Multimodal Route Planning Integrating Soft Mobility: A Real-World Case Study for Student Mobility

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Keywords: Multimodal Route Planning, Public Transport, Soft and Active Mobility, Susbtainable Mobility, Student Mobility.

Abstract: Soft and active mobility (SAM) integration into multimodal route planning is a critical innovation for advancing sustainable transportation. This study explores the inclusion of shared (SSAM) and personal (PSAM) soft and active mobility modes within public transport systems. Leveraging a time-expanded model, the proposed approach optimizes route planning by introducing reliability as a novel metric for selecting transportation options. The methodology is tested on real-world data from student commutes in Strasbourg, providing a practical demonstration of its applicability. Results highlight the significant benefits of integrating SSAM and PSAM, including improved route efficiency, enhanced reliability, and seamless transitions within multimodal networks. This case study underlines the potential of combining innovative models with real-world data to address contemporary transportation challenges effectively.

1 INTRODUCTION

In the context of reducing greenhouse gas emissions, sustainable mobility planning is a major challenge. In France, daily travel, especially between home and study/working locations, significantly contributes to CO_2 emissions, largely due to private car usage (Drouin et al., 2010). Student mobility is particularly important, as students frequently travel for academic purposes. Their rigid schedules and financial limitations make them an important target for sustainable mobility strategies. However, their preference for public transport and active modes like cycling and walking makes them ideal candidates for cost-effective, eco-friendly transport solutions. As such, student mobility presents a valuable opportunity to advance sustainable transportation initiatives.

Integrating multimodal transport is one of the most effective ways to reduce the carbon footprint of daily commutes. This approach combines various transport modes, such as trains, buses, and trams, to meet users' needs flexibly. With the rising ecological awareness, multimodal systems have been expanded to include soft and active mobility (SAM) options like bicycles and scooters (ADEME, 2023), allowing transitions between the different modes of transportation. While studies have explored incorporating shared-SAM (SSAM) as an independent mode of transport (Horstmannshoff and Ehmke, 2022; Delling et al., 2013; Alessandretti et al., 2023) or as a transfer solution between modes (Potthoff and Sauer, 2021; Phan and Viennot, 2019), a notable gap remains in their ability to seamlessly integrate SSAM into transitions between transport systems. Furthermore, there is a lack of integration of personal-SAM (PSAM) throughout the journey while respecting the various constraints of the trip. This limitation prevents the full optimization of the overall SAM into user's journey.

In the modeling of transport networks, two main approaches are commonly used to address temporal constraints in public transport (PT) systems: time-dependent and time-expanded models. Temporal constraints are crucial in PT, where travel times are governed by fixed schedules and vary depending on the time of day. The time-dependent model (Brodal and Jacob, 2004) represents stations as nodes and connec-

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Abdellaoui, R., Caillard, S., Foucras, M. and Baudry, D.
Multimodal Route Planning Integrating Soft Mobility: A Real-World Case Study for Student Mobility.
DOI: 10.5220/0013431400003941

In *Proceedings of the 11th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2025)*, pages 596-604
ISBN: 978-989-758-745-0; ISSN: 2184-495X

tions as arcs, with travel times defined by a monotonic function $f_e(t)$ of the departure time. This ensures consistent travel times and avoids logical inconsistencies. However, the model assumes deterministic travel times, and does not account for delays and uncertainties inherent in real-world systems. Since PT is often affected by operational disruptions, delays, and fluctuating traffic conditions, the time-dependent approach may struggle to accurately capture the real-time dynamics of transport networks. Conversely, the time-expanded model (Pyrga et al., 2008) introduces a temporal dimension by duplicating each node for every vehicle departure and arrival event, offering a more detailed representation of schedules and transfers. However, a major drawback is the substantial increase in graph size, as the number of nodes and arcs grows exponentially with the number of time intervals considered. This makes the model computationally expensive and challenging to scale for large, real-world networks. Despite these limitations, the time-expanded model is particularly valuable for capturing variable schedules and the multimodal nature of journeys (Bast et al., 2015; Lienkamp and Schiffer, 2024; Goel et al., 2016).

