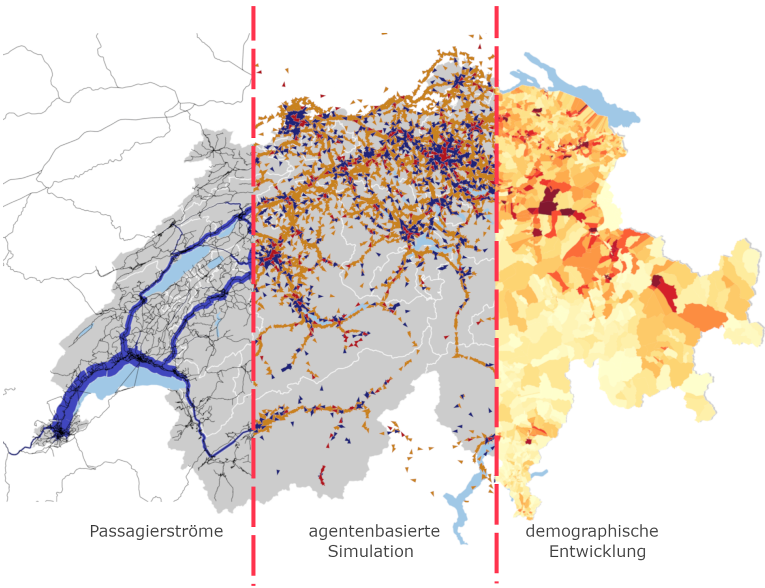
Differentiation of Modal Preferences in Public Transportation:

Analysis and Enhancement of the MOBi Model for Scenario Simulation in Lausanne



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Abstract

Rail and light rail are often preferred over bus due to their higher level of service and better readability. This rail or light rail bonus indicates a user preference for rail-based systems even when service levels are comparable. However, quantifying this preference remains challenging. Stated and revealed preference (SP/RP) surveys struggle to capture the complexity of this behavior. Additionally, constant recalibration of alternative-specific constants (ASCs) is necessary for accurate modeling.

We address these challenges by using observed count data to differentiate public transport modes in Lausanne, Switzerland. Enhancements were made to the SIMBA MOBi model, the activity-based, agent-based demand model of the Swiss Federal Railways. It includes improved modeling of student behavior, car availability, and campus attractivity. The calibration and validation of constants for different public transport modes improve the model's accuracy. The new model was tested with data from Lausanne and applied to a fictive scenario of the city's upcoming tram line.

The results confirm a preference for light rail over buses. The enhanced model accurately predicts passenger demand and mode preferences, capturing competition between bus and light rail. It demonstrates its potential to estimate the impact of new transit infrastructure. This study provides a reliable tool for improving urban transit planning and supports the development of sustainable decision-making for public transport systems.

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1 Introduction

Metro and tram lines are often perceived as superior to buses. This preference comes from their higher level of service (greater frequency, reliability, and comfort) and from their better readability, with fixed routes that are easy to understand and navigate. Moreover, compared to buses, tram lines are separated from the traffic network, avoiding traffic jams. This assumption, often referred to as the rail or light rail bonus, suggests that users prefer rail-based systems over buses even when service levels are similar.

Even though this assumption is widely accepted, accurately quantifying and predicting it remains a challenge. Stated preference (SP) surveys, used to analyze transportation choices, have struggled to capture the complex factors behind this phenomenon in a way that allows for reliable predictions. In Switzerland, attempts to differentiate public transport modes in SP surveys have not been successful. As a result, this differentiation will not be continued in the next 2025 SP survey. However, it is still useful to find a model that accurately predicts user preference. In Lausanne, a new tram line is set to open in 2026. Although the project has already been approved, it is important for operators to accurately estimate passenger demand to plan the required rolling stock. As part of this project, understanding user preferences will help create scenarios and predict how many people will use the tram. To address this gap, we use count data from transportation companies, specifically passenger counts. By analyzing observed data, our goal is to understand the differentiation between public transport modes and refine models that can predict user behavior more accurately. This study focuses on leveraging count data to improve our understanding of public transport preferences and improve simulation models for decision-making in urban transit planning.

This report explores the differences in public transport modes. We look at how this can improve urban transit planning. First, we review the existing research to understand the key ideas and findings on this topic. Then, we describe the SIMBA MOBi model, explaining its main components and current state. Next, we suggest improvements to the model to accurately predict traffic flows in the Lausanne region. Only then, we focus on how to account for tram and bus preferences. Finally, we test the updated model and apply it to the Lausanne tram project. This shows how the model can predict passenger demand and support planning decisions.

2 Literature review

2.1 Historical point of view: Superiority of rail over bus alternatives

Developing a new public transport line requires to define the type of rolling stock. Subways and tramways have higher investment costs than buses. However, users may prefer light rail over buses. It is therefore important to understand users' preferences for each mode of public transport, to make informed decisions.

The debate over the superiority of rail versus buses has been widely discussed in the literature. Vuchic and Stanger (1973) compared a train line and a bus system serving the same corridor in the United States. The Lindenwold single rail line proved to carry 70% more passengers. He showed that the train was more efficient than the bus due to all-day service, simpler operations, and higher service quality. However, the train was more expensive to build and operate, requiring greater investment from authorities.

Babalik-Sutcliffe (2002) analyzed the factors that indicate whether an urban rail system is successful after implementation. He highlighted five key factors:

- High patronage, which corresponds to the number of passengers using the service,
- Cost-effective construction and operation,
- Increasing public transport use,
- Reducing traffic congestion and pollution,
- Improving land use and urban growth.

However, he warned that the impact of rail on traffic is often overestimated. Mackett and Edwards (1998) also have a critical view. They argued that politicians' expectations on rail can be too high compared to reality. They showed that light rail projects do not always have the expected impact on traffic.

The previous studies show the need to have a model that can accurately predict the difference in public transport usage depending on the type of public transport (rail-based or not). While these authors agree that both public transport systems are useful and complementary, they never analyze users' preferences for these two modes of transport. This is what we will explore in the rest of this literature review.

2.2 Preference-Based Models for Public Transport Modal Differentiation

The question of preference between modes can be addressed through choice experiments. The goal of such experiments is to analyze user preferences for different public transport modes. They allow to estimate parameters that can be latter used in transport models. Such models thus reproduce behavioral trade-offs that travelers do and provide forecasts as decision-aid tools.

In public transport, the question of rail's advantage over bus alternatives has been widely studied. Cohen-Blankshtain and Feitelson (2011) pointed out that light rail projects can be irrational to finance. However, they can serve two specific purposes: either responding to existing demand or inducing new demand by improving accessibility. Our goal is to have a robust tool to understand the impact of both types of projects.

To define whether a transport mode is attractive for users, Göransson and Andersson (2023) conducted a comprehensive literature review on the factors that make a public transport system attractive. The main factors identified are related to service level, such as reliability, frequency, waiting time, transfers, and distance. Only after these factors are satisfied do "soft" factors like comfort and safety become important for users.

Bunschoten, Molin, and Nes (2013) analyzed user preferences for different public transport modes to determine whether the "tram bonus" really exists. To do so, they conducted a stated preference survey, asking users to choose between a bus and a tram for a given trip. The stated preference survey allowed them to create a hypothetical scenario where the service level was the same for both options. They used five service level attributes (frequency, access and egress time, in-vehicle travel time, transfer and waiting time). By simply analyzing the alternative specific constant for trams in their logit model, they showed that users seem to prefer trams over buses. The results were similar when using a panel mixed multinomial logit model.

To go further in their analysis, they also asked questions about perceptions of characteristics such as comfort and information availability, asking users which mode of transport they preferred for each characteristic. They combined these factors using factor analysis and integrated them into a new model using effects coding. Three variables produced significant results (atmosphere, comfort, travel information). This new model showed that these variables were perceived more positively for trams and that they impacted users' preference for this mode of transport. Once these variables were integrated into the model, the ASC for trams became insignificant, proving the impact of these characteristics.

However, in his report on public transport in Dresden (DVB), Axhausen et al. (2001) is more moderate in his conclusion. His model included multiple data sources such as a one-day travel diary and two stated preference surveys, one within mode and one within public transport modes. He showed that there is a light rail bonus, but it is relatively weak. He demonstrated this through "lower willingness-to-pay for travel time improvements, lower disutility of in-vehicle time, higher valuation of new and improved vehicles, but also a higher transfer penalty." He also pointed out that frequent public transport users have a higher preference for trams. This is in line with Bunschoten, Molin, and Nes (2013)'s segmentation analysis.

Ben-Akiva and Morikawa (2002) are even more critical in their conclusion. They show that analyzing the alternative specific constant is not enough to conclude a preference for light rail or train. In fact, the higher value is due to a dislike of transfers in other modes. Their analysis, based on a combination of revealed and stated preference data, showed that the rail bonus is not significant if the service level is the same. Therefore, it is important not to introduce bias in choice models by adding a rail bonus, but instead to consider more complex demand characteristics. Train (2003) also points out that the alternative specific constant is difficult to estimate. However, it is always necessary to recalibrate it.

Scherer (2011) analyzes user preferences for different public transport modes using latent variables. Her goal is to identify the cause of this preference through the image that people have of public transport modes. This would allow us to model more precisely where this bias comes from. Her study was conducted in Switzerland with residents of Bern, Lucerne, and Zurich, three cities with a wide choice of buses and trams. According to the results of her differential semantic attribution survey, trams receive more positive ratings than buses, except for stop location, noise, and speed. Twelve rational aspects are rated statistically higher than for buses. However, for affective-emotional aspects, the difference in perception between buses and trams is not statistically significant. To continue her analysis, users were segmented into three groups: frequent users, occasional users, and non-users. The results show that frequent users have a more positive image of trams than occasional users and non-users. This aligns with the literature. The highest ratings for trams are for traffic flow and environmental friendliness. These positive perceptions of trams influence users' mobility choices. However, a model that incorporates these attributes is missing, such as in an Integrated Choice and Latent Variable model (ICLV).

Dubé, Legros, and Devaux (2018) analyze the impact of shifting from a bus rapid transit line to a light rail transit on the real estate market. They proved that the market responds to such a large project from the moment it is announced, with localized effects up to 500m from the stations. This shows the limits of a choice model, which would not account for these indirect effects when predicting user numbers. Light rail systems improve accessibility, and increase land and property values (D. Knowles and Ferbrache 2016). Modelling its full impact thus needs a land use and economic development model. From a policy point of view, it requires coordinating transport and urban planning (Gallez et al. 2013, Kaufmann and Sager 2006). This is out of scope for a discrete choice model, but can be integrated in a transport model, when combined with a land use model.

In this subsection, simple models show a clear tram bonus, suggesting that users prefer trams over buses. However, deeper analyses of alternative-specific constants (ASC) and more complex attributes prove that this initial tram bonus is not always significant. Instead, it highlights that specific characteristics, such as comfort or travel information, play a larger role in shaping preferences. Then a more complex model should take into account these differences. Finally, the perception of the different modes across different segments of population seems to play an important role.

In Switzerland, differentiation in the stated preference survey will not be pursued (Federal Office for Spatial Development 2024). It has proved too complicated to differentiate within public transport. For this reason, it is interesting to analyze this differentiation using a different type of data.

More generally, estimating the alternative specific constant from choice data is considered difficult due to various sources of errors (see e.g. Ben-Akiva and Morikawa 2002). It is common practice to use aggregate measurements to calibrate the alternative specific constant. This allows to match aggregate market shares. A heuristic is e.g. suggested in Train (2003).

2.3 Simulation-Based Models for Public Transport

As of today, no literature has been found about differentiation across public transit in MATSim scoring. In their report, Marburger and Kaddoura (2021) integrate different types of public transport into MATSim using conversion models and the LinTim tool. Both methods successfully generate public transport schedules. However, they do not consider user preferences for different modes of public transport. Their focus was more on a realistic representation of the number of vehicles needed for each mode of transport.

Chayan and Cirillo (2024) also discuss current issues in simulation models for accurately estimating public transport usage at the network and stop levels. They proposed a pipeline with three agent-based travel demand models. The first model deals with synthetic population, the second creates travel demand, and the third uses MATSim as the traffic simulation model. They had to create a multimodal network using OpenStreetMap and integrate public transport schedules. However, for MATSim scoring parameters, they used default values. They did not take into account user preferences for different public transport modes. Their model was robust in their case study of the Washington Metropolitan Area. However, what is interesting for our project is that they warn that education trips are not represented in their model.

