

Regional-Scale Multi-Modal Service Optimization for Innovative Air Mobility

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Abstract—By 2050, ninety percent of European travelers are expected to complete door-to-door journeys within 4 hours, requiring expanded transport infrastructure coverage, particularly in rural areas where 19.2% of the population resides. Innovative Air Mobility (IAM), which enhances connectivity with minimal infrastructure, offers a promising solution. Building on this potential, this paper presents a passenger-centric IAM service optimization framework that models the multi-modal network as a time-expanded graph and sequentially optimizes passenger journeys and IAM dispatching strategies using A* search and dynamic programming. A simulation based on the Catalan Pyrenees validates the framework, demonstrating its effectiveness in generating optimal IAM dispatch strategies and supporting multi-modal schedule coordination. Based on the findings, this paper offers recommendations for future IAM development, including per-vehicle capacity planning, pricing strategies to avoid direct competition with existing transport modes, and other operational considerations.

Keywords—Urban and Innovative Air Mobility (UAM/IAM), Service Optimization, Time-Expand Graph, A star, Dynamic Programming, Multi-modal Transport Network

I. INTRODUCTION

According to Flightpath 2050 [1], Europe's vision for aviation is to maintain global leadership while meeting societal needs, including allowing 90% European travelers to complete their journeys, door-to-door, in four hours. Achieving this goal requires attention to rural areas, as approximately 19.2% of the European Union population resided in predominantly rural regions [2]. Without extending connectivity to these regions, the vision outlined in Flightpath 2050 cannot be fully realized.

Providing adequate accessibility in rural regions remains a persistent challenge. Traditional solutions—such as expanding road or rail infrastructure—often require very high investments, while the relatively low population density of these areas makes it difficult to justify such costs. This structural imbalance has encouraged researchers and policymakers to look for alternative mobility concepts. One promising avenue is Innovative Air Mobility (IAM)—an extension of Urban Air Mobility covering suburban and rural areas—is gaining attention [3]. By employing new generations of aircraft—such as electric, hybrid, or hydrogen-powered STOL/VTOL—IAM offers the potential to enhance regional connectivity while minimizing both infrastructure requirements and environmental impacts. Building on this vision, the SESAR Joint Undertaking has launched the PRIAM project, which explores how

IAM infrastructure and services can be effectively integrated into regional multimodal transport networks [4], with other studies (e.g., CORUS-XUAM [5]) providing complementary insights.

This paper forms part of the PRIAM project, which aims to optimize regional-scale multi-modal services for IAM. Given a set of travel demands and a fixed fleet of IAM vehicles stationed at designated vertiports, the study focuses on determining optimal dispatch strategies to ensure IAM operations complement the existing public transport network, which is considered static and provided as input data. Moreover, to enable practical cooperation between IAM and traditional transport modes, passenger journeys must also be optimized, as multi-modal integration is fundamentally human-centered and built upon the efficient movement of people. Hence, there are two interrelated sub-problems to be solved in this paper:

- Firstly, IAM trajectory optimization is Non-deterministic Polynomial-time hard (NP-hard). In the single-vehicle scenario, where one IAM vehicle connects multiple Origin-Destination (OD) pairs, representing the network as a directed graph reduces the task to finding a minimum-cost tree spanning all service nodes, equivalent to the Directed Steiner Tree problem [6], which is NP-hard. In the multi-vehicle scenario, coordinating trajectories across multiple vehicles further generalizes the problem, thereby preserving its computational hardness.
- Secondly, passenger journey optimization is also NP-hard. Since passengers have distinct OD pairs, the problem can be formulated as a Multi-Commodity Flow Problem [7], where each passenger represents a separate commodity whose flow through the network is optimized to minimize overall travel time or cost while satisfying vehicle capacity and routing constraints. Solving it requires routing multiple flows simultaneously through a shared network under capacity and demand constraints, making it computationally intractable in the general case.

Both sub-problems are inherently NP-hard, posing significant computational challenges even when addressed separately. Attempting to integrate trajectory and passenger journey optimization into a unified framework, with the goal of improving overall performance, further amplifies the complexity.

To address these challenges, this paper proposes a novel



IAM service optimization framework. First, a staggered rolling time horizon strategy is adopted to reduce computational burden while mitigating the impact of uncertainty over long horizons. Second, a time-expanded transport network graph is constructed to capture both the spatial and temporal characteristics of the transport supply. Third, an approximate optimization approach is developed to solve the two sub-problems, striking a balance between solution quality and computational efficiency. Finally, a case study based on the Catalan Pyrenees is conducted to validate the framework. The region provides a representative example of accessibility challenges in mountainous and predominantly rural areas, where geographical barriers, limited road and rail infrastructure, and the presence of significant tourist flows highlight the potential benefits of IAM services.

The contribution of this study is threefold: (1) characterizing the transport supply-demand environment in the Catalan Pyrenees using existing algorithms, providing a foundation for subsequent validation of the proposed framework; (2) proposing a regional-scale multi-modal IAM service optimization framework that addresses vehicle dispatching and passenger journey optimization while balancing computational efficiency and solution quality; and (3) providing guidance for regional IAM deployment and multi-modal integration, demonstrating the framework's applicability in rural areas and informing policy-making and transport planning.