This study presents an innovative approach to route planning, introducing additional considerations associated with the integration of soft and active mobility. By incorporating both SSAM and PSAM into a generic model capable of accommodating any number of SAM, the proposed approach enhances flexibility in selecting transport modes throughout a journey. The challenges are then to manage transitions between personal and shared SAMs and optimize their usage based on the user's travel requirements. This approach demands a more nuanced analysis of transport mode choices, temporal constraints, transfer times, and the feasibility of journey continuity, particularly for certain SAMs that require specific authorizations, such as bringing a bicycle onto a bus. This work forms part of the "Mon Trajet Vert" (Mon Trajet Vert, 2025) initiative, which aims to provide dynamic, multimodal, and sustainable route planning solutions tailored to the specific needs of students. To ensure the essential punctuality demanded by students with strict time constraints and to address the temporal complexity and multimodal integration of intermodal journey planning, this work adopts a time-expanded model as an appropriate approach. The problem is described in Section 2, along with the corresponding modeling approach 3. The algorithm developed to solve it is detailed in Section 4. Its results are given in section 5, using real-world data derived from students' schedules, offering a practical alternative to the random data generation methods often employed in existing studies. Finally, section 6 concludes the paper by presenting perspectives and directions for further research.

2 PROBLEM DESCRIPTION

The main challenge of this research is to design a route planning system for the students, that is able of seamlessly integrating various modes of SAM within the multimodal solution of the PT. This includes the integration of SSAM, which requires availability nearby, and PSAM, that provides flexibility without the need for retrieval. We propose to categorize SAM into two types:

- **Heavy SAM (HSAM)** corresponds to devices such as bicycles or scooters, which are not always allowed on PT and cannot be carried in a bag. For instance, trains and trams often have designated areas for hanging bicycles. When these spaces are full, boarding the train with a bicycle is no longer permitted. Similarly, during peak passenger traffic times, boarding public transport with an HSAM may be restricted.
- **Light SAM (LSAM)** is the rollerblades or skateboards, and are devices that are unconditionally allowed on PT and can be easily combined with HSAM.

Several assumptions are considered in this work:

1. SSAM lies in the HSAM category.
2. We cannot use two HSAM simultaneously, nor carry one while using the other.
3. PSAM can be Heavy (HPSAM) or Light (LPSAM).
4. Because of assumption 1, 2, and 3, SSAM cannot be used with HPSAM. Indeed, it is useless for a user that already have a personal bicycle to rent another bicycle.

Each student has a specific request type, which can be categorized as either campus-to-home or home-to-campus. This distinction allows for tailored optimization of route planning:

- For a home-to-campus request, the objective is to maximize the departure time while guaranteeing arrival at a fixed time, such as the start of classes.
- For a campus-to-home request, the goal is to minimize the arrival time while respecting a fixed departure time, such as the end of classes or activities.

Given that our target audience is students, the reliability of routes becomes a crucial consideration for home-to-campus trips, where arrival time is known, and timely arrival is critical. PT systems are subject to unforeseen events, such as delays or operational disruptions, while SSAM systems can also suffer from reliability issues, such as the unavailability of bicycles or scooters upon arrival at a station. These uncertainties may result in missed schedules or delayed journeys. Consequently, even a well-planned route may lead to tardiness. To address this, in addition to departure time, a ranking of possible routes is performed to propose the most reliable options. This ranking considers factors such as transport frequency, punctuality, number of transfers, and available spaces for SSAM.

3 MODELIZATION

The proposed model, illustrated in Figure 1, is a directed graph $G = (N_{PT} \cup N_{SSAM}, A_{PT} \cup A_{SSAM} \cup A_{TFR})$ structured into two distinct layers: the public transport layer $l_{PT} = (N_{PT}, A_{PT})$ and the shared soft and active mobility layer $l_{SSAM} = (N_{SSAM}, A_{SSAM})$. Here, N_{PT} and N_{SSAM} denote the sets of vertices, while A_{PT} and A_{SSAM} represent the sets of arcs for their respective layers. Additionally, a specific subset of arcs A_{TFR}, represented as yellow dotted lines in Figure 1, enables transfers between modes of transport. For instance, a transfer can occur from a bicycle in the SSAM layer to a bus in the PT layer, or between a bus and a train within the PT layer.