This project responds to two different needs. Firstly, decision-makers seem to agree that preferences between public transport modes are difficult to differentiate. What they need is a tool for deciding which mode of transport is best suited to a given situation. Secondly, current choice models fail to isolate preferences between public transport modes. Using count data, rather than stated preference surveys, this project attempts to define a light rail bonus.

3 Model: SIMBA MOBi

In this project, we use the SBB multimodal, agent-based simulation model, SIMBA MOBi. The architecture of SIMBA MOBi consists of several key modules represented in Figure 1 designed to comprehensively represent mobility behaviour.

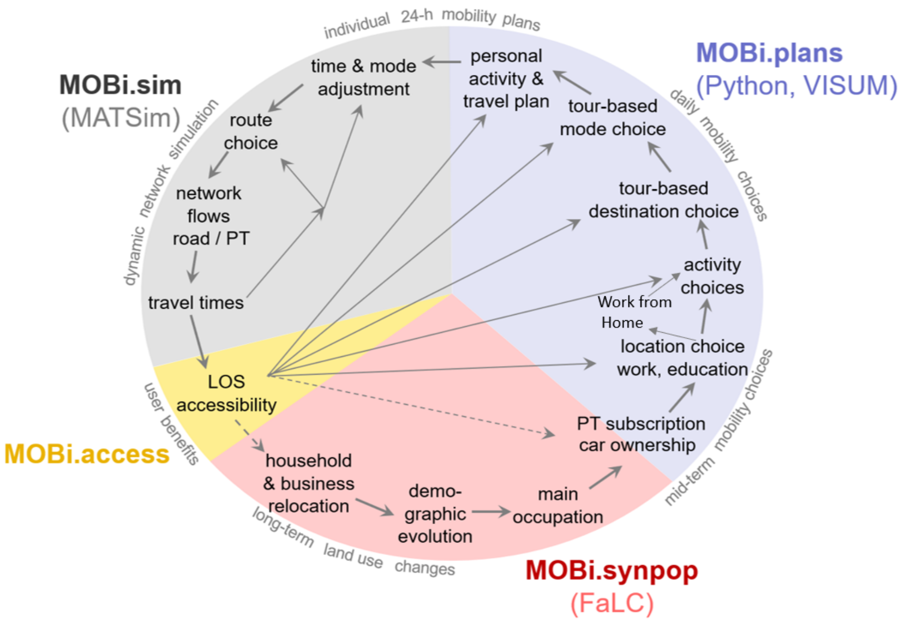


Figure 1: Representation of SIMBA MOBi

The main features of SIMBA MOBi are

- **Coverage:** The model covers the whole of Switzerland and Liechtenstein, including the neighbouring regions such as the trinational Basel area.
- **Multimodality:** It is multimodal, i.e. it considers all relevant transport modes (walk, bike, public transort, car).
- **Agent-Based Approach:** SIMBA MOBi operates at a microscopic level, where decisions are made at the level of individual agents, allowing a detailed representation of mobility behaviour.

SIMBA MOBi provides valuable insights into mobility dynamics in Switzerland. It also has limitations that need to be considered. These limitations come from its reliance on synthetic population data and the challenges of modelling individual behaviour at small spatial resolutions. Understanding these limitations is important for accurately interpreting model outputs and making informed decisions in transport planning and policy.

3.1 Transportation Supply

In addition to the main modules of SIMBA MOBi, the transport services module shapes the mobility landscape within the model. This module is not explicitly shown in the figure 1. It defines for each transport mode the cost, and the possible departure time (for public transport). Factors such as travel time and cost are derived from a road network for cars, a bike network and a time table for public transport. This influences agent decisions within the simulation.

The transport supply includes various services and infrastructure elements, including

- **Pedestrian and bicycle network:** In MOBi.sim, the pedestrian are teleported to their destination. The bycycles agents are routed on the road network, similarly than passengers in car mode (ride). The bicycles paths have been added in the network, as well as the information of the altitude, to get the slope. The travel time is calculated using the distance multiplied with a detour factor and a constant walking/cycling speed.
- **Road Network - MOBi.street:** The whole road network of Switzerland and neighbouring countries is described on MOBi.street. The network is derived from the federal transport model (ARE 2024). It works as a node-edge graph.
- **Motorized Individual Transportation - MIV parking:** This module account for the access time and cost of parking for travellers by car. SIMBA MOBi doesn't simulate how hard it is to find a parking spot. To respond to this problem, parking zones are defined with calculated access times and parking costs.
- **Passenger transport model - MOBi.PT:** In order to simulate the entire Switzerland with MATSim, the network as well as the offer of public transport was implemented in Switzerland. Regarding the railway system, SBB expertise was used in accordance with the new national passenger transport model (NPVM: ARE 2024). Other public transport modes where derived from the national timetable (GTFS 2023).

3.2 MOBi.access

A global, macroscopic accessibility is calculated. Generally, accessibility is defined as "the expected utility of all travel opportunities that can start from a location." The calculation takes into account the attractiveness or capacity of each other location for various activities and the distance from the origin location. It's important to note, however, that these values are representative of zone-to-zone averages and may not accurately capture individual variations.

3.3 Synthetic Population - MOBi.synpop

The synthetic population module, MOBi.synpop, plays an important role in transportation modelling, since it represents the first input in the model. It integrates key features that enable the representation of demographic characteristics and behaviours for mobility simulations.

MOBi.synpop covers 100% of Switzerland's resident population and facilities, with households and facilities geo-referenced by exact x/y-coordinates. It includes socio-economic attributes such as age, level of education, nationality, and income, as can be seen in Table 1, which significantly influence mobility choices and behaviours.

Individuals information	Foreign Nationality	Population movements	Households
Date of birth	Residence permit	Births	Number of private households
Gender (not included)	Duration of stay	Deaths	Number of cars
Marital status		Immigrations	
Nationality		Emigrations	
Place of residence		Acquisition of Swiss citizenship	
Place of birth			
Place of origin			
Household affiliation			

Table 1: The most important variables of the personal and household dataset

The synthetic population was created through collaboration between SBB, the Federal Office for Spatial Development (ARE), and Wälli AG Ingenieure. (Bundesamt für Raumentwicklung (ARE) and Schweizerische Bundesbahnen (SBB) 2024). For the current state (2022), they utilized the FaLC model, integrating data from sources such as STATPOP and STATENT, which contain information on registered Swiss residents and businesses, respectively.

The model ensures realistic population distribution at both macro and microscopic levels. It aims to achieve macroscopic accuracy by respecting cantonal control totals and ensuring that individual households are well-distributed within the synthetic population. Future projections (2030, 2040, 2050) were generated by simulating population ageing and land use dynamics using FaLC, calibrated on historical data and Federal Statistical Office projections. The socio-economic features are simulated and assigned to individuals and households after the aging process, using control totals from various sources for calibration.

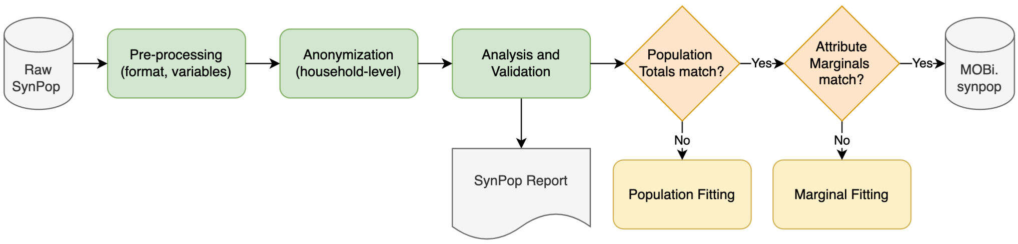


Figure 2: SynPop pipeline

Data within MOBi.synpop is anonymised to protect the privacy of individuals. This process erases the geographical information associated with households, preventing users from identifying specific individuals at specific locations. Instead of generating new coordinates, households within the same NPVM zone have their coordinates randomly swapped. This method preserves the essential characteristics of the zone, such as population size and density, while keeping the household structure unchanged. However, MOBi.synpop has limitations. Quality controls were applied to compare the synthetic population with official projections to ensure accuracy at both macro and microscopic levels. It is adjusted to average values, so results for very small sites should be interpreted with caution. In addition, population adjustment methods were used to adjust for discrepancies between the synthetic population and real-world data.

3.4 Daily activity plans - MOBi.plans

MOBi.plans generates daily activity schedules for each individual based on the synthetic population. This module simulates through logit models and rules various decisions made by individuals regarding their daily activities and mobility patterns.

- Determining the location of permanent activities (workplace and educational institution).
- Identifying the desired number and types of activities an individual executes in a day.
- Bundling activities into tours and determining the sequence of tours and activities within each tour (e.g. HWLH - Home, Work, Leisure, Home).
- Assigning precise geographical locations for each activity.
- Select the mode of transport for each tour or sub-tour.
- Assign the duration and time of day for each desired activity.

The different decision are predicted in the following sequence, see figure 3.

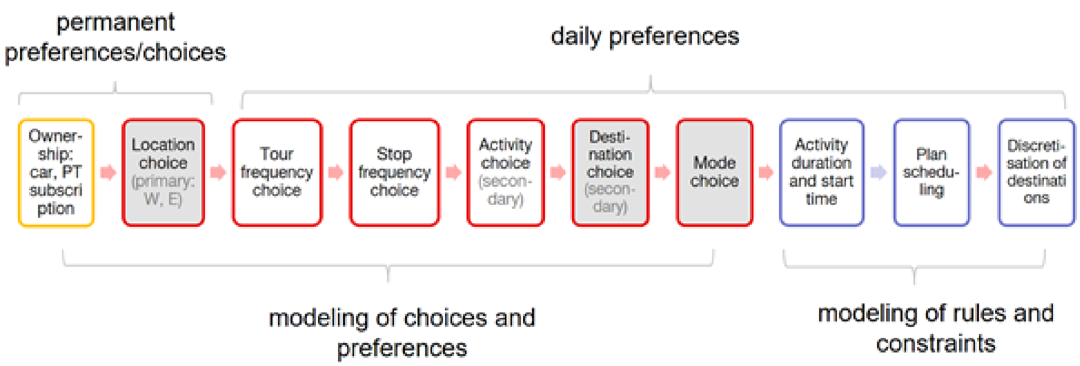


Figure 3: MOBi.plans: Sequence of simulation

3.4.1 Mobility Tool Ownership

The ownership of mobility resources in Switzerland is analyzed through sequential logit models. These models account for individual driving license ownership, household car ownership, public transport subscriptions, and ownership of fast e-bikes (up to 45 km/h). As seen in Figure 4, first the permanent decisions are estimated, then the long-term and only finally the annual/monthly ones, since the prior influences the latter. These models, developed in collaboration with the TRANSP-OR laboratory at EPFL (Hillel et al. 2020), are based on data from the Swiss Mobility and Transport Microcensus (Office fédéral de la statistique 2017 (MTMC)). They aim to estimate a comprehensive mobility tool availability model. The results are integrated into MOBi by estimation with consistent variables, simulation of decisions in MOBi.synpop, comparison with aggregated spatial control totals, and full validation of all models.

Parameter are estimated using maximum likelihood with PandasBiogeme (v. 3.2.13 Bierlaire 2023). Each model includes a range of variables such as age, nationality,

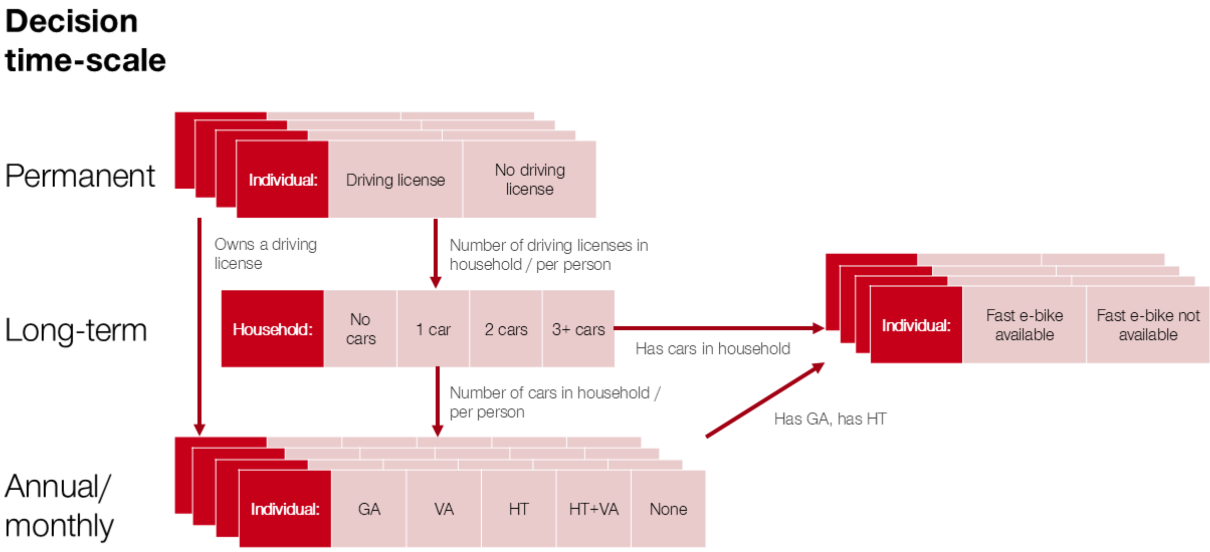


Figure 4: Mobility tool landscape

employment level, household structure, language, accessibility measures and urban type.