The subsequent parts of this paper are organized as follows: Section II outlines the problem setup, covering the simulation environment and rolling time horizon-based demand collection. Section III explains the design and implementation of the optimization framework. Section IV presents an experimental study to validate the applicability and effectiveness of the proposed framework. Finally, Section V concludes and suggests steps for further research.

II. PROBLEM SETUP

This study focuses on a future-oriented problem, no real environment is available for reference. To address this, this section first constructs a simulation environment in subsection II-A. Building on this setup, subsection II-B introduces a staggered rolling time horizon strategy to emulate real-world demand occurrence.

A. Simulation environment establishment

This study selects the Catalan Pyrenees as the basis for establishing the simulation environment, as it provides a valuable example of the accessibility challenges faced in mountain areas. Geographical barriers constrain the development of high-quality road infrastructure and rail connections. Although predominantly rural, the region attracts significant tourist flows and serves as the gateway to the country of Andorra.

The General Transit Feed Specification [8] data was first retrieved from Spain's official National Transport Data Access Point [9] to describe the existing public transport supply. Figure 1a illustrates the dataset, which comprises 8,742 public transport stations, shown as black dots. Despite the total

number of stations, their distribution is highly uneven, reducing overall accessibility. Most stations are clustered around Barcelona, while rural areas have relatively few. Consequently, before constructing the public transport network graph from these stations, node compression is applied. This step reduces the graph size, thereby accelerating the subsequent optimization of scheduling or routing problems.

In the node compression process, the Leiden algorithm [10] was employed to replace groups of nodes with representative nodes. The Leiden algorithm is a state-of-the-art method for community detection in large networks, improving upon the widely used Louvain algorithm [11] by addressing issues related to disconnected communities and convergence to sub-optimal partitions. It ensures well-connected communities and generally produces higher-quality partitions more efficiently.

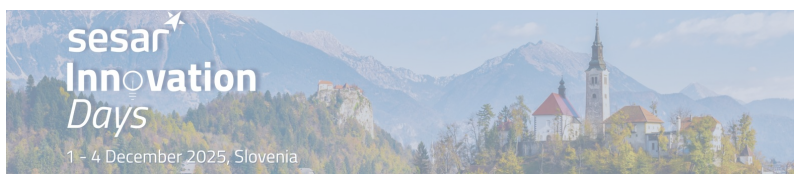
Resolution is the key parameter in the Leiden algorithm, determining the scale of detected communities. To determine the optimal value, this study conducted experiments varying the resolution parameter. Increasing the resolution from 0 to 10^{-3} raised the number of clusters from 8 to 436, while the clustering quality decreased from 0.98 to 0.66 (Figure 2). The clustering quality is measured by the constant pots model [12]. By selecting a resolution of 10^{-4} , the analysis yielded 105 clusters with a clustering quality of 0.85.

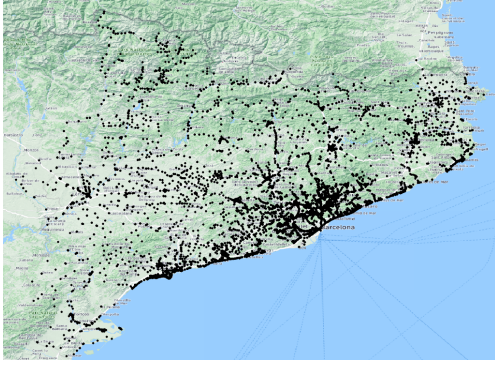
In addition to the existing public transport supply, it is necessary to define the potential supply of vertiports, as this study addresses a future-oriented problem in which IAM services are not yet implemented at this scale. Potential vertiport locations are determined by projected IAM use cases and the availability of existing heliports suitable for infrastructure upgrades. Figure 1 depicts the vertiports considered in our simulation environment, where red stars indicate projected IAM use cases (e.g., airports, hospitals, ski resorts) and blue stars denote existing heliports.

The remainder of this subsection explains how travel demand is estimated based on the supply information described above. To model the probability of trips between origins and destinations, existing trip distribution laws [13]–[16] are applied, which require population data for each region. For this purpose, the gridded population dataset of Spain was obtained from the WorldPop Hub [17]. The population distribution of the Catalan Pyrenees is shown in Figure 3a.

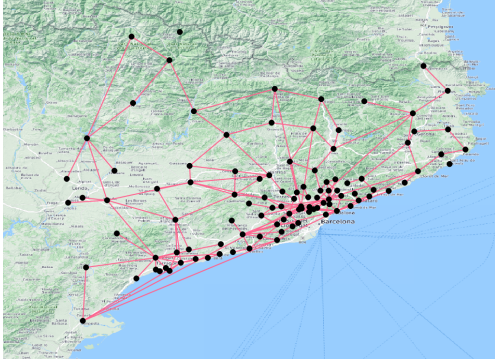
First, population values are allocated to each public station or assumed vertiport using a Voronoi diagram [18], which partitions the area into cells around a set of seed points, with each cell containing all locations closest to its corresponding seed. As shown in Figure 3b, each node (public station or potential vertiport) serves as a seed, generating a Voronoi cell. The population associated with each node is estimated by overlaying the Voronoi partition with the population distribution map, assigning the population of each pixel to the node whose cell contains it.