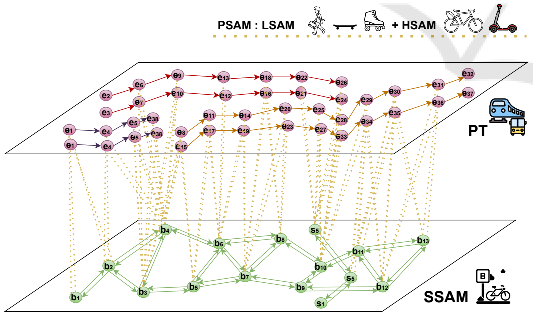

Figure 1: Representation of the multimodal transportation network.

3.1 Public Transport Layer

It represents a time-dependent transportation system and is structured around predefined events, trip and routes, as shown in Figure 2. Let be R, T and N_{PT} respectively the set of routes, trips and events. An event $n \in N_{PT}$ corresponds to an arrival n_{arr} and departure n_{dep} times at predefined schedules of a vehicle at a station n_s. Each event is associated with a parameter n_{aHSAM} a boolean (true or false) that indicates whether boarding the vehicle is allowed at this schedule using a HSAM. Additionally, events are characterized by a reliability parameter n_{rel}, which is detailed further in Section 4.1. Each event belongs to a unique trip. A trip $t \in T$ is a sequence of events and then corresponds to a specific journey, from station to station at defined schedules. Finally, each trip follows a unique route $r \in R$, which corresponds to a specific transit line r_{line}. A route is carried out by a specific type of vehicle r_{type} such as a metro, tram, or bus, and corresponds to a path that starts from a departure station r_{start}, stopping at different stations in a predetermined order, until reaching an arrival station r_{end}. We note r_n the route to which the event n belongs.

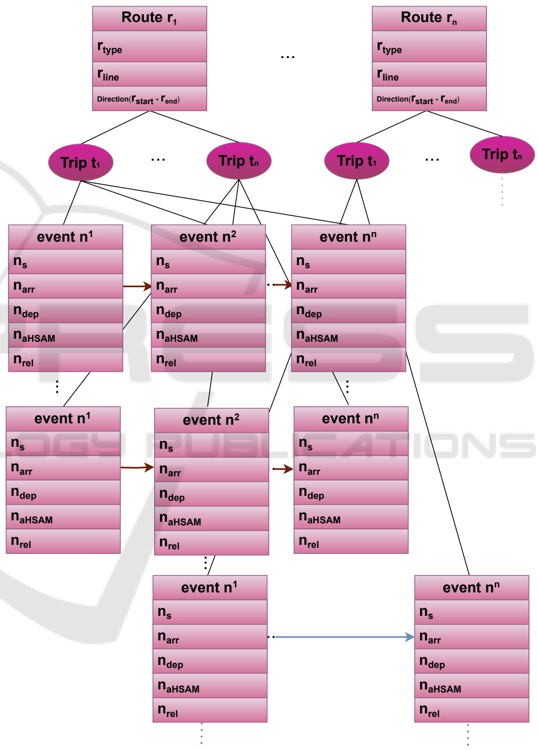

Figure 2: Representation of the PT network.

3.2 Shared Soft and Active Mobility Layer

It captures the stations and potential connections for shared mobility options such as bicycles and scooters. N_{SSAM} corresponds to the SSAM stations, and A_{SSAM} is the set of arcs between stations. Each station $n \in N_{SSAM}$ is identified by an ID n_{id}, and in addition to its location n_{loc}, it has the following attributes: $n_{cappick}$, which indicates the available capacity for picking up vehicles, $n_{capdrop}$, which gives the capacity for dropping off vehicles. The values of $n_{cappick}$ and $n_{capdrop}$ are dynamically updated in real-time during each user query, reflecting the actual capacity at the time of the request. Additionally, each station is characterized by n_{type}, which indicates the type of the station itself (e.g., bicycle station, scooter station, etc.).