The driver's license ownership is modeled as a binary variable with socio-economic characteristics similar to the ones of the car ownership model represented in Table 2.

The household car ownership is represented with the following variables, with 0,1, 2 or 3+ cars for choice:

Socio-economic Factors	**Household Factors**	**Network Factors**
language	Number of adults	Accessibility to cars
single	Number of children	Accessibility to public transport
	Number of driving license	Accessibility to multiple modes
	Urban	Cost of parking

Table 2: Variables used in the model for household car ownership

Public transportation subscription ownership
The public transportation subscription ownership model is formulated as a logit model with five alternatives: General Abonnement (GA), Half-price Travelcard (HT), Half-price and Regional Travelcard (HTV), Regional Travelcard (VA), and no subscription (None). Using demographic, socio-economic, and household factors, the model predicts the likelihood of choosing each alternative. The reference alternative, None, is normalized to 0. Estimation is based on both the 2015 and 2021 MTMC. Variables include car availability, nationality, employment status, age (piecewise formulation), and household information.

Car Availability
Currently, car availability is defined using a simple rule, see Algorithm 1. As shown in Figure 4, the current model determines the number of vehicles in a household based on the number of driving licenses in that household. However, this does not necessarily mean that all individual within the household will have a vehicle available to them. In reality, all individuals with a driving licence within a household owning cars do not necessarily have a car available. There is a competition for the car between the household members.

Algorithm 1 Rule-based Car Availability

Input: Household data and personal data
Output: `car_available` field for each person

Initialize `car_available` for all persons to **False**

For each person:
if person has a driving license **and** number of cars in household > 0 **then**
→ Set `car_available` to **True**
end if

3.4.2 Plans

The location choice model follows the mobility tool ownership models, as seen in Figure 3:

The permanent locations (workplaces and schools) are assigned to individuals who are employed or studying. This assignment is based on personal attributes, such as public transport subscriptions, ensuring realistic spatial distributions of activities. The location and destination choice model is based on a mode choice nested into destination choice. For the trip generation, the number of employees per demand segment and zone are taken into account. The total number of jobs per zone are also used to create attraction factors (A_j being the attraction of zone j). Similarly, the number of students per education type and zone are taken into account for education. The probability of destination j is:

$$p(j|i) = \frac{A_j \cdot exp(\theta \cdot EMU_{ij})}{\sum_k (A_k \cdot exp(\theta \cdot EMU_{ik})}$$

With EMU being the Expected Maximal Utility over all modes and V_{ijm} the utility of mode m for destination j, with origin i:

$$EMU_{ij} = ln\left(\sum_m (\frac{exp(V_{ijm}}{\theta})\right)$$

Calibration and validation steps refine the accuracy of this process.

Next, the tour and activity generation step determines how daily activities are structured. This includes deciding how many tours and sub-tours an agent will make, the number of stops within those tours, and the type of secondary activities at each stop. Such representation can be seen in Figure 5, with one main work tour, with a sub-tour, and an additional “other” tour, with secondary activities only. A tour is defined as a sequence of activities that starts and ends at home. The result is a detailed plan for each agent, specifying the number and sequence of their activities for the day. Estimation of logit

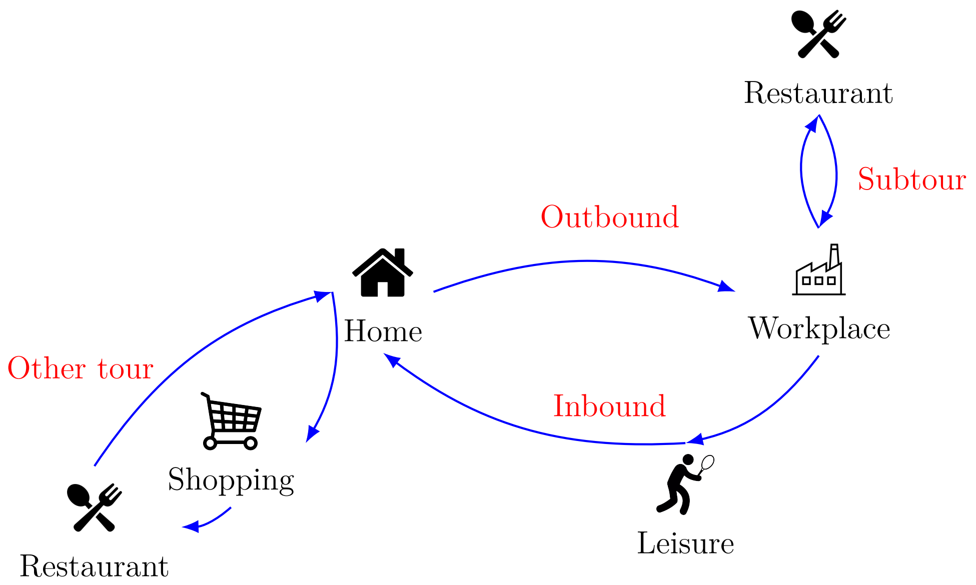


Figure 5: Illustration of the tours and sub-tours in the tour and activity generation model

parameters are done using the MTMC data, with “no other tour” taken as the base alternative. Calibration ensure these choices align with observed behavior.

The destination choice model assigns locations for secondary activities like leisure, shopping, or business. These are selected from 8,000 zones using a rubber-banding method to integrate them into trip chains, creating realistic movement patterns, with realistic distances. Attraction factors are attributed to every activity in every zone. The matrix of attraction looks like:

$$[z, A] = [z, S] \times [S, A]$$

Where the matrix $[z, S]$ integrates the socio-economic variables for all zones z, such as number of jobs, school places. The matrix $[S, A]$ is used to calibrate the rates of attraction.

Attribute	**Attr_A**	**Attr_B**	**Attr_O**	**Attr_EC**	**Attr_L**	**Attr_S**
pop_total	0.03915	0.00258	0.0525	0	0.2382	0
jobs_total	0.0783	0.0559	0.105	0.0625	0	0
visitors Leisure	0.03915	0	0	0	2.382	0
visit Shopping_st	0.03915	0	0	0	0	0.38144
visit Shopping_lt	0.03915	0	0	0	0	0.27416
school enrolment 1	0.0783	0	0	0.0125	0	0
school enrolment 2	0.03915	0	0	0.025	0	0
school apprentice	0.02349	0	0	0.025	0	0
school enrolment 3	0.02349	0	0	0.025	0	0

Table 3: Attraction Values for Various Categories

Activity durations are then calculated to ensure feasibility, followed by iterative plan building, where schedules are fine-tuned to create plausible daily plans. The model also incorporates a tour-based mode choice step to assign transportation modes for each tour. It concludes by calibrating and setting activity start times to align with realistic travel behavior.

3.4.3 Working from home

Another significant module in MOBI Plans is the working from home component. This module is important for understanding the impact of telecommuting on overall travel demand and congestion, as well as for planning future transport policies.

The "Working from Home" module in SIMBA MOBi uses a binary logit model (Danalet, Balmer, et al. 2022) based on data from the Mobility and Transport Microcensus 2010, 2015, and 2020. The synthetic population used includes the 2021 base with predictions for 2030, 2040, and 2050. The model distinguishes between two alternatives: "some home-based telecommuting" (answering "yes" or "sometimes" to working from home and reporting a work percentage higher than 0) and "not working from home at all". The attributes in the model include socio-economic and household information, transport accessibility, and work-related details such as business sector. These variables are essential for predicting the likelihood of telecommuting among different population segments.

3.5 Simulation - MOBi.sim

The simulation predicts a travel plan for each agent for a common day. Depending on the number of iterations, the same day will be resimulated with slight changes. The number of iterations must be chosen in order to have a model that converges. Figure 6 represents the loop carried out at each iteration (Horni, Nagel, and Axhausen 2016).

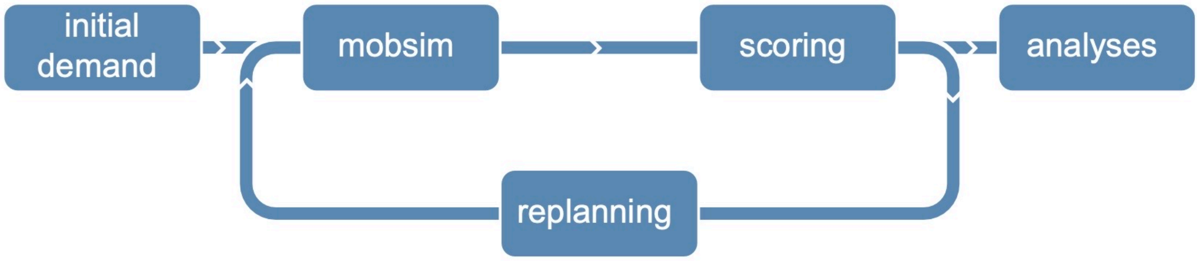


Figure 6: MATSim loop

The *initial demand* includes every agent's daily activity chain, produced for the population in the study area. It corresponds to the output of the MOBi.plans module. During each iteration, the goal is to optimize the travel plans of each agent. The metric used to compare these plans is an econometric utility. The score for each plan is computed as follows:

$$S_{\text{plan}} = \sum_{q=0}^{N-1} S_{\text{act},q} + \sum_{q=0}^{N-1} S_{\text{trav,mode}(q)} \tag{1}$$

The utility of a plan is the sum of all activities utilities and all travel utilities.

$$S_{\text{act},q} = S_{\text{duration},q} + S_{\text{wait},q} + S_{\text{late\_arrival},q} + S_{\text{early\_departure},q} + S_{\text{short\_duration},q} \tag{2}$$

The travel (dis)utility takes into account the marginal utility of time spent traveling, the marginal utility of money, and the marginal utility of distance, as well as penalties for public transport when there are various transfers.
In the simulation, at each iteration, the agent selects a plan from memory depending on its score. Then, for a fraction of the population (e.g. 10%), *replanning* can be done. There are four main modifications:

1. The departure time can be changed.
2. The route can be modified.
3. The transportation mode can be different.
4. The destination can also be changed, this feature is however not used.

After these modifications, the simulation of the network loading can be done with the MATSim mobility simulation, *mobsim*. The new iteration is compared to the others thanks to the *scoring*. The key performance indicators are observed in the *analysis* part. Mode shares, distances traveled, and average trip duration are analyzed.

To have a successful simulation, an equilibrium state for the transportation system must be found. This means that the number of iterations should result in a constant score and a constant distribution of the shares of the transportation modes.

3.5.1 Mode selection

Mode choice in MOBi follows specific rules. Public transport and walk modes are fully interchangeable within a tour or sub-tour. Car use is limited to those with a driver's license and is necessarily chain-based. This mode must start and end at home. The car can be parked at primary locations while a sub-tour is conducted with another mode. Public transport stations acess and egress modes, called feeder modes, have restrictions based on stop attributes and person attributes. Pedestrians and cyclists can access any stop, while taxis and cars are limited to rail stops. Person attributes for feeder modes are assigned based on age, car ownership, and education. Car to Public Transport (Car2PT) is restricted to car owners. If an agent uses Car2PT, he cannot use ride to Public Transport (ride2PT). Feeder modes are not restricted by chain-based modes or other sub-tour trips. A person can bike to a station in the morning and return by car in the evening.

3.5.2 Scoring

The scoring function in MATSim is supposed to converge during the simulation. Its purpose is to evaluate each agent's daily plan by assigning a score. This score reflects the utility of performing activities and the disutility of travel. Figure 7 shows this, with travel penalties in red and activity rewards in blue.

It is interesting to note that the scoring function is not a logit model. It is based on an econometric utility framework. The activity utility is not linear. For example, arriving early at work does not give a positive score. The scoring becomes positive only after a certain time. A step function models this behavior, ensuring realistic scenarios. Short activity durations are also penalized, reflecting that very brief activities are often unrealistic.