Second, based on the node compression results, Voronoi cells with seeds corresponding to the same compressed node are merged into a unified service area. As illustrated in Figure 3c, this process aggregates the original coverage areas

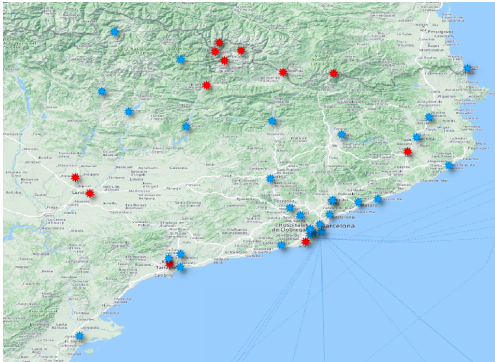




(a) The public transport stations within the Catalan Pyrenees. Each black dot denotes a bus station. There are a total of 8742 stations.



(b) The public transport network graph of the Catalan Pyrenees. Each black dot denotes an abstract node, and each pink edge denotes a public connection. The graph has 105 nodes and 152 edges.



(c) The potential vertiports of the Catalan Pyrenees. Each red star denotes a key area, and each blue star denotes a civil heliport. There is a total of 42 potential vertiports in the Catalan Pyrenees.

Figure 1. Acquisition of transport supply information.

into larger regions, each representing the service zone of a compressed node.

Through this merging process, the population values of individual Voronoi cells are summed, so that the total population assigned to each compressed node reflects the cumulative population of its merged region. This abstraction preserves demand accuracy while enabling more efficient regional planning and subsequent modeling.

Finally, using the population data and travel distances obtained from the Google Maps Distance Matrix API [19], trip probabilities between locations are calculated with the Radiation model [14], a parameter-free method that accounts

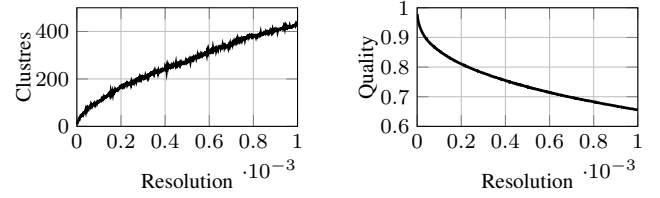


Figure 2. Performance of the Leiden algorithm as a function of resolution: increasing the resolution increases the number of clusters but reduces quality (measured by the Constant Potts Model [12]).

for intervening opportunities. Given these trip probabilities, travel demand at each timestamp can be generated by sampling from the probability distributions.

B. Staggered rolling time horizon strategy

This subsection presents the staggered rolling time horizon strategy adopted in this study, which offers three major advantages: (1) emulating real-world demand occurrence; (2) reducing computational burden, since the optimization framework does not need to process all traffic demand simultaneously; and (3) mitigating the impact of uncertainty over long planning horizons.

As shown in Figure 4, each optimization cycle consists of two phases: a 5-minute travel requests collection phase followed by a five-minute optimization phase. The choice of a 5-minute interval is based on a trade-off between computation time, information transmission delays, and passenger acceptable waiting time: a shorter interval may not allow sufficient time to solve the optimization problem, while a longer interval could result in unacceptably long waiting times for passengers. While the current optimization is in progress, the system concurrently gathers demand data for the upcoming time window, which covers the trips to be planned in the next scheduling cycle. This pipeline structure ensures continuous operation with minimal idle time and reduced latency. During each optimization phase, the IAM vehicles' scheduling established in previous iterations must remain unchanged. This ensures that once a passenger's travel request is accepted, it will neither be delayed nor canceled.

Passengers submit travel requests by specifying four key attributes: origin, destination, preferred departure time, and demand level. The demand level is represented by a positive integer that reflects the passenger's willingness to pay above the base fare. For instance, a passenger with a demand level of 1 is willing to pay €50, whereas a passenger with a demand level of 5 is willing to pay €250.

The demand collection module continuously monitors incoming requests and selects those whose preferred departure times fall within the upcoming five-minute window. These requests are aggregated into groups and compiled into a demand table, as illustrated in Table I. Each entry in the table includes the origin, destination, volume (i.e., the number of passengers), and priority (i.e., the total demand level of all passengers within the group). The entries are sorted in descending order based on priority.

