preserved because the fleet makes journeys only when necessary. Moreover, these journeys are more cost-effective due to the higher occupancy of the vehicles.

As seen throughout Section 2, demand-responsive systems present a high number of operation modes and configurable parts. The present work describes one of the many approaches that could work to modernize and improve rural mobility. Ideally, the proposed system would completely replace the inefficient, traditional transportation options. However, in reality, the adoption rate of DRT tends to be low, even more in rural contexts, due to the necessity to explicit a travel request. The easiest methods to do so consist of smartphone applications and call centers, being the former generally harder to manage for the older population. Because of that, the deployment of a demand-responsive system would initially complement the current mobility options providing, for instance, connection to the most stranded settlements with the main means of public transportation.

Finally, we want to assess the lack of publicly available demand data, which hardens the research on rural mobility. In the context of rural DRT, this issue is aggravated by the lack of rural-specific or low-demand datasets. There are a small number of DRT pilot projects, and among them, an even smaller number share the collected data. Still, the data that can be found about pilot projects is very dependent on the specific area and the socio-demographic context where the pilot took place. To deal with data shortage, synthetic data generation is often employed, basing generation on population, age, occupation, and any other kind of survey that characterizes the potential users of the system.

## 6. Conclusion

In this paper, DRT has been characterized, together with the challenges rural mobility presents for the implementation of efficient modes of public transportation that satisfy the population. A DRT system has been proposed to match the rural mobility demand and provide such a quality service. The system has been described in depth, implemented, and tested by means of simulations. A rural area in the region of Valencia, Spain, has been chosen for the deployment of the system. The mobility demand, in terms of travel requests, has been generated with a synthetic demand generator according to the population of the deployment area and a series of configurable parameters. The research results prove the potential that DRT holds to develop dynamic, reliable, and cost-effective public transportation in the rural context. This research contributes with a system proposal and its validation to the field of rural mobility, which has a general lack of innovation when it comes to displacement proposals.

In terms of future research, we observe two paths. On the one hand, the proposed system can be further improved. Different system configurations must be assessed to find the best match for the deployment area. In addition, the parameters of the proposed system could also be fine-tuned through more experimentation. To further improve results, global optimization techniques can be implemented in order to further optimize the obtained itineraries. For instance, considering request exchange among vehicles could decrease global costs. Finally, we would like to include transfer operations as an option for the scheduler to allocate requests. These operations have the potential to simplify the fleet operation, cutting costs. On the other hand, regarding experimentation, it would be interesting to assess the impact of different levels of demand dynamism, tighter request time windows, or different dispatching strategies, to mention a few. Finally, simulation results could be enhanced by considering factors such as vehicle autonomy or strategic agent behavior.

As closing remarks, we want to state that there is a need for specific investigations on the successful implementation of DRT. To bridge such a gap, researchers must go beyond service quality to focus on the adoption rate and usage of the system. For instance, we believe in the potential pricing policies that could both attract new users to the system and, in addition, influence how they use it to improve the overall quality of service.

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**Pasqual Martí** is a Ph.D. student and researcher at the Valencian Research Institute for Artificial Intelligence (VRAIN) of the Universitat Politècnica de València. He began his career in research through a scholarship, participating in 2 R&D projects related to Multi-Agent Systems and Urban Fleets. From such work, he has published several articles in indexed journals and international conferences.

**Jaume Jordán** is a postdoctoral researcher at the Valencian Research Institute for Artificial Intelligence (VRAIN) of the Universitat Politècnica de València. He finished his Ph.D. in 2017 with a grade of Outstanding Cum Laude and international mention. He has participated in more than 10 R&D projects (1 as principal investigator). He has more than 40 works published in relevant international conferences and JCR journals.

**Vicente Julian** holds the position of Full Professor of Computer Science at the Universitat Politècnica de València (UPV) where he has taught since 1996. He is a member of the Valencian Research Institute for Artificial Intelligence (VRAIN), and the Coordinator of the Computer Science Ph.D. Program at the UPV. 4 international projects, 2 international excellence networks, 25 Spanish projects, and 4 technology transfer projects have covered his research on Artificial Intelligence. He has more than 300 works published in journals with outstanding JCR positions or in relevant conference proceedings, and supervised 10 Ph.D. Thesis.

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