This approach helps agents adjust their schedules, balancing activity durations and travel times. By comparing scores, agents modify their plans in the next iteration. This replanning process drives the simulation toward an equilibrium state.

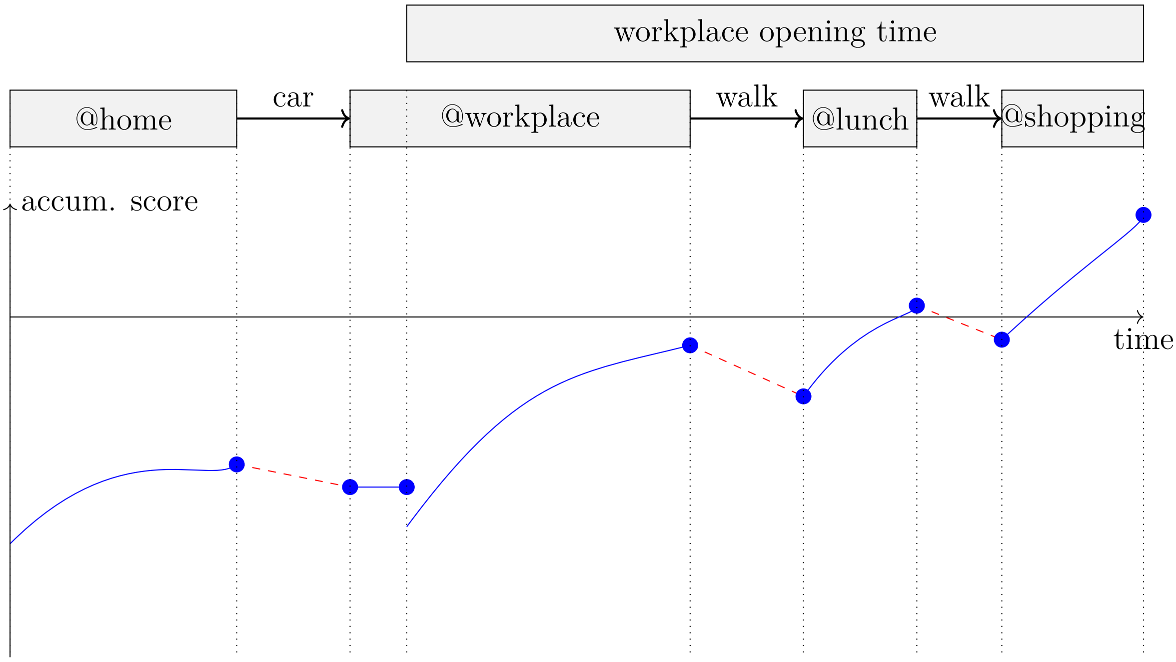


Figure 7: Illustration of the scoring function in MATSim

In MOBi.sim, the scoring parameters reflect travel behaviors and preferences. Global parameters apply to both routing and modal choice. They include the marginal (dis) utilities of cost, travel time, travel distance, and waiting time. Alternative-specific constants capture mode-specific preferences, like the perceived advantage of driving or using public transport.

Person-specific parameters correct the scoring. Agents are grouped based on their characteristics, such as public transport subscriptions (GA, half-fare, or none) or car availability. For example, agents with a GA have no monetary cost for public transport trips, while half-fare users pay reduced fares. Regional adjustments account for geographic differences, such as travel behavior in Ticino, French-speaking Switzerland, or urban centers.

Calibration ensures realistic results by fine-tuning mode-specific constants. This approach reflects diverse travel preferences and behaviors across Switzerland.

3.5.3 Outputs

MATSim provides several key outputs that are needed to evaluate the performance and accuracy of the simulation. These outputs include scoring convergence and mode statistics. They help understand the behavior of agents and the overall transportation system. Scoring convergence is a critical metric in MATSim, indicating how well the simulation has stabilized. It involves tracking the scores of agents' plans over multiple iterations. The goal is to reach a state where the scores no longer change significantly, suggesting that agents have optimized their travel plans. The worse, best and medium scores are tracked to assess the performance of the simulation.

Mode statistics provide insights into the usage of different transportation modes. These statistics include passenger hours traveled (PHT) and passenger kilometers traveled (PKT). They measure the total time and distance traveled by passengers, aggregated for each mode. Both PHT and PKT need to converge, meaning that their values should stabilize over multiple iterations. Convergence of these statistics indicates that the simulation has reached a steady state where the travel patterns of agents are consistent.

3.5.4 SwissRailRaptor

SwissRailRaptor is a fast public transport router for MATSim. It is based on the RAPTOR algorithm (Delling, Pajor, and Werneck 2015) The default MATSim router is slower and uses more memory. SwissRailRaptor is optimized for speed and efficiency (M. Rieser, Métrailler, and Lieberherr 2018). It reduces memory usage and initialization time. In addition, it uses minimum transfer time instead of additional time. SwissRailRaptor integrates with the standard transitRouter config module.

4 Problem Definition

Our goal is to differentiate between public transport modes. As seen in the literature review, SP/RP surveys have not given clear results of light rail bonus. Therefore, we will try to isolate the rail bonus using passenger count data and attempt to replicate it in the model. To achieve this, we must identify an area where our model accurately reflects reality for comparison. This area should include different public transport modes.

We have chosen Lausanne for our analysis, since we already studied the impact of students on the m1. First, we will assess the current situation and compare model loadings with passenger counts from Transports publics lausannois (tl).

4.1 Current state of the model

To analyze the current state of the model, we will consider the MOBi.sim results from the current version of MOBi, simulating a weekday in 2023. The count data will cover working days outside vacation periods, averaging 250 days.

According to the direct comparison in Table 4, the model overestimates bus boardings and underestimates metro boardings. The ratio is calculated per line. A negative value means the model predicts fewer boardings than the TL data, while a positive value indicates an overestimation. The results align with expectations and support the project's goal. It allows us to isolate the preference for rail modes. However, to better understand what happens within a metro, we need to zoom in and analyze the strength of this preference.

Line	**Ratio**
m1	-31.70%
m2	-50.30%
Bus 1	-18.54%
Bus 7	-0.29%
Bus 17	29.84%
Bus 9	50.36%

Table 4: Comparison of Boardings in tl and MOBi

In Lausanne, there are currently two metro lines. The first light metro line (m1) was inaugurated in 1991 (Bovy 1992), connecting Flon to Renens CFF station. It was mainly designed to serve the Dorigny campus (UNIL and EPFL). The m1 was formerly called TSOL (for the South-West Lausanne Tramway Company). The second metro line (m2), as known today, was inaugurated in 2008 (Cameroni 2018). It replaced the "Ficelle", a funicular originally opened in 1877. This line looks more like a usual metro, mostly underground, with a relatively high frequency of 2 minutes and 20 seconds during peak hours. Our main idea was to focus on these two lines and extract the rail bonus.

By comparing the model data with the count data, as shown in Figure 8, we see that the model does not capture the specific features of the m2. The line has a steep slope, and demand is higher uphill than downhill, with a peak between Lausanne station (CFF stop) and Flon.

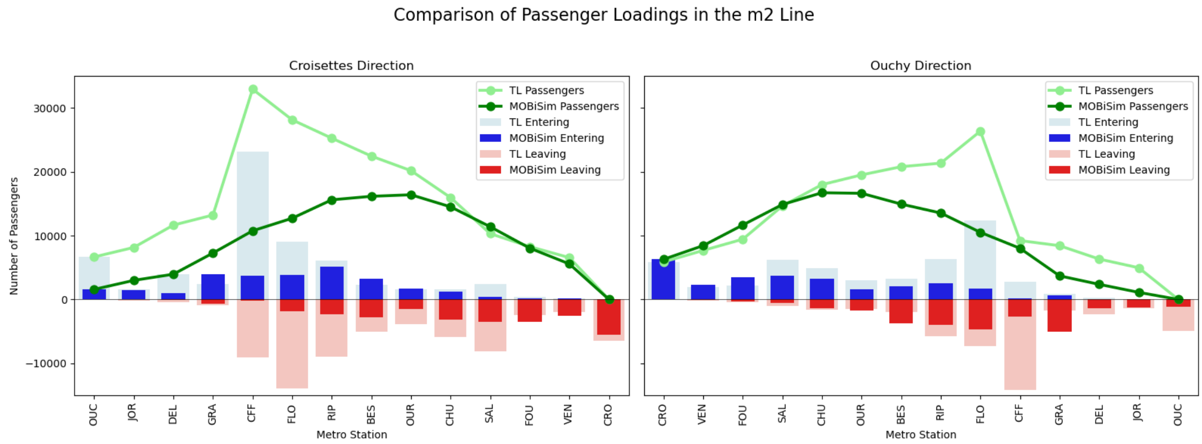


Figure 8: Comparison of count data for the m2 line in Lausanne

The m2 line presents several challenges that make it unsuitable for our analysis. The model underestimates what happens at the train station and on the Ouchy-Gare route.

First, the slope of the m2 line is quite steep, which significantly influences the mode choice of passengers. This slope effect is not adequately captured in the current model, leading to discrepancies between the simulated and actual passenger counts. Ideally, slope could be included in the simulation model to explain the shift from walking to public transport. However, this is outside the scope of this project. Secondly, there is a problem at the Lausanne train station. Since the model fails to estimate the peak in Lausanne station, we want to analyse what the model predicts there. The boarding/alighting data for trains are calibrated by the model, so it is surprising not to see more people in the metro.

This analysis is shown in Figure 9. We can see a peak of people arriving in the train station, of around 35'000 people. However, the model predicts only around 3'800 people using the m1 line in the train station, and 3'600 people using the different bus lines at the station. Both the buses and the metro appear to be underestimated.

By examining the main modes used to reach the station (access and egress modes), we find that walking is predicted for most agents, as shown in Figure 10. Therefore, the walking mode is likely overestimated. This overestimation skews the results, as many passengers who would typically use the metro or other public transport modes are instead predicted to walk.

Additionally, the CHUV (Centre Hospitalier Universitaire Vaudois) acts as a significant attractor on the m2 line. The hospital's high demand for public transport is maybe not perfectly reflected in the current model, leading to further inaccuracies in the simulation results.

Due to these reasons, including the slope effect, the overestimation of walking at Lausanne train station, and the high attractor effect of CHUV, we have decided not to use the m2 line in our analysis. Instead, we will focus on the m1 line, which presents fewer complexities and allows for a more accurate assessment of the model's performance.

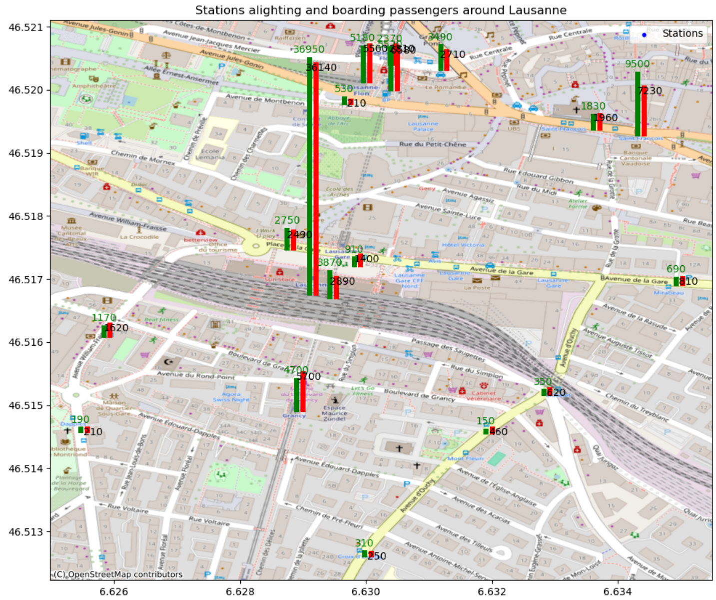


Figure 9: Zoom of the MOBi outputs around Lausanne train station

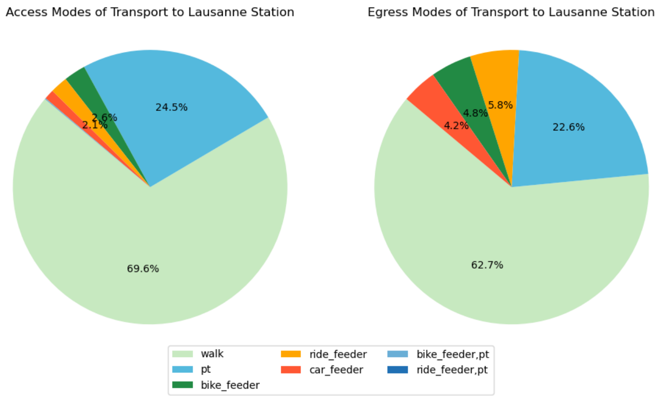


Figure 10: Access/Egress main modes to Lausanne Station

The current estimation of the model for the m1 line shows that the loading curve is similar between the predicted one and the real one from the count data. However, the model underpredicts the number of passengers. It aligns with our expectation since the model does not differentiate between public transport modes and lacks a light rail bonus. Despite this, we cannot directly attribute the difference between the two curves to the rail bonus alone. We must ensure that no other effects have been overlooked. By examining the entering and leaving bars, we realize that the model underestimates the number of people entering and leaving the metro at the campus stations (UNIL Chamberonne to EPFL). This suggests that we should take a closer look at the student group in the model to improve accuracy.