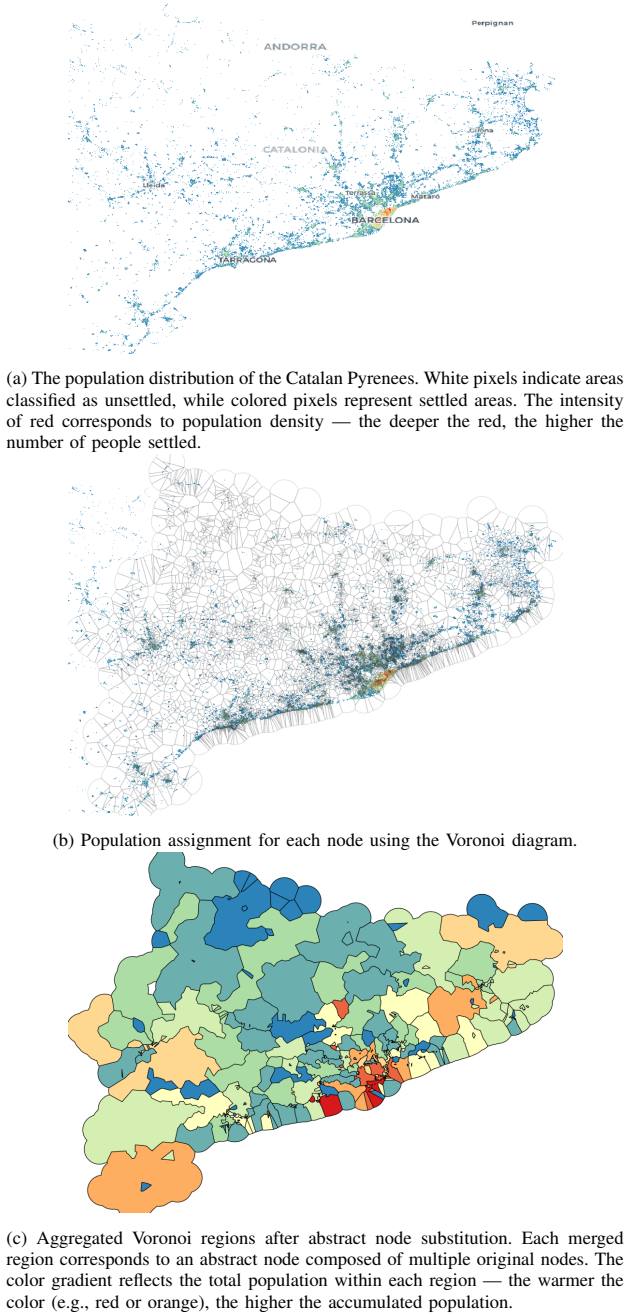


Figure 3. Acquisition of transport demand information.

This prioritization mechanism ensures that OD pairs with higher aggregate willingness to pay are assigned higher priority. As a result, when IAM vehicle availability is limited, requests with greater priority are more likely to be served, leading to increased revenue.

III. METHODOLOGY

This section first introduces a novel IAM service optimization framework in subsection III-A and a time-expanded transport network graph in subsection III-B to support the framework's implementation. It then details the two main

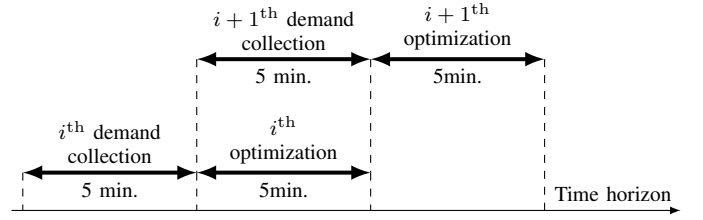


Figure 4. Scheduling optimization with a staggered rolling scheme. Such a scheme requires the proposed framework to output solutions within 5 minutes.

TABLE I. TRAVEL DEMAND TABLE.

Origin	Destination	Volume	Priority
V_1	V_4	12	12
V_3	V_5	2	6
V_2	V_4	5	5
$\vdots$	$\vdots$	$\vdots$	$\vdots$

components of the framework: A*-based passenger journey optimization in subsection III-C, and Dynamic Programming (DP)-based IAM trajectory optimization in subsection III-D.

A. Framework

As discussed in the introduction, the problem addressed in this study is NP-hard. To accelerate the optimization process, an approximate approach is employed, balancing solution quality with computational efficiency.

Figure 5 illustrates the framework of this approximate optimization approach. A*-search [20] and DP [21] are used within the framework, both of which have polynomial-time complexity. Consequently, although the original problem is NP-hard, this framework provides a polynomial-time method that generates feasible, high-quality approximate solutions.

The first step in Figure 5 is demand and supply estimation, which serves as an initialization step and is detailed in Sec-

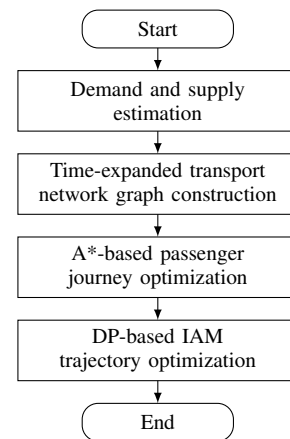


Figure 5. The framework of the approximation optimization process. The A*-based module determines optimal trajectories for all passengers and assigns demand-related rewards to each edge, followed by a DP-based module that optimizes IAM dispatch based on this information.

tion II. Since this estimation can be completed prior to the following processes, it is treated as an offline step.