The set of arcs A_{SSAM} represents possible transitions between stations. An arc $(n^1, n^2) \in A_{SSAM}$ is weighted by its travel time $\tau_{SSAM}(n^1, n^2)$. It is an estimation of the distance between n^1 and n^2 (using a route adaptation tool like OSRM) multiplied by the speed associated to the vehicle type n^1_{type}. An edge $(n^1, n^2) \in A_{SSAM}$ only if:

1. $n^1_{type} = n^2_{type}$ and $n^1 \neq n^2$, meaning that only stations of the same type are linked. We cannot drop a scooter to a bicycle station.
2. $\tau_{SSAM}(n^1, n^2) \leq \tau^{max}$, where τ^{max} is the maximum threshold duration, that ensures a device is not rented for distances considered too far by most users.

3.3 Transfers Arcs

The management of transfers requires additional adjustments to our model. A transfer is the transition from one mode of transport to another using SAM, involving a change in the means of transport used to continue the journey (switch from bus to train), or a transition into two different route of a same/different transport type (for example, switch from bus line C1 to bus line E5 or to train n°1235). Instead of adding a dedicated transfer node, we chose to introduce arcs between the nodes of different trips when it is feasible in regards with the operational constraints and the schedules.

Each arc $(n^1, n^2) \in A_{TSF}$ (the set of transfer arc) represents the possibility to go from vertex n^1 to n^2 using one or more SAM. Then, arcs are associated with multiple weights. We note $\tau^{tsam}_{(n^1,n^2)}$ the time required to traverse arc (n^1, n^2) with the SAM of type *tsam*. To generate transfer arcs, and because there are several constraints to respect that are specific to HSAM or LSAM, we proceed per stage. First stage, we generate all feasible arcs with the fastest HSAM in regard to the constraints. Then we iterate over type of HSAM to compute weight associated to arcs. The second stage proceeds identically with LSAM, but only generates arcs that were not previously created during the first step. If the arc already exists, the LSAM type-specific weight is directly added to it. Below, the list of constraints to respect according to the kind of transfers:

First, each arc $a \in A_{TSF}$ must respect a maximum threshold duration to avoid transfers deemed too long ($\tau^{tsam}_{tsf}(a) \leq \tau^{max}$). Since the time required to travel an edge depends on the SAM used, each of which has specific average speeds, it is possible to reach certain stations with one type of SAM but not with another. Similarly, if a station n does not accept HSAM (i.e., $n_{aHSAM} = \text{false}$), then $\tau^{tsam}_{tsf}(a)$ is set to ∞, as transfers are infeasible in both cases.

We will now describe the various kinds of transfer that can be performed and their specifics constraints:
Inside PT layer: $(n^1, n^2 \in N_{PT})$ to do a transition from a route to another $(r_{n^1} \neq r_{n^2})$. The arrival time at vertex n^1 plus the time required to go to n^2 must be less or equal to the departure time at n^2 $(n^1_{arr} + \tau^{tsam}_{(n^1,n^2)} \leq n^2_{dep})$. In addition, if $n^1_s = n^2_s$, the transfer occurs within the same station. If $\tau^{tsam}_{(n^1,n^2)}$ is allowed, then the time considered is $\tau^{walking}_{(n^1,n^2)}$. Notably, even when using a bicycle, transfers within a station are performed on foot because it is neither permitted nor appropriate to do so by bicycle. Figure 3 illustrates these two cases: an outside-station transfer (Figure 3a) and an inside-station transfer (Figure 3b).

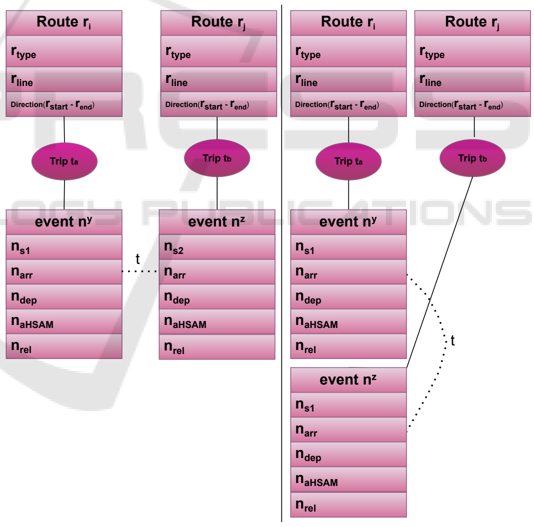

Figure 3: Representation of Event Transfers within PT layer outside-station(a) and inside-station(b).