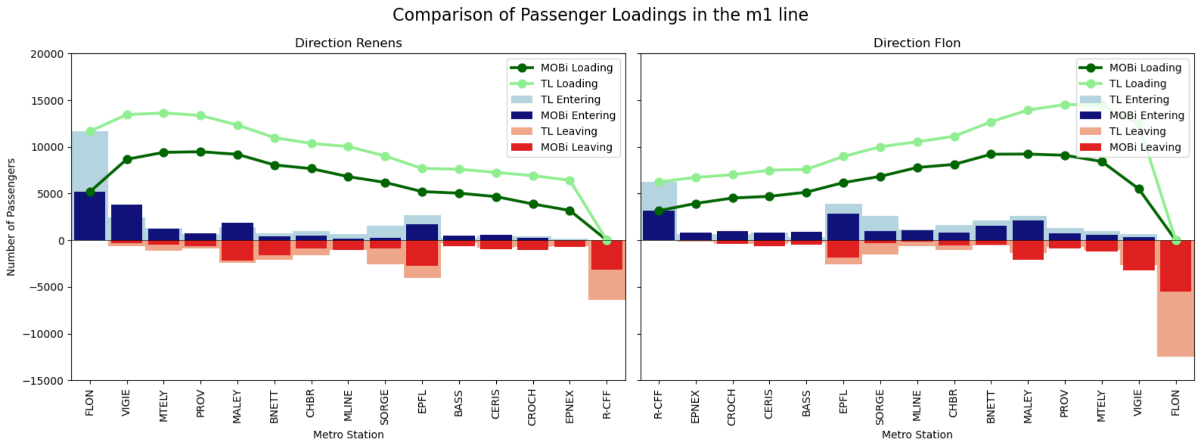


Figure 11: Comparison of count data for the m1 line in Lausanne

5 Model Enhancement

To accurately capture the "rail effect" and differentiate modal preferences, the existing MOBi model needs enhancements. The current model has limitations in reflecting the demand dynamics observed on Lausanne's m1 line, especially around the university campus.

Our main hypothesis is that students are underrepresented and do not use public transport enough in the model. To address this issue, we propose sequential model improvements and observe their effects on the simulation. The enhancements focuses on the following aspects:

1. The different mobility tools such as the public transportation subscription ownership model and the driving license ownership model.
2. The car availability rule-based model.
3. The attractiveness of secondary destination choice model.

We explain these improvements in the following paragraphs and monitor their effects.

5.1 Mobility tools

5.1.1 Public transportation subscription ownership model

The first step in enhancing the SIMBA MOBi model is to revisit the logit model for public transportation subscription ownership. This model is the first step in the MOBi.plans pipeline.

It has 5 different alternatives: General Abonnement (GA), Half-price Travelcard (HT), Half-price and Regional Travelcard (HTV), Regional Travelcard (VA, as in "Verbundabo" in German), and no subscription (None). The model is based on a utility function that predicts the likelihood of an individual owning each type of subscription based on various demographic, socio-economic, and household factors. It is based on both the 2015 and 2021 MTMC. None subscription is the reference alternative, normalized to 0.

The model is estimated using a logit model with the utility function for each subscription type defined as follows:

$$
\begin{aligned}
V_{\text{GA}} = & \beta_{\text{ASC\_GA}} \\
& + \beta_{\text{CARS\_PER\_ADULT\_GA}} \cdot \text{cars\_per\_adult} \\
& + \beta_{\text{LANG\_GERMAN\_GA}} \cdot \text{is\_German} \\
& + \beta_{\text{IS\_SWISS\_GA}} \cdot \text{is\_Swiss} \\
& + \beta_{\text{FULLTIME\_GA}} \cdot \text{full\_time} \\
& + \beta_{\text{PARTTIME\_GA}} \cdot \text{part\_time} \\
& + \beta_{\text{AGE\_18\_22\_GA}} \cdot \max(0, \min(\text{age}, 22.5)) \\
& + \beta_{\text{AGE\_23\_26\_GA}} \cdot \max(0, \min(\text{age} - 22.5, 4)) \\
& + \beta_{\text{AGE\_27\_69\_GA}} \cdot \max(0, \min(\text{age} - 26.5, 43)) \\
& + \beta_{\text{AGE\_70\_89\_GA}} \cdot \max(0, \min(\text{age} - 69.5, 20)) \\
& + \beta_{\text{AGE\_90\_PLUS\_GA}} \cdot \max(0, \min(\text{age} - 89.5, 30.5)) \\
& + \beta_{\text{COUPLE\_WITHOUT\_CHILDREN\_GA}} \cdot \text{couple\_without\_children} \\
& + \beta_{\text{COUPLE\_WITH\_CHILDREN\_GA}} \cdot \text{couple\_with\_children} \\
& + \beta_{\text{SINGLE\_PARENT\_HOUSE\_GA}} \cdot \text{single\_parent\_house} \\
& + \beta_{\text{ONE\_PERSON\_HOUSEHOLD\_GA}} \cdot \text{one\_person\_household} \\
& + \beta_{\text{HOUSEHOLD\_TYPE\_NA\_GA}} \cdot \text{household\_type\_NA} \\
& + \mu_{2021} \left(\sum_{i \in 2021} \beta_i \cdot \text{Variables}_{2021} \right)
\end{aligned}
$$

Multiple socio-economic and demographic variables are included in the model, such as the number of cars per adult in the household, the language spoken at home (German or not), the employment rate or the age and the household structure.

We revisit the model by adding variables specific to students. By enhancing the public transportation subscription ownership model, we aim to better reflect the actual mobility patterns observed in the EPFL and UNIL mobility surveys. The added variables appear in red in Table 5.

First, we add a variable specific to students. This variable is a binary variable that takes the value of 1 if the agent is a student and 0 otherwise. The data from the MTMC do not provide exact information on whether the respondent is a student or not. Therefore, we had to create a rule-based definition to determine the student variable. We tried two different definitions, one where students are defined as people in formation, and one where students are defined as people in formation and having a high-school diploma. Both definitions take into account only people aged above 18. The first definition was chosen as it had a better fit to the data (MTMC). Two models were estimated, with the different student definition. We compared them and realised the first definition lead to better results with a better explanation of the variance. However, it is wider than the actual definition of a UNIL or EPFL student. This variable is expected to have a positive impact on the likelihood of owning a public transportation subscription, as students are more likely to use public transportation than employees. This observation can be seen in

	Distance Modeling	Demographic Factors	Socio-economic & Household Factors
GA	Piecewise (20 km cuts)	Age, Employment, Swiss nationality	Cars per adult, Household type, Language (German)
HT	Linear	Age, Student, Employment, Swiss nationality	Household type, Language (German)
HTV	Linear	Age, Student, Employment, Swiss nationality	Household type, Language (German)
V	Piecewise (5 km cut)	Age, Employment, Swiss nationality	Cars per adult, Household type, Language (German)

Table 5: Variables Associated with Public Transportation Subscription Types

Figure 12.

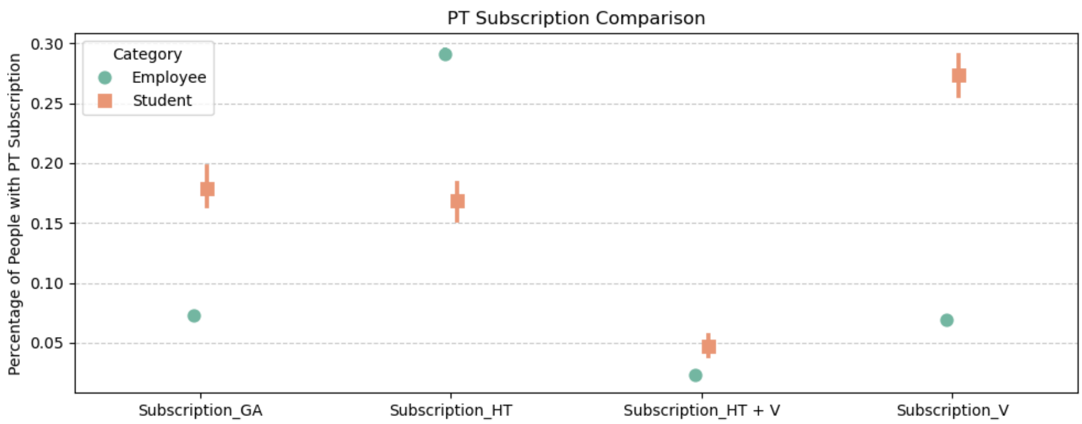


Figure 12: Public Transport subscription ownership (MTMC)

Then, we include a distance variable in the model for students. This variable represents the distance between the agent's home and the university campus. The distance variables should have a more complex impact on the likelihood of owning a public transportation subscription. We would assume people living further away from campus, to either have a GA, or no subscription and using a different mode of transport. People living in the agglomeration would be more likely to have a VA subscription. People living really close to campus would be more likely to walk or bike.

In order to explain this complex relationship between distance from home to university and PT subscription ownership, we use a piecewise function for the GA, with a single cut at 20km. We also use a piecewise for the VA, with a single cut at 5km. The piecewise function allows for a variable impact of distance on subscription ownership, with a different effect for longer distances. The different cuts are chosen on a trial and error basis, to best fit the data. For the Half-price Ticket (HT) and HT plus Regional Travel Card (HTV) models, a linear distance measurement is used to indicate a direct relationship between commuting distance and subscription ownership.

The results of the model estimation are presented in Table 6. The models are compared using the likelihood ratio test. The final log likelihood and rho-square values also indicate that this model is the most accurate model.

Parameter	Value	Rob. Std Err	Rob. t-test
ASC_GA	2.01	0.444	4.52
ASC_HT	1.63	0.471	3.45
ASC_HTV	5.82	0.601	9.68
ASC_V	6.60	0.502	13.1
beta_STUDENT_HT1521	0.304	0.079	3.84
beta_STUDENT_HTV1521	0.581	0.104	5.61
beta_DIST_H_U_HT1521	0.149	0.022	6.88
beta_DIST_H_U_HTV1521	0.136	0.029	4.76
beta_DIST_H_U_0to20_GA1521	0.823	0.051	16.1
beta_DIST_H_U_0to5_V1521	1.15	0.149	7.68
beta_DIST_H_U_20+_GA1521	0.163	0.024	6.73
beta_DIST_H_U_5+_V1521	-0.077	0.042	-1.83

Table 6: Estimated Parameters with Robust Standard Errors and t-tests

5.1.2 Driving License Ownership

The binary model for driving license ownership in MOBi.plans aims to predict whether an individual possesses a driving license. The decision is modeled as a binary outcome, owning a driving license against not owning one.