The second step in Figure 5 is the construction of a time-expanded transport network graph, which incorporates both the existing public transport network and the IAM service network to facilitate cooperation between IAM vehicles and public transport. This step serves as the problem formulation stage, generating the graph on which the subsequent optimization algorithms (A and DP) operate.

The third step in Figure 5 is the A*-based passenger journey optimization. In this step, passenger journeys are optimized under the assumption of unlimited vehicle availability, meaning that passengers can move freely between nodes in the graph without constraints imposed by specific transportation modes. The decision variables correspond to the selection of edges included in each passenger's path, and the constraints ensure that each path forms a continuous connection from the origin to the destination. The objective is to minimize the total cost along the selected paths. As a by-product of this process, each edge is assigned a passenger-demand-related reward reflecting its relative popularity, which serves as input for the subsequent DP-based vehicle dispatch optimization.

The fourth step in Figure 5 is the DP-based IAM trajectory optimization. In this step, the dispatching strategy for IAM vehicles is optimized to meet passenger demand on each edge of the graph. The optimization determines the routes of each vehicle and their departure times, while ensuring that each IAM performs only one task at a time, routes form continuous feasible paths, and the existing transport dispatching strategy is maintained. The objective is to maximize the total passenger-demand-related reward obtained from the previous model, efficiently fulfilling passenger travel requests.

It is worth noting that there is no need to jointly optimize the passenger journey (third step) and IAM dispatching (fourth step). This is because the third step assumes unlimited vehicle availability, meaning its results are independent of the actual dispatching outcomes. Consequently, the results of the fourth step do not influence the third step, and no iterative process between the two steps is required.

It is clear that this framework may not achieve a global optimum, as passengers' journeys and the IAM dispatching strategy are difficult to optimize simultaneously. This situation is analogous to air traffic flow optimization in air traffic management, where traffic flows (corresponding to passenger journeys) and sector configurations (corresponding to IAM dispatching) are challenging to optimize at the same time and are typically addressed through iterative approaches [22]. Nevertheless, the framework provides a practical way to obtain an acceptable solution within a reasonable time frame.

B. Time-expanded transport network graph

This subsection outlines the construction process of the time-expanded network graph.

As shown in Figure 6a, a simple transportation network comprises three vertices: V_1 , V_2 , and V_3 . The links between

V_1 - V_2 and V_1 - V_3 are bidirectional and served by IAM vehicles, whereas the connection from V_2 to V_3 is unidirectional and operated by a bus. Based on the schedule illustrated in Table II, an IAM is scheduled to depart from V_1 to V_2 at time t_2 , and a bus is scheduled to depart from V_2 to V_3 at time t_3 .

Figure 6b presents the corresponding time-expanded network graph, which incorporates both the spatial structure from Figure 6a and the temporal information from Table II.

In the time-expanded graph, each column represents the set of vertices at a particular time step, while each row corresponds to a specific physical location across multiple time steps. Solid directed edges between two nodes indicate confirmed travel arcs based on the given transport schedules, whereas dotted directed edges represent candidate travel arcs that may be available but are not yet confirmed. In addition, the final column contains white vertices representing virtual destination nodes. Each black vertex in the last time step is connected to the corresponding white vertex in the same row by a zero-cost directed edge, allowing an immediate transition to the virtual node once the physical destination is reached, thereby marking the completion of the optimization process.

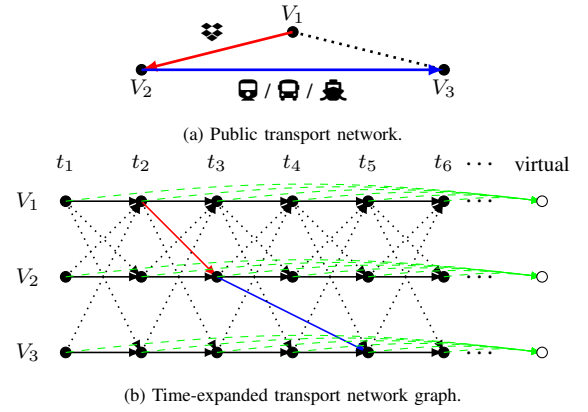


Figure 6. Time-expanded transport network graph construction with public transport network information.

TABLE II. TEMPORAL INFORMATION IN TRANSPORTATION.

	O	D	T_{dep}	Duration
	V_1	V_2	t_2	$\tau(V_1, V_2)$
	V_2	V_3	t_3	$\tau(V_2, V_3)$

C. A*-based passenger journey optimization

This subsection describes how to optimize passenger journey recorded in the travel demand table (Table I).

The optimization process is outlined in Algorithm 1, which assigns OD pairs based on edge costs and annotates the edges with demand-related rewards, providing the basis for subsequent DP-based optimization.

The cost for each edge ($V_i \rightarrow V_j$) at time t_k can be calculated via Equation (1), which considers multiple factors such as the time-dependent attenuation, mobility requirements,

Algorithm 1 OD Pair Assignment with A* Path Planning.