From PT/SSAM to SSAM/PT Stations: $(n^1 \in N_{PT}$ and $n^2 \in N_{SSAM})$ or $(n^1 \in N_{SSAM}$ and $n^2 \in N_{PT})$ to switch from PT to SSAM of any kind in order to reach the final destination, or a station in PT that is far way for a light PSAM. In addition, in case of transfer from SSAM to PT, and if the user wants to keep the SSAM device with him, n^2_{aHSAM} must be true. Indeed, the user will not be allowed to board in the vehicle during busy periods. Otherwise, only arcs with light PSAM are generated. Figure 4 illustrates possible transfer arcs from a station n^i in SSAM layer to events related to different stations in PT layer. The fastest LSAM and HSAM zones represent the maximum distance a user can travel using LSAM or HSAM, respectively, within the time threshold τ^{max}. Note that station n^2 is accessible using a HSAM since n^2_{aHSAM} is true, whereas this is not the case for station n^1.

Inside SSAM Layer: $(n^1, n^2 \in N_{SSAM})$ to use another type of SSAM device $(n^1_{type} \neq n^2_{type})$. Figure 4 represents the transfer arcs associated with station n^i of type n^i_{type1}. We observe that only stations of $type2$ within the fastest LSAM zone are linked. Indeed, we chose to not include HSAM in these transfers, as it would make little sense for a user to rent a bicycle when they already own and use one.

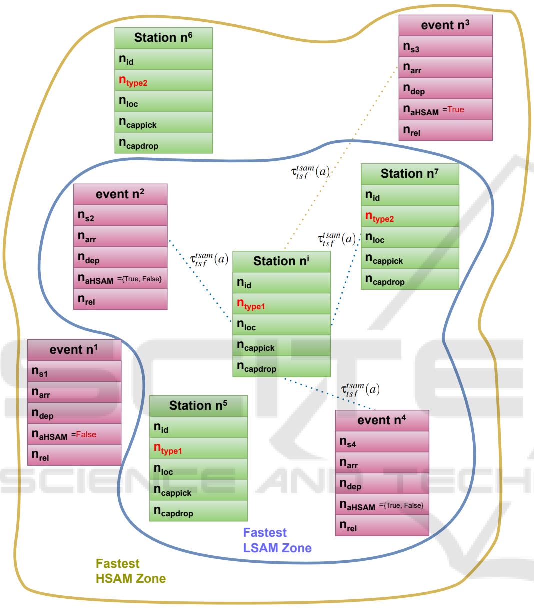

Figure 4: Transfer Arcs in SSAM and PT Layers: Inside SSAM and Between SSAM and PT Stations.

4 PROPOSED ROUTE PLANNING ALGORITHM: INTEGRATION OF SAM WITH RAPTOR

4.1 Description of the Solution & Objective

The proposed solution is designed to address journey requests from students, considering their mobility options and constraints. A student u is characterized by:

- A latest acceptable arrival time (deadline) u_{dl} (for home-to-campus) or a departure time $t_{\text{dep},u}$ (for campus-to-home).
- A personal mobility list u_{psam}, which includes available modes such as HSAM or LSAM. By default, all students are assigned an LSAM of type "walking."
- Departure and arrival locations $(u_{\text{start}}, u_{\text{end}})$, defining the origin and destination of the journey.

Let be S_u the set of solutions proposed to the student u. A solution $s \in S_u$ is described as a sequence of events $\mathcal{E}_u = \{e^1, e^2, \ldots, e^k\}$, which defines the journey from the starting point to the destination. Each event e^i represents a specific action or transition during the journey. If the event belongs to the PT layer, it is characterized by a specific trip t_{e_i}, corresponding to a route $r_{t_{e_i}}$ that defines the transit line and schedule, as well as the station s_{e_i}, with its associated arrival time t_{arr,e_i} and departure time t_{dep,e_i}. If the event belongs to the SSAM layer, it is defined by the mode of transport m_{e_i}, such as cycling, along with the start and end locations s_{start,e_i} and s_{end,e_i}.