The logistic regression framework uses a utility function defined as:

$$
\begin{aligned}
V_{\text{DL}} = {} & \beta_{\text{ASC\_DL}} \\
& + \beta_{\text{FULLTIME}} \cdot \text{full\_time} \\
& + \beta_{\text{PARTTIME}} \cdot \text{part\_time} \\
& + \beta_{\text{ACCESSIB\_PT}} \cdot \text{boxcox\_accessib\_pt} \\
& + \beta_{\text{ACCESSIB\_MULTI}} \cdot \text{boxcox\_accessib\_multi} \\
& + \beta_{\text{PARKING\_COST\_CAR}} \cdot \text{pc\_car} \\
& + \beta_{\text{PARKING\_COST\_CAR\_LOG}} \cdot (1 - \text{free\_parking\_car}) \cdot \text{parking\_cost\_car\_log} \\
& + \beta_{\text{FREE\_PARKING\_CAR}} \cdot \text{free\_parking\_car} \\
& + \beta_{\text{IS\_SWISS}} \cdot \text{is\_swiss} \\
& + \beta_{\text{COUPLE\_WITH\_CHILDREN}} \cdot \text{couple\_with\_children} \\
& + \beta_{\text{COUPLE\_WITHOUT\_CHILDREN}} \cdot \text{couple\_without\_children} \\
& + \beta_{\text{SINGLE\_PARENT\_HOUSE}} \cdot \text{single\_parent\_house} \\
& + \beta_{\text{HOUSEHOLD\_TYPE\_NA}} \cdot \text{household\_type\_NA} \\
& + \beta_{\text{LANG\_FRENCH}} \cdot \text{french} \\
& + \beta_{\text{AGE\_0\_22}} \cdot \max(0, \min(\text{age}, 22.5)) \\
& + \beta_{\text{AGE\_23\_26}} \cdot \max(0, \min(\text{age} - 22.5, 4.0)) \\
& + \beta_{\text{AGE\_27\_69}} \cdot \max(0, \min(\text{age} - 26.5, 43.0)) \\
& + \beta_{\text{AGE\_70\_89}} \cdot \max(0, \min(\text{age} - 69.5, 20.0)) \\
& + \beta_{\text{AGE\_90\_120}} \cdot \max(0, \min(\text{age} - 89.5, 30.5))
\end{aligned}
$$

where:

- V_{DL} represents the utility of owning a driving license.
- β_i are parameters estimated from the data.
- Age, Income, and X_n are explanatory variables influencing the ownership decision.

In this model, the utility of not owning a driving license is normalized to zero. The coefficients (β) are estimated using maximum likelihood estimation. Positive coefficients indicate that the likelihood increases.

To enhance the model's accuracy, especially for predicting student behaviours, we integrate specific variables that reflect student status. Just as in the previous section, we add a binary variable to distinguish students from employees. This variable is expected to have a negative impact on the likelihood of owning a driving license, as students are less likely to own a car than employees. We also include the same student definition as in the Public transportation subscription ownership model.

As we can see in Table 7, most of the coefficients are statistically significant, except the student variable. The coefficient for the student variable is positive and statistically insignificant. This result is not consistent with what we found in the MTMC. In the MTMC conducted in 2015 and 2021, only around 58% of students possess a driving license, as can be seen in Figure 13.

Scope	Variable	Value	T-test
Individual	Age 18-22 (piecewise)	0.398	14.37
	Age 23-26 (piecewise)	0.0301	1.21
	Age 27-69 (piecewise)	0.0201	12.49
	Age 70-89 (piecewise)	-0.118	-33.84
	Age 90+ (piecewise)	-0.19	-3.73
	Nationality: Swiss	0.635	16.87
	Language: French	0.156	4.69
	Percentage of employment: Full-time	1.54	32.79
	Percentage of employment: Part-time	0.827	18.42
	Being a student	0.0481	0.60
Household	Type of household: couple with children	0.57	14.43
	Type of household: couple without children	0.551	15.59
Zone	Accessibility PT (Box-cox)	-0.892	-7.46
	Accessibility multi (Box-cox)	0.662	5.64
	Parking cost (linear)	-0.785	-6.86
	Free parking	-0.598	-5.17

Table 7: Parameter Estimates with t-test for Driving License model

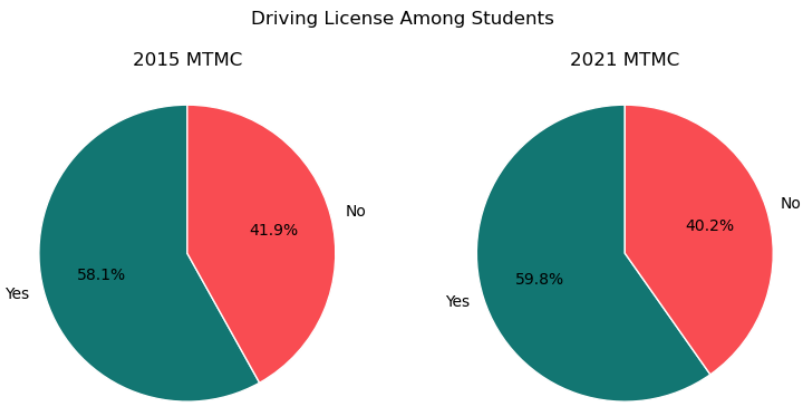


Figure 13: Driving License among student group

In order to verify this intuition, we ran the model without the age variable. The results showed that the student variable is negative and statistically significant. This indicates that students are less likely to own a driving license than employees. This result is consistent with the MTMC, where students were less likely to own a driving license than employees. Therefore, we can hypothesize that the student variables take into account more than just being a student. Students come from different backgrounds and have different characteristics. The fact they are more prone to own a driving license could be due to their socio-economic status. In Switzerland, students are more likely to come from wealthier families, which could explain why they are more likely to own a driving license. So, the new model was still an improvement. However, when we will run again the simulation, the problem of students in the model having too many cars will still be present. It can even be worse than before, since more driving license are given to our synthetic population. We need to adjust the number of cars available to students in the model to better reflect the actual availability of cars among students.

5.2 Car availability

In this section, we discuss further developments that could be made to the car availability rule in the SIMBA MOBi model.

The rule determines whether an agent has a car available for use. The current rule allocates cars to agents based on their driving license ownership and household characteristics. The rule is defined as follows:

- If an agent has a driving license and is part of a household with at least one car, they have a car available.
- If an agent has a driving license but is part of a household with no cars, they do not have a car available.
- If an agent does not have a driving license, they do not have a car available.

The model does not look at the availability of cars in the household if multiple people use it at the same time. Therefore, it is possible that the model overestimates the number of cars available to agents. It is usually students and young people who do not have a car available. It might be why the model overestimates the car mode for students in the previous section. The MTMC defines three levels of car availability: always, never and on demand. The on demand option is currently not modeled in SIMBA MOBi. This may be a limitation in representing the actual conditions faced by students.

We need to adjust the number of cars available to students in the model to better reflect the actual availability of cars among students. To do so, we have different sources of data. The first one is the MTMC, which provides information on car ownership and driving license ownership in Switzerland. A report about “Mobility of Children and Adolescents” (Sauter 2019), gives us some intuition on how many students have a car available. The second source is the mobility surveys conducted at UNIL, which gave us information on car availability among students. Only 24.3% of students have access to a car. This is much lower than what was given in the MTMC.

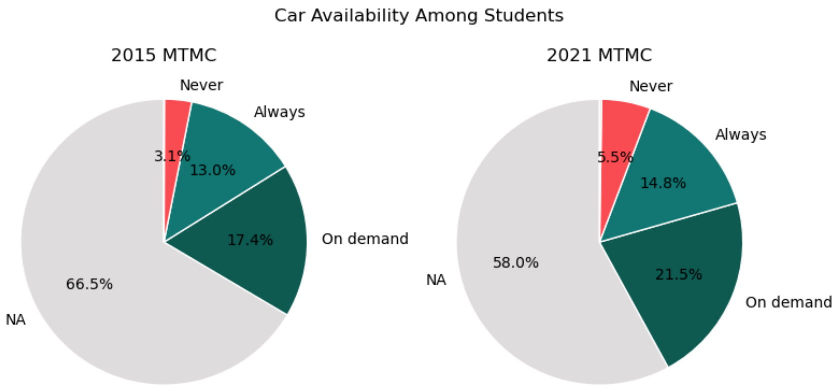


Figure 14: Car availability among students (MTMC)

Figure 14 provides an overview of car availability among all students. It shows that in 2021, only a small fraction of students (5.5%) never have access to a car, while the majority have a car available either always (14.8%) or on demand (21.5%). This data highlights the necessity to reconsider the car availability rule in the model to better represent the actual conditions faced by students, particularly in a university setting. Most students who responded to the survey having a car available on demand, might refer to to special occasions or emergencies. It might not be the best representation of the reality.

For further enhancements, we propose to set a specific percentage of students who have a car always available. In order to include the majority of students, we would set the percentage of students with a car always available to 15%, based on the mobility survey data. To do so, we will implement a rule-based algorithm in the MOBi.plans pipeline to adjust the number of cars available to students. The goal is to increase the amount of students using the public transport modes in the model. The algorithm is presented in Algorithm 2.

Algorithm 2 Rule-based Car Availability

Input: Household data and personal data
Output: `car_available` field for each person

Initialize `car_available` for all persons to **False**

For each person:
if person has a driving license **and** number of cars in household > 0 **then**
  → Set `car_available` to **True**
end if

Identify students
if `current_num_students_with_car` > `target_num_students_with_car` **then**
  Randomly choose among `num_to_remove` students to set `car_available` to **False**
end if

The presumed impact of this algorithm is to reduce the number of students with a car available in the model. This change is expected to increase the share of students using public transport, better reflecting actual conditions in a university setting.

This modification remains rule-based. Future research could develop a choice model that incorporates the socio-economic characteristics of students and the general population to predict car availability. Such a model already exists for the 2023 synthetic population (Bundesamt für Raumentwicklung (ARE) and Schweizerische Bundesbahnen (SBB) 2024, section 2.12).

5.3 Campus attractivity

In the current model, the attractivity of the campus primarily impacts the choice of secondary activity locations. However, the model currently assigns only a small attractivity value to the campus, and this attractivity is limited to activities such as accompanying someone or continuous education. To better reflect the actual usage of the campus, we propose to increase its attractivity by including additional factors such as business, shopping, leisure, and other activities. These factors are based on the existing attractivity for continuous education.

We implement two different approaches to increase the campus attractivity. In the first approach, we will multiply every attractivity factor by 5. In the second approach, we will multiply every attractivity factor by 10.

By comparing the impact of these changes on the m1 line, we aim to identify which approach better reflects the actual number of boardings and alightings at the campus stations. This adjustment will help us achieve a more accurate representation of the campus's role in the transportation model and improve the overall simulation results.

5.4 Impact of the model enhancements

First, we check if the public transcription ownership model predicts the right amount of students having a subscription. in Figure 15, we can see that the model predicts a higher amount of students having a subscription than in the base initial model. The black dashed row represents the actual amount of people having a subscription. This value comes from SBB market team. However, no distinction between students and employees is made.

The constants from the logit model were calibrated and validated using the different values per zone from SBB and MTMC.

The driving license ownership model was also validated. The model predicts a higher amount of students having a driving license than in the base initial model. The constants were also calibrated and validated using the different regional values.

The two next steps are to adjust the car availability rule and the campus attractivity. Since the modifications are just rule-based, we will directly run the simulation to see the impact of the changes.

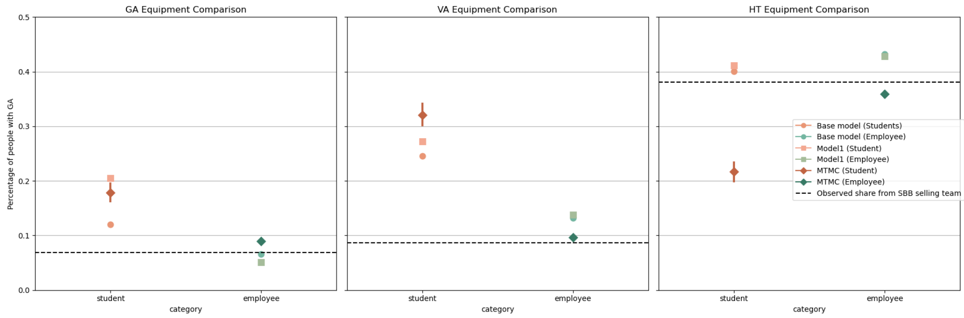


Figure 15: Comparison of Public Transportation Subscription Ownership Models

5.4.1 Simulation results

The different models enhancement are summarized in Table 8. The improvements were done sequentially, with each modification informing the next. The final model (36e) is the one with the highest attractivity for the campus.