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1: Initialize the priority score of each edge to zero.
2: while unassigned OD pairs remain do
3:   Select OD pair  $(V_i, V_j)$  with highest priority
4:   Update network graph based on demand and residual supply
5:   Find lowest-cost path from  $V_i$  to  $V_j$  using A*
6:   if no reachable path is found then
7:     Remove the OD pair from travel demand table
8:   continue
9: end if
10: if lowest-cost path has non-zero residual supply then
11:   Assign as many passengers as possible to the path
12:   Update network supply by reducing assigned path capacity
13:   Update travel demand by subtracting assigned volume
14:   if remaining demand volume for  $(V_i, V_j)$  is 0 then
15:     Remove the OD pair from travel demand table
16:   end if
17: else
18:   for all edges with no supply on the shortest path do
19:     Add the OD pair's demand to the edge's reward
20:   end for
21:   Remove the OD pair from travel demand table
22: end if
23: end while

```

supply-demand balance, pricing adjustments, and the actual travel time between the vertices. This formulation allows the model to dynamically capture both temporal and spatial variations in travel cost.

$$c_{i,j,k} = \lambda_k \cdot \eta_{i,j} \cdot \xi_{i,j,k} \cdot \zeta_{i,j} \cdot \tau_{(V_i, V_j)} \quad (1)$$

where factor λ_k denotes the attenuation coefficient which can be calculated via Equation (2), factor $\eta_{i,j}$ denotes the mobility requirement coefficient, which can be calculated via Equation (3), factor $\xi_{i,j,k}$ describes the supply and demand coefficient which can be calculated via Equation (4), factor $\zeta_{i,j}$ denotes the price coefficient, which can be calculated via Equation (5), factor $\tau_{(V_i, V_j)}$ denotes the travel time from V_i to V_j .

The factor λ_k reduces the edge cost over time, making it more likely that the edge used in this time window will serve future travel demands.

$$\lambda_k = \alpha + \beta^k \quad (2)$$

where $\alpha + \beta = 1$, $k \in \mathbb{Z}^+$, $\alpha \in (0, 1)$, and $\beta \in (0, 1)$. When k increases from 1 to ∞ , λ_k decreases from 1 to α . In this study, α and β are set to be 0.9 and 0.1, respectively, based on preliminary tests and operational considerations. These values serve as a baseline, and future work will explore alternative settings and conduct a systematic sensitivity analysis.

The factor $\eta_{i,j}$ lowers the cost of edges where passengers remain at the same location and only need to wait briefly, without requiring any mobility.

$$\eta_{i,j} = \begin{cases} 1 & i \neq j \\ 0.5 & i = j \end{cases} \quad (3)$$

where $i \neq j$ means that V_i and V_j are vertices with different physical locations, $i = j$ means that V_i and V_j are vertices

with the same physical location but different in time step. If $i = j$, then passengers just need to wait at the same place for a while to transfer from V_i to V_j ; otherwise, passengers need to take transportation to transfer from V_i to V_j .

The factor $\xi_{i,j,k}$ reduces the cost of edges with residual supply, with greater reductions applied to edges that have higher residuals.

$$\xi_{i,j,k} = (1 - \kappa) + \frac{\kappa \cdot (d + d^*)^2}{s_{i,j,k}^2 + (d + d^*)^2} \quad (4)$$

where $s_{i,j,k}$ describes the remaining supply from vertex V_i to vertex V_j at time t , d describes the demand of an OD pair, d^* denotes the residual demand of the preceding OD pairs carried over from previous iterations. When $s_{i,j,k}$ increases from 0 to $(d + d^*)$, $\xi_{i,j,k}$ decreases from 1 to $1 - \frac{\kappa}{2}$. When $s_{i,j,k}$ increases from $(d + d^*)$ to ∞ , $\xi_{i,j,k}$ decreases from $1 - \frac{\kappa}{2}$ to $1 - \kappa$. In this study, κ is set to be 0.8. While it provides a reasonable baseline, future research will further examine its effect on system performance.

The factor $\zeta_{i,j}$ is the cost ratio, which determines the relative expense of IAM travel compared to conventional modes: a ratio of 1 means IAM costs are equivalent to those of rail or bus transport, while a ratio of 20 indicates that IAM costs are twenty times higher.

$$\zeta_{i,j} = \begin{cases} \Upsilon & \text{from } V_i \text{ to } V_j \text{ requires IAM} \\ 1 & \text{other} \end{cases} \quad (5)$$

where $\zeta_{i,j}$ increases the travel cost from vertex V_i to vertex V_j if IAM is required, since Υ is always larger than 1.

D. DP-based IAM trajectory optimization

This subsection presents the optimization of the IAM dispatching process based on the edge rewards (the edge priorities defined in subsection III-C).

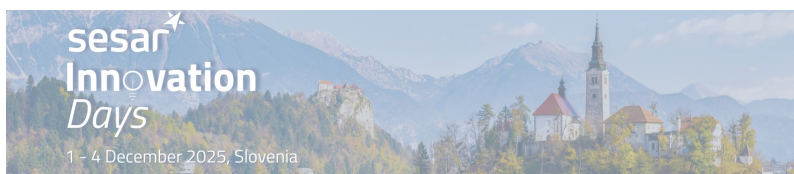