A solution $s \in S_u$ is selected based on the optimization of the journey duration, as described in Section 2. Specifically, the optimization focuses on either maximizing the departure time for home-to-campus trips or minimizing the arrival time for campus-to-home trips, while respecting the corresponding time constraints.

Once the optimal journey in terms of departure or arrival time has been determined, the total reliability of the solution is used as a ranking criterion to select the most robust route. The reliability of a journey is computed by considering the reliability of public transport (PT) stations ($\sum F_{\text{PT}}$) and shared soft and active mobility (SSAM) stations ($\sum F_{\text{SSAM}}$), penalized by the number of transport mode changes ($N_{\text{transfers}}$), as defined by Equation (1).

$$\text{Total Reliability} = \frac{\sum F_{\text{PT}} + \sum F_{\text{SSAM}} + \beta \cdot N_{\text{transfers}}}{N_{\text{transfers}} + 1} \tag{1}$$

In this formulation, β is a positive coefficient that determines the weight of the penalty applied to the reliability based on the number of transfers. The reliability of PT stations (F_{PT}) is determined as the product of a weight α_m, representing the punctuality of the specific transport mode m (e.g., metro, train, tram, or bus), and the service frequency f_i', expressed as the number of services per hour at a given station. For SSAM stations, the reliability (F_{SSAM}) is calculated as the ratio between the available capacity ($C_{\text{available}}$), defined as the number of available units (e.g., bicycles or scooters), and the maximum capacity ($C_{\max}$), which represents the total number of units the station can accommodate.

4.2 Resolution Method

Our resolution approach, illustrated by the diagram in Figure 5, is based on greedy algorithms, with tasks from the original algorithm depicted in blue and our contributions shown in white. In our study, we apply this methodology to the RAPTOR algorithm (Delling et al., 2015), which is recognized as one of the best algorithms for public transit networks. RAPTOR operates in rounds, where each round represents a potential transfer. The algorithm traverses each transit line at most once per round, calculating arrival times to minimize both travel time and the number of transfers.

In our case, we have enhanced this approach by integrating the management of soft and active mobility (SAM). The algorithm evaluates specific transfer times based on the mobility modes used, ensuring a smooth transition between different types of SAM and public transit. Leveraging this method, our approach provides feasible and reliable journeys, addressing the specific constraints of heavy and light SAM while maintaining the efficiency of RAPTOR for processing complex networks.

To explain this diagram in more detail, we assume that each user starts their journey with a PSAM, which consists of HSAM and LSAM. For each PSAM, the algorithm calculates a route based on the associated type of mobility (HSAM or LSAM). If the PSAM is an LSAM, the algorithm searches for the best route using both the PT and SSAM layers. Each time the user passes through an SSAM node, the algorithm assigns SSAM = 1 - SSAM. This prevents the algorithm from proposing routes that pass through SSAM nodes without taking or dropping off a vehicle, thus avoiding unnecessary transitions. Furthermore, each time SSAM = 1, the public transport event nodes ($n \in N_{PT}$) must have n_{aHSAM} = true, meaning these stations must allow HSAM onboard. A route is valid if it ends with SSAM = 0, ensuring that the SSAM is properly returned. If the PSAM is an HSAM, the algorithm uses only the PT layer and selects only the event nodes with aSAM = true.

This approach provides optimal routes for each user by considering the available modes of soft mobility (HSAM or LSAM) and ensuring the necessary transfer conditions are met.