Model	Specification	Ref
ref	Corresponds to MOBi 5	-
36b	Integrated model specification with student parameters for both the PT subscription model and the DL model	ref
36c	Changed the car availability rule	36b
36d	Increased the attractivity attributes for the school zones by 5	36c
36e	Increased the attractivity attributes for the school zones by 10	36c

Table 8: Sequential Modifications

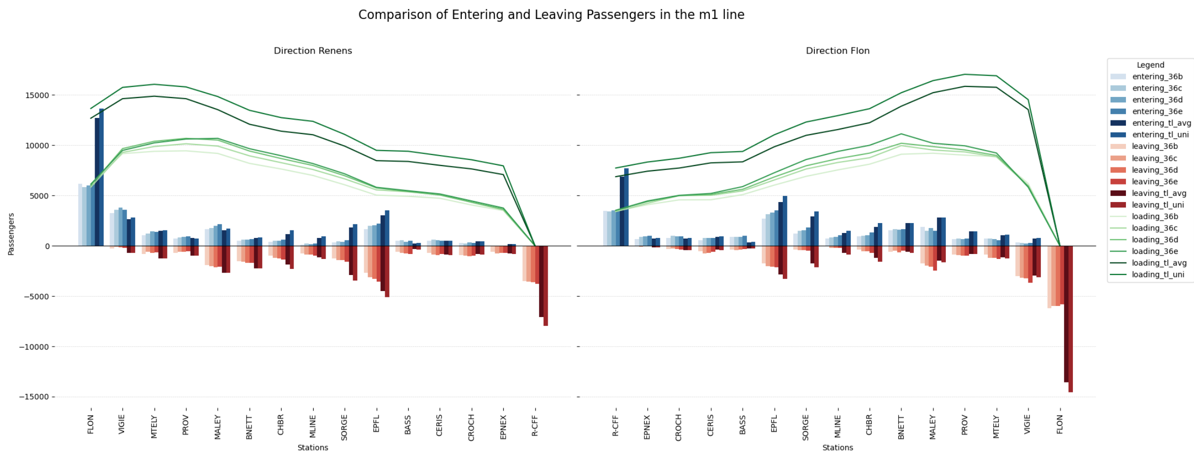


Figure 16: Comparison of m1 line models

The results of the simulation are presented in Figure 16. This figure is similar to the one seen on the 4 section. The highest loading curve represents the count data of a university day in average. It corresponds to the maximum daily average values for the m1.

However, it is important to note that the SIMBA MOBi model represents a working average day. There is no distinction on university week or not. Since university weeks are only around 28 weeks out of 52, the average daily values differ if we take all working days into account. Therefore, we plotted the average values for the m1 line just below. This value is the targetted value for the model.

The results show that the model with the highest attractivity for the campus (36e) is the one that best reflects the actual number of boardings and alightings at the campus stations. This model also has the highest number of students using public transport modes, which aligns with the actual conditions faced by students in a university setting.

The model proves there's an improvement in the simulation results. However, on the first part of the trip, the model still overestimates the boarding at some stop, and underestimates the boarding at the first stop. However, it seems unplausible to get a better fit with the current model. It is important to note that the model is still underestimating the number of passengers. However, we can see that the model is now closer to the actual data. The difference between the simulation and the count data is now around 14% for the m1 line. This difference could correspond to the “light rail bonus” we are trying to capture.

6 Differentiation across public transportation modes

6.1 Historical Context of Public Transport Modeling

Transportation models are essential for predicting changes in mobility behavior and evaluating the impacts of infrastructure projects. In the Lausanne region, the EMME/2 (Leyvraz 2007) model was used around 2005-2010 to simulate motorized demand. This model relied on fixed origin-destination (O-D) matrices for the morning peak hour. It included two matrices: TIM (Transport Individuel Motorisé) for private motorized transport and TC (Transport en Commun) for public transport. The main purpose of the EMME/2 model was to compare different transport variants. It used a logit function to model transfers between car and public transport. The hypothesis was that the model should only be used to compare variants and not to predict absolute values, such as the number of passengers.

However, the model had significant limitations. It neglected induced demand and ignored transfers from active modes like walking and cycling to motorized modes. The model assumed that the mechanisms explaining modal choices in 2005 would remain the same for 2020. It limited its ability to adapt to changes to extrapolation with new number of inhabitants and workers. Observations from the Leyvraz, Bierlaire, and Paulus (2007) report highlighted further issues. Road and transit projects were studied separately, without accounting for the ability to create modal shifts. For key destinations like EPFL and the University of Lausanne, transit shares were underestimated because the model did not account for differences in behavior between students and workers. Furthermore, the model lacked differentiation between rail and bus travel. The report already notes evidence that rail is more attractive under equal travel time conditions.

The EMME/2 model was criticized for its limitations. The m2 metro line was highly underestimated, leading to a lack of confidence among decision makers regarding the reliability of any model.

These limitations demonstrate the need for better modeling of public transport preferences. In our project, we aim to address these issues by integrating differentiation between public transport modes, such as tram and bus, in the Lausanne area. This approach will improve the accuracy of demand forecasts and support better decision-making for future transportation planning.

6.2 Motivation for Differentiation

In the previous section, we discussed the enhancements made to the SIMBA MOBi model to better reflect the actual mobility patterns observed in the EPFL and UNIL mobility surveys. We integrated the difference in mobility behavior in the student group. However, the model still faces challenges in accurately predicting ridership for different public transportation modes. The current model treats all public transportation modes as a single entity, which we are arguing is not the best approach.

in Table 9, we see that the 36e model predicts good results for the Lausanne network overall. However, a finer analysis shows that it overestimates bus ridership and underestimates tram (m1+m2) ridership. These effects cancel each other out.

Relative Difference	Base Model
Tram Constant	-0.21
Bus Constant	-0.21
Overall (Bus + Tram)	0.98%
Overall Bus	20.18%
Overall Tram	-24.87%
Over M1	-13.63%

Table 9: 36e Model Relative Differences

To adress this, we propose to differentiate between tram, bus, rail and other modes. We will do it in the MOBi.sim model, which corresponds to the last of the three main steps of the model. Specifically, we will focus on the constant of the different modes in the scoring parameters. As seen on section 3.5.2, mutliple parameters are used to reflect travel behaviors and preferences. We won't change the scale parameters, such as the marginal utilities of time and cost, since we want to capture a preference for a mode. The level of service is already taken into account in the model, so we will focus on the constant of the different modes.

The differentiation process is done by calibrating mode-specific constants, focusing on tram and bus constants. To do so, we start using the initial public transport constants from the MOBi 5 model. Then, we calibrate the tram constant first. The calibration is done using the m1 metro line, which shares characteristics with tram systems. We use trial-and-error to adjust the tram constant incrementally. The calibration is guided by aggregated metrics for overall public transport boarding counts. Once the tram constant is calibrated, we move on to the bus constant. The interdependence of these two constants is taken into account, as adjustments to one impacts the results for the other.

6.3 Calibration

Calibration is a complex task in agent-based models. Heppenstall et al. 2021 highlights it as a significant methodological challenge for agent-based models. In Switzerland, the Federal Department of Environment, Transport, Energy and Communications (DETEC) provides guidelines for calibrating transport models. In Vitins et al. 2021, the authors discuss the complexity of calibrating agent-based models. They emphasize the difficulty of finding high-quality, granular data for calibration. Empirical comparisons are essential for calibration, comparing travel times from simulation with observed data to calibrate and confirm model reliability.

N. Rieser et al. 2018 also speaks about different validation criteria for transport models. They include travel behavior metrics such as the number of trips, travel distance, travel time per person, modal split accuracy, traffic counts, and observed vs. predicted traffic volumes. In our case, the only available data is the count data from TL. We will still compare the difference across models of all other metrics. An empirical formula used in N. Rieser et al. 2018 is the GEH statistic. It is used to compare modeled traffic volume with observed traffic volume. A smaller GEH value indicates a better fit between observed and modeled data. A GEH value of 5 or less is considered an excellent fit, while a value above 20 indicates a poor fit requiring calibration. In addition to this metric, we will use the relative difference of the number of passengers between the models and the count data. We will also compute the mean squared error, and the mean absolute error, to find the best model.

Even though, the study area is limited to Lausanne, the calibration process is non-trivial due to the high number of parameters in the model. We decided to calibrate only the tram and bus constants. The computational time burden also limits the number of simulations that can be run. In our study area, simulating only 10% of the population already takes more than 3 hours, using a single node on the SCITAS cluster. The simulation is executed with 8 CPU cores and 60 GB of memory. The memory is allocated to ensure sufficient computational power for processing large datasets and running the MATSim mobility simulation. Despite optimizations in the SwissRailRaptor, see section 3.5.4, the iterative nature of the simulation and the detailed representation of the transport network contributes to the runtime.

6.3.1 Tram Constant

From our results in the previous section, we found that the model was underestimating the m1 by around 14% in the Flon direction. We start with the same constant as the MOBi 5 model, which uses the same value across all public transport modes. In this model, the base alternative is the taxi mode. To address this underestimation, we increase the tram constant by 14% to better reflect the reality of the tram mode in Lausanne.

However, we quickly realize that the impact is lower than expected. To refine the calibration, we increase the tram constant incrementally without changing any other parameters. The base scenario, referred to as 36e, includes all the adjustments from the previous section. We then test scenarios with tram constant increases of 14%, 20%, 30%, 60%, 75%, and 85%. The details of these scenarios are presented in Table 10.

Model	Tram constant	Increase
36e	-0.2100	0%
36f	-0.1806	14%
36g	-0.1680	20%
36h	-0.1470	30%
36i	-0.0840	60%
36j	-0.0525	75%
36k	-0.0473	77.5%
36l	-0.0420	80%
36m	-0.0315	85%

Table 10: Tram Constant Modifications

To find the best model, we compare the relative difference of the number of passengers between the models and the count data for the m1 line. We compute the overall daily boardings for both direction, per direction, and also a finer analysis per direction and per stop.

Model	Global	Renens	Flon	Tram increase (%)
36e	-13.63	-12.80	-14.46	0.0
36f	-12.18	-11.49	-12.87	14.0
36g	-9.19	-8.36	-10.02	20.0
36h	-8.13	-7.19	-9.07	30.0
36i	-2.49	-1.89	-3.08	60.0
36j	-0.40	1.13	-1.92	75.0
36k	1.35	2.62	0.09	77.5
36l	1.24	3.36	-0.86	80.0
36m	1.14	2.48	-0.19	85.0

Table 11: Comparison of Relative Differences and Tram Constant Changes

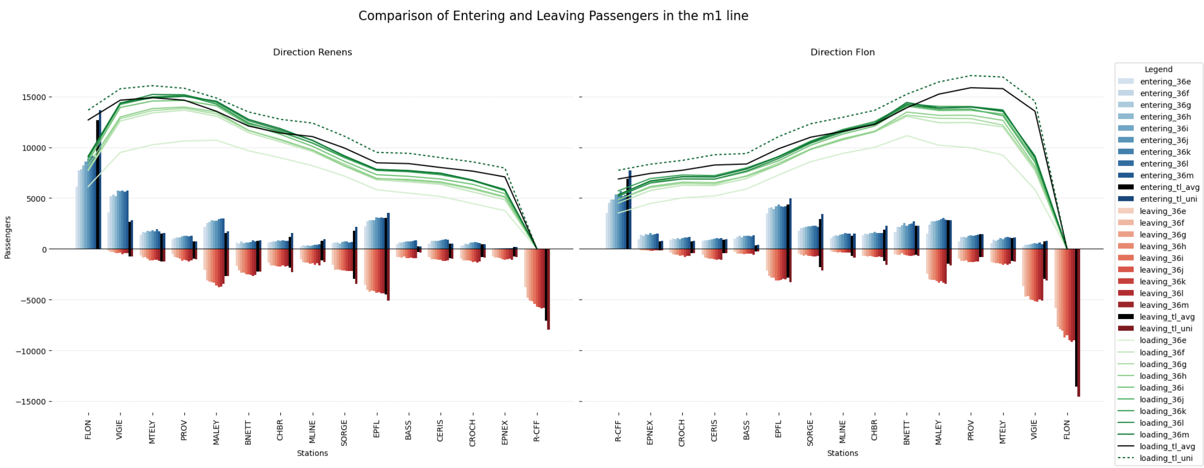


Figure 17: Comparison of m1 line models

The results are presented in Table 11 and Figure 17.
Table 11 shows that it's only after having increased the tram constant by 77.5% that we overestimate the tram mode globally. In the Renens direction, the model overestimates the number of people boarding daily the tram already with an increase in tram constant of 75%. In the Flon direction, the model overestimates the number of people boarding daily the tram with an increase in tram constant of 77.5%. Overall, a 5% relative difference is considered a good fit, we don't want to over calibrate. It already happens with an increase of 60% in the tram constant. We will monitor the changes in the network globally on the next section.

We also plot a sensitivity analysis with different metrics such as the mean-squared error (MSE), the mean-absolute error (MAE) and the GEH formula. The GEH is calculated as follows:

$$GEH = \sqrt{\frac{2 \cdot (M - O)^2}{M + O}}$$

where: M is the modeled traffic volume and O is the observed traffic volume. The results are presented in Figure 18.