This study plans IAM vehicles sequentially (one-by-one), with each trajectory obtained via a single DP step on the time-expanded transport network, which is a directed acyclic graph (DAG). Each DP step solves a single-source maximum-reward problem. Since edges only connect to later time layers, the topological order is naturally given by the temporal structure, allowing DP to proceed directly in chronological order. For a single run, each node is visited once and each edge relaxed once, resulting in relatively low computational complexity.

Although the DP formulation is inherently suited for single-source, single-sink problems, some IAM vehicles do not have fixed destinations. To accommodate these cases, as shown in Figure 7, a virtual sink node is introduced manually, enabling the DP to handle trajectories without predetermined endpoints.

IV. EXPERIMENTAL STUDY

This section presents simulation results to validate the applicability of the proposed framework and to provide some meaningful information for future policy-making in developing IAM.

The simulation focuses on the Catalan Pyrenees region to investigate traffic operations during the morning peak period.



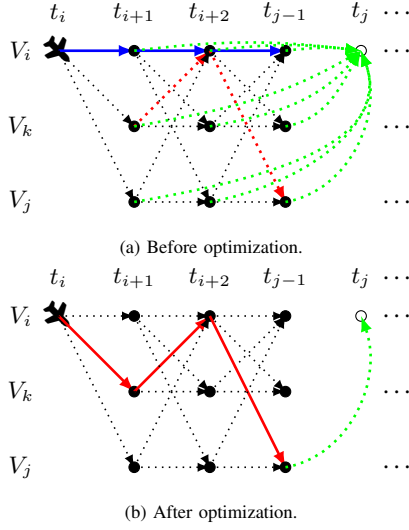


Figure 7. Single IAM vehicle routing with departure constraints. The blue solid edges represent the original route of the IAM vehicle. The black dotted edges denote candidate edges that the vehicle may traverse. The red dotted edges indicate high-priority edges. The red solid edges represent the optimized route of the IAM vehicle. The green dotted edges represent the auxiliary edges directed to a virtual vertex.

The simulation considers a one-hour time window from 08:00 AM to 09:00 AM, which corresponds to the typical commuting hours when a significant number of residents and visitors generate travel demand for commuting, schooling, and short-distance trips within the region. This period provides a representative snapshot of the traffic system under high-load conditions.

To capture the dynamic nature of travel demand, this study assumes that approximately 250 passengers submit new travel requests every five minutes. Over the course of the one-hour simulation, this results in a total of 3,000 travel demands that need to be accommodated.

Firstly, this paper assumes that the capacity of each IAM is 10 passengers and that the unit distance cost ratio relative to ground transportation is 20 (the specific setting is discussed later). The IAM fleet size is then gradually increased from 0 to 50. The results are summarized in Table III. Three key findings emerge:

- Increasing the IAM fleet size does not substantially reduce passengers' reliance on ground transportation. The number of passengers requiring ground transport decreases only slightly, from 1550 to 1542, corresponding to a reduction of just 0.5%. This limited effect can be explained by the fact that, as shown in Figure 8a and Figure 8b, the main contribution of IAM lies in improving accessibility for remote and previously underserved areas. In contrast, for already busy regions the accessibility patterns remain largely unchanged, so the overall reduction in ground transport demand is not substantial.
- The introduction of IAM services allows a larger share of passenger demand to be met. Without IAM, many travelers rely on private cars. The benefits of IAM are

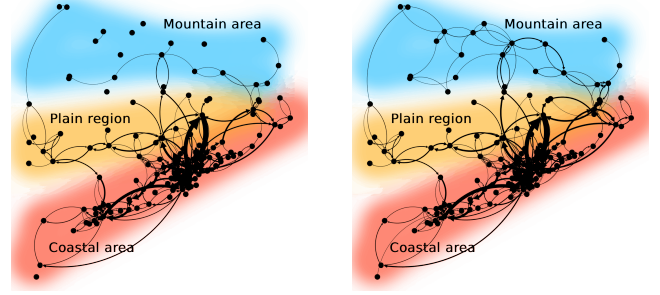


Figure 8. Accessibility improvement after adopting IAM service. While coastal and plain areas experience only modest gains, mountainous areas—benefit substantially, highlighting the IAM service's pronounced impact where accessibility was previously limited.

particularly pronounced when the first 10 vehicles are introduced, as the proportion of satisfied demand increases by nearly 10%.

- The average computation time for optimizing the IAM service is approximately one minute, well below the five-minute threshold. This indicates that the proposed framework can generate solutions within the time constraints of the staggered rolling scheme described in subsection II-B, which requires results to be produced within five minutes in each round.

TABLE III. ENHANCEMENT OF MULTI-MODAL SERVICES ENABLED BY IAM (IAM CAPACITY = 10, UNIT DISTANCE COST RATIO=20).

IAM fleet	Ground only passengers	IAM-served passengers	Demand met (%)	Ave. Opt. time per round(s)
0	1550	0	51.7%	57
10	1546	291	61.2%	52
20	1542	360	63.4%	52
30	1542	380	64.1%	64
40	1542	386	64.3%	56
50	1542	405	64.9%	60