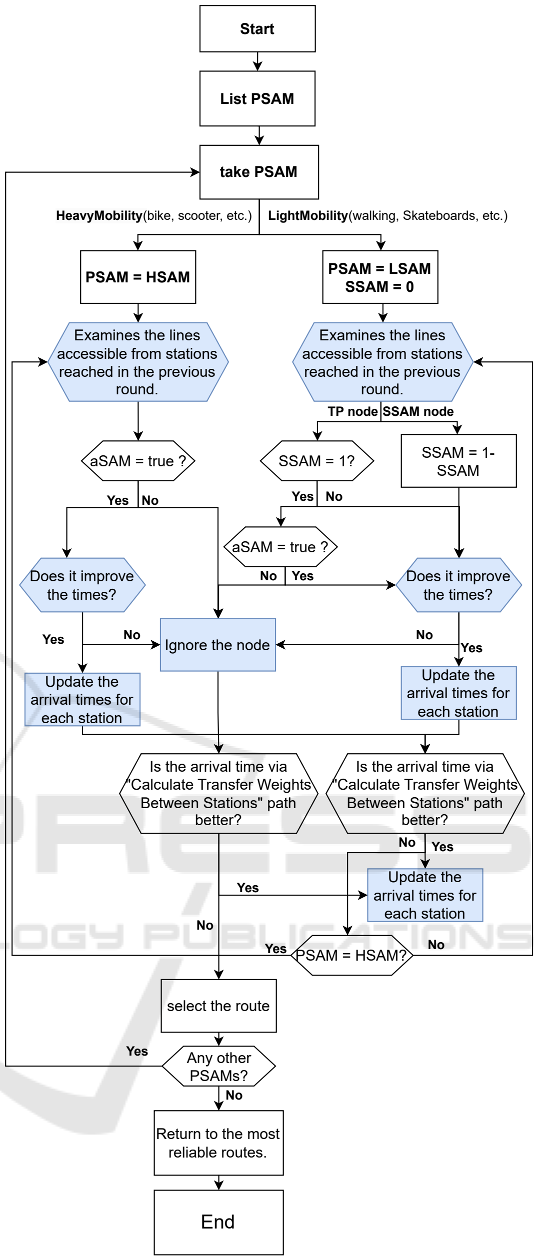

Figure 5: Diagram illustrating the proposed approach.

5 EVALUATION AND RESULTS

5.1 Real-World Data

The data used in this study come from three main sources for Strasbourg city in France.

Bike-sharing data includes 32 stations located across the city, with a total of 265 links connecting stations within a 5 km radius. These stations are equipped with varying numbers of bike docks, and the data provide insights into the availability of bikes and docking stations. This network forms the basis for evaluating the integration of bike-sharing as a transfer mode in multimodal route planning. Additionally, real-time availability of bikes and docks is obtained through an API provided by the city of Strasbourg (Velhop, 2025).

Public transport data for Strasbourg include information from several sources. GTFS data from the CTS (Compagnie des Transports Strasbourgeois) network were collected from the national platform for public transport data in France (Ministère du partenariat avec les territoires et de la décentralisation, 2025b). Additionally, schedules for the TER SNCF lines were integrated, filtered to retain only stations within a 100 km radius of Strasbourg (Ministère du partenariat avec les territoires et de la décentralisation, 2025a). The resulting network includes 2,513 stops distributed across 115 routes, supporting a total of 31,344 daily trips. It also records 416,124 stop times and 2,418 transfers between stops.

Furthermore, the study uses data collected from **student trips from CESI Strasbourg**, comprising a total of 371,063 instances. This dataset contains relevant information such as the locations of students' homes and the campus, as well as the course schedules of each student, allowing us to identify the times when students travel to or from campus. The dataset includes 987 students, and the selected day, May 21, 2024, shows the highest number of recorded trips, with 285 trips for the home-to-campus and campus-to-home journeys.

5.2 Results

For our experimentation, the weights (α_m) used for calculating the reliability of public transport (PT) stations were defined based on the punctuality of specific transport modes available in Strasbourg. The values were set as follows: tram = 0.5, bus = 0.25, and train = 1. It is important to note that there is no metro system in Strasbourg, so no α_{metro} was considered.

These values were used as approximations while awaiting real-world data. The actual data will be derived from the difference between the theoretical GTFS schedules and the historical GTFS data, which reflect the real-time operation and delays of the transport system. This will allow for more accurate calibration of the reliability weights (α_m) in future work.

Table 1 provides a comparison of the different approaches using real-world data based on three key criteria: the percentage of solutions found (*% of Solutions Found*), the average journey time (*Avg Journey Time (s)*), and the average reliability (*Avg Reliability*).It is important to note that the reliability values range between 0 and 1, with 1 representing the highest possible reliability.

Table 1: Comparison of different approaches in terms of solution percentage, journey time and reliability.