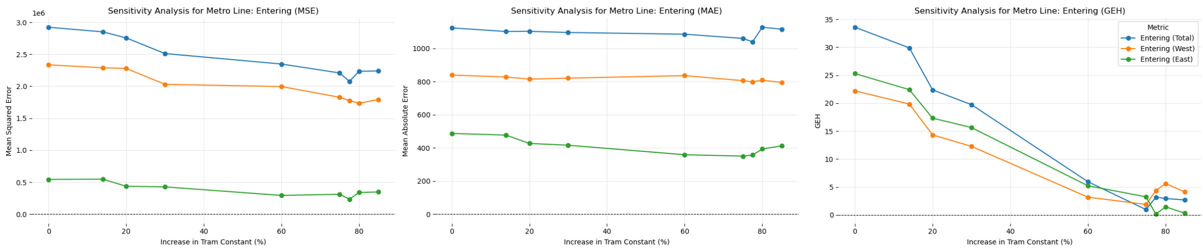


Figure 18: Sensitivity analysis of the different models

Lookings at the MSE, the value that seems to minimise the error is the 36j model at 75% increase in tram constant. Similar results, yet not as clear are seen in the MAE curves. It is also only for an increase greater than 50% that the GEH value is below 10, which is considered an acceptable fit. The best models, looking only at the m1, seems to be the 36j one.

When we look into the finer analysis in Figure 17, we can see that our models are much better than the base scenario, 36e, represented in paler shades. The target is always the black curve and black bars, representing the average daily values for the m1 line, for a working average day. In this plot, we realise, that overall we tend to overestimate the first stops, and mostly Vigie and Malley. EPFL metro station predicts good results, but we still understimate the number of entering and leaving passengers in Sorge and Mouline, two university stops.

However, we never overestimate and go above the dashed line, representing average university days.

6.3.2 Bus Constant

Once the tram constant was reasonably calibrated, we moved on to the bus constant. The two constants have an impact on the overall network. If we increase the boardings in the tram mode, the bus mode becomes less attractive for the same route with bus and tram alternatives. However, the tram route might attract users transferring from bus routes. Therefore, the two constants are interdependent.

Before changing the bus constant, we monitored how the tram constant affected the bus network. We compared the model outputs with the count data for 38 different bus lines in Lausanne. The data corresponds to working days, averaged over the year. We computed the overall daily boardings for all lines and compared them with the model outputs.

In Table 12, we see that the overall bus relative difference increases with the tram constant. This could be because public transport becomes more attractive when the tram constant increases. The bus boardings increase due to new trips generated by the tram mode, with transfers from bus to tram. Across the models, the bus constant remained the same at -0.21. Even with a significant increase in the tram constant, the impact on the bus mode was small (3% max). However, the bus mode is now even more overestimated than before.

Model	Tram increase (%)	Overall Bus Rel. Diff. (%)
36e	0	20.18
36f	14	21.78
36g	20	21.16
36h	30	21.70
36i	60	23.27
36j	75	23.27
36k	77.5	22.59
36l	80	23.63
36m	85	23.83

Table 12: Comparison of Tram Constants and Overall Bus Relative Differences

Since the model tends to overestimate bus boardings, we decreased the bus constant. We used multiple scenarios for comparison:

- 36e, with both constants unchanged,
- 36j, with a 75% increase in the tram constant,
- 36k, with a 77.5% increase in the tram constant,

For all of them, we tried to find a plausible bus constant. The different scenarios are presented in Tables 13 and 14.

Model	Bus constant	Decrease	Rel. Diff. Bus	Rel. Diff.
36e	-0.21	0%	20.18%	2.03%
36j	-0.21	0%	23.27%	9.52%
36j1	-0.31	50%	2.61%	6.43%
36j2	-0.33	60%	-1.03%	-6.06%
36j3	-0.35	70%	-4.31%	-8.13%

Table 13: Bus Constant Modifications

Model	Bus constant	Decrease	Rel. Diff. Bus	Rel. Diff.
36e	-0.21	0%	20.18%	2.03%
36k	-0.21	0%	22.59%	9.31%
36k1	-0.2625	25%	13.17%	3.39%
36k2	-0.294	40%	7.20%	-0.33%
36k3	-0.315	50%	3.84%	-2.72%
36k4	-0.3675	75%	-7.16%	-9.82%

Table 14: Bus Constant Modifications

To find the best model, we compared the relative difference in the number of passengers between the models and the count data for 38 different bus lines in Lausanne. The count data had a different format than the one used for the m1 line. For the m1 line, we preprocessed the data to compute the average daily boardings for all stops, per direction. However, for this dataset, there was no differentiation by direction. We only had the stop codes of the stops. We computed the overall daily boardings for all lines and compared them with the model outputs.

In Table 13, we can see that the best model is 36j2. The model is now underestimating the bus boardings by -1.03%. This result is closer to the actual data. A decrease of the bus constant by 50% is already enough to bring the relative difference below 5%. However, the overall relative difference, considering both tram and bus modes, is now -6.06%.

If we look at the models derived from model 36k in Table 14, we can see that the best model is 36k2. The model is now overestimating the bus boardings by 7.20%. However, we reach really good values overall with -0.33% relative difference across tram and bus modes. It is interesting to see that the need to decrease the bus constant is lower. Looking at Table 12, we would have thought a bigger increase in tram constant would need a bigger decrease in bus constant. However, as seen before, the model is not performing perfectly linearly.

We also performed a finer analysis to see what was happening for a specific bus line. We chose to display the results for bus line 17, as it runs more or less parallel to the m1 line. The Lausanne public transport network can be seen on Figure 31. Bus line 1 would have been a good comparison, but its route only changed in August 2023 to reach EPFL. Therefore, we selected bus line 17 instead. The results are presented in Figure 19.

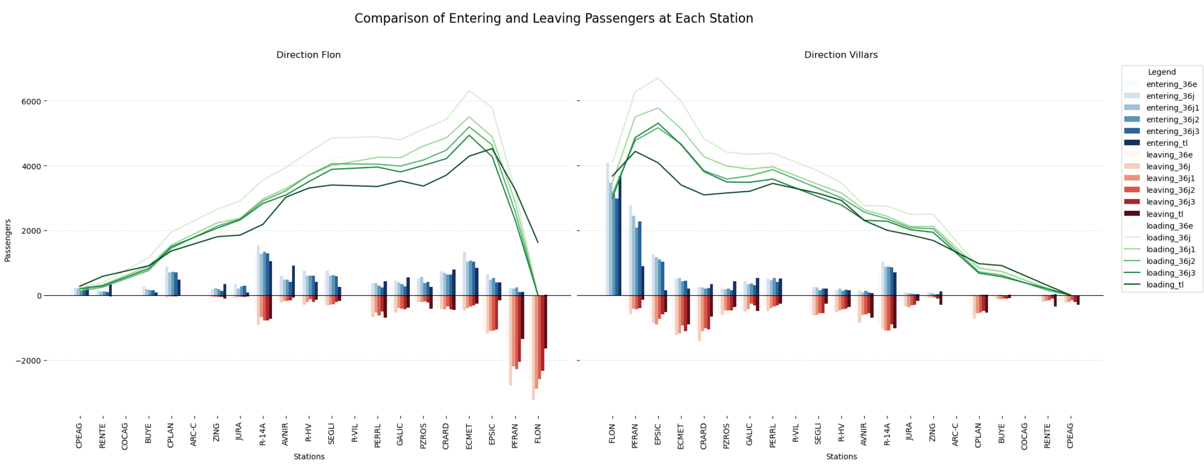


Figure 19: Comparison of bus 17 line models

In Figure 19, we can see that the initial model (lighter shade) is not that far off from the target (darker shade). However, model 36j, overestimates the number of boardings by far, only a decrease in the bus constant can help to get a better fit.

From these analysis, we are confident the differentiation of public transport modes is necessary. As expected, we had to increase the tram constant to account for the light rail bonus. The bus constant was then decreased to account for the increase in attractiveness of the bus due to the increased usage of the tram. The two constants are however interdependant, as the Figure 19 shows. An increase in tram constant leads to an increase in boardings in the bus line.

6.3.3 Interaction of constants

As seen in Table 12, changing the tram constant impacts bus boardings and vice versa. To illustrate this interaction, we created a 3D surface plot in Figure 20. The x-axis represents the tram constant, the y-axis represents the bus constant, and the z-axis shows the overall relative difference in predictions in Lausanne. We used radial basis function (RBF) interpolation to create a smooth surface. The interpolation is not perfect since the data is quite sparse. Key points are highlighted on the plot, such as the initial base model (36e), which shows good overall results but fails to accurately predict tram and bus boardings separately, as can be seen in Figure 21. Final models, 36j2 and 36k2, are also represented to show improvements in balancing predictions across modes.

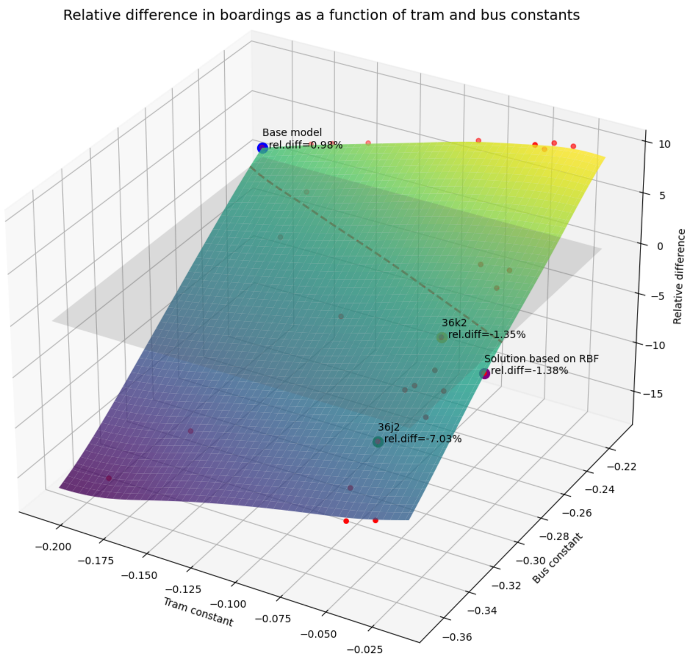
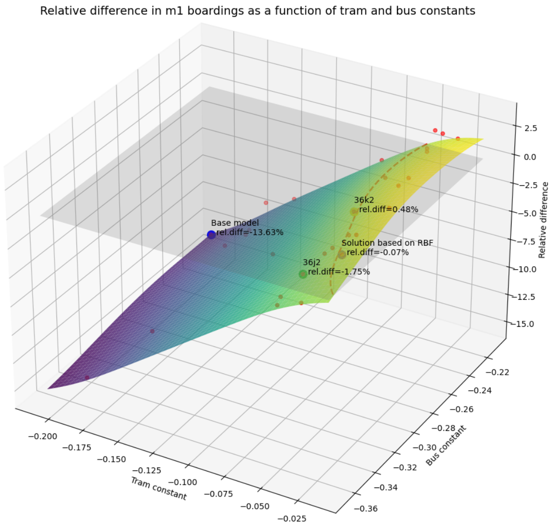


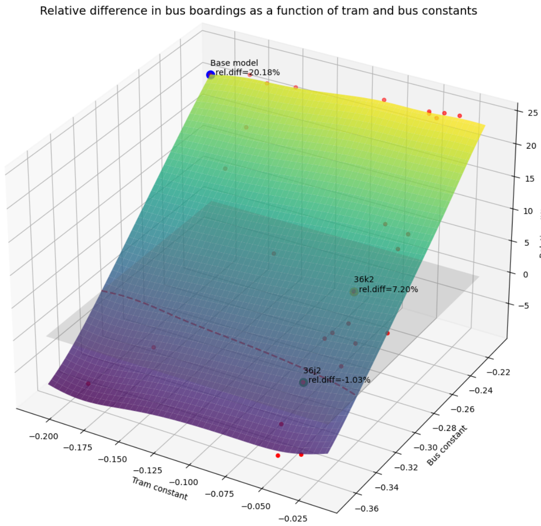
Figure 20: RBF interpolation of the overall relative difference across models

The 3D plot reveals a clear trend. A high tram and bus constant overestimates predictions, while low values for these constants underestimate them, as expected. Our objective is to find a compromise around the z=0% relative difference plane, represented in grey. Among the models, 36k2 appears to be the best overall. It performs slightly better than 36j2 for the m1 relative difference. However, 36j2 gives the best results for the bus relative difference. This highlights the trade-off in achieving balanced predictions across both modes.

From Figure 20, we see that there is a set of solutions to minimize the difference between predictions and reality. However, Figure 21 (a) clearly shows the need for a larger increase in tram constants. Only values above -0.10 (50% increase) start to produce good results. In contrast, for bus predictions, Figure 21 (b) shows that only values below -0.28 (35% decrease) begin to give good results. Multiple solutions are still possible, but