To support better decision-making for operators, as shown in Figure 9, this study analyzes the impact of IAM vehicle capacity (capacity here refers to the maximum passengers per IAM, not fleet size). Increasing the per-vehicle capacity from 0 to 1 passenger leads to a substantial improvement in demand satisfaction, from 51.7% to 61.9%. However, further increases from 1 to 20 passengers yield only marginal gains, reaching 64.9%. This can be observed from Figure 8: IAM mainly improves accessibility in remote areas, where per-trip demand is relatively low, so very large per-vehicle capacities are not necessary.

The result in Figure 9 suggests that while introducing IAM is essential, expanding vehicle capacity beyond a moderate level offers limited additional benefit. From a practical perspective, if larger capacity vehicles entail significantly higher deployment costs, it may be more rational to prioritize other strategies, such as expanding the number of IAMs, rather than pursuing very high per-vehicle capacity

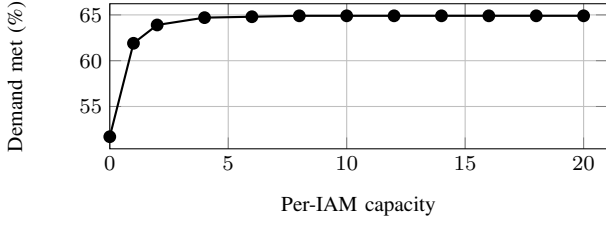


Figure 9. Impact of IAM capacity on demand met rate.

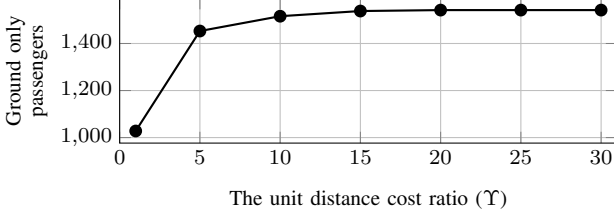


Figure 10. Impact of unit distance cost ratio on demand met rate.

In addition, this study investigates the pricing strategy for IAM. We assume that travel cost is positively correlated with travel distance and introduce a unit distance cost ratio to represent IAM pricing relative to ground transportation. By varying this ratio, we examine how different IAM price levels affect system operations. As shown in Figure 10, when the unit distance cost ratio equals 1—meaning that travelling by IAM costs the same as by train or bus—many passengers are likely to switch to IAM due to its faster travel time. Such a shift can reduce the utilization of existing ground transport, potentially leading to underuse of current resources.

To ensure efficient use of existing resources and prevent under-utilization, IAM prices should be set appropriately. For instance, when the unit distance cost ratio is increased to 20, most passengers continue to use conventional ground transportation, thereby avoiding waste of existing capacity. Under this pricing scheme, passengers use IAM primarily when it is genuinely needed. It is worth noting that this result is somewhat simplistic, as it does not account for passenger demand elasticity. Future work will examine the sensitivity of the results to alternative cost ratios, providing a more realistic assessment of pricing strategies.

Based on this preliminary study, a set of recommendations is derived for the potential implementation of regional IAM services. However, as the project is still ongoing and the simulation environment has not yet been fully validated against real-world conditions, these findings should be considered indicative rather than conclusive.

V. CONCLUSION

This paper develops a simulation environment based on the Catalan Pyrenees and proposes a novel IAM service optimization framework for regional-scale multi-modal transport. Simulation results show that this framework can efficiently generate optimal IAM dispatching strategies and support

multi-modal schedule design, enabling effective coordination between IAM and other modes.

The preliminary findings of this study, which should be interpreted with caution given that the project is still ongoing and the simulation environment has not yet been fully validated, are as follows:

- Increasing the IAM fleet size does not substantially reduce passengers' reliance on ground transportation. The number of passengers requiring ground transport decreases slightly (about 0.5%).
- The introduction of IAM services allows a larger share of passenger demand to be met. The proportion of satisfied demand increases by more than 10%.
- The proposed framework can efficiently compute dispatching strategies with computation times of less than five minutes.
- Increasing IAM passenger capacity yields limited benefits. Given the higher costs of larger vehicles, expanding fleet size may be a more effective strategy than pursuing very high per-vehicle capacity.
- To prevent IAM from competing directly with existing transport modes, the unit distance cost of IAM should be set around 20 times higher than that of ground transportation.

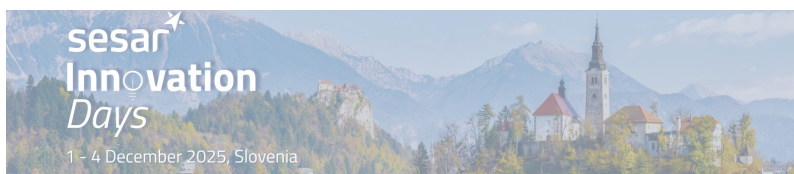
In summary, the proposed framework demonstrates promising application potential and provides valuable guidance for the future deployment of IAM services. Future work will extend the analysis to additional case studies and explicitly incorporate environmental impact assessments to ensure that the proposed solutions contribute to sustainable and responsible aviation development.

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