Approach	% of Sol Found	Avg Journey time(s)	Avg Reliability
PT	93%	2673	0.31
PT + SSAM	93%	1933	0.44
PT + SSAM + PSAM	100%	2699	0.51

The results highlight some interesting insights into the performance of the different approaches. The slightly higher average journey time for the **PT + SSAM + PSAM** approach is explained by the fact that it considers 100% of the requests, including the 7% of requests not covered by the other approaches. Because our approach achieves 100% solution coverage, it naturally includes more distant locations, which inherently require longer travel times.

Furthermore, the fact that the **PT + SSAM** approach does not find more solutions than **PT** alone is due to the specific context of Strasbourg, where **SSAM** stations are generally located close to public transport stations. This proximity limits the ability of **SSAM** to fill gaps in areas far from public transport. Nevertheless, the **PT + SSAM** approach remains effective in optimizing the average journey time by leveraging the availability of shared mobility options near public transport stations.

This demonstrates the effectiveness of integrating both **SSAM** and **PSAM** into the routing methodology. Figure 6 provides an example illustrating how traditional methods (without **PSAM**) fail to identify adequate routes for certain complex scenarios. By incorporating **PSAM**, our approach successfully proposes efficient and realistic routes tailored to real-world conditions.

In addition to **PSAM**, **SSAM** also led to significant route optimizations, providing more effective solutions in terms of travel time and reliability. Figure 7 presents an example where the integration of **SSAM** results in improved routes, maximizing the benefits of shared soft mobility within the multimodal network.

6 CONCLUSIONS

In this study, we proposed an innovative solution for multimodal route planning tailored to the mobility needs of students, integrating both shared and personal soft mobility into public transport systems. By

Figure 6: An example of the limitation of solutions that do not use PSAM.

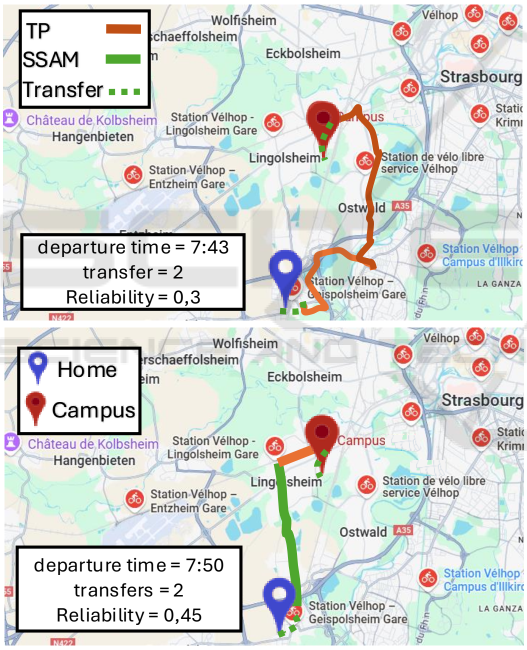

Figure 7: An example of the difference between a solution considering the SSAM and one considering only the PT.

focusing particularly on the reliability of journeys, we aim to provide a comprehensive and practical solution to the challenges faced by students. The approach also seeks to extend mobility solutions to locations farther from traditional public transport networks. Thus, students living in isolated areas are no longer forced to rely on personal cars, encouraging a shift toward more sustainable transport modes. Using real data from students also allows us to concretely evaluate the impact of this solution on their daily commutes.

A key direction for future research is to enhance our approach to reliability by leveraging real-world data on the punctuality of various transport modes concerning their schedules. In addition to the tests conducted in Strasbourg, this project aims to extend experiments to multiple university campuses across France, including Paris Nanterre, Rouen, La Rochelle, Toulouse, and Lyon. This selection will allow us to assess the model's robustness by considering the diversity of campuses from different perspectives. Expanding the study in this way seeks to ensure the generalizability of the results and refine recommendations for the broader integration of bike-sharing as a transfer mode in multimodal route planning.

It would also be relevant to compare the optimized routes in terms of CO_2 emissions and costs against traditional transport modes.

ACKNOWLEDGEMENTS

This work has been supported by the Mon trajet vert project (previously MobE) in the framework of the French energy saving certificate program (CEE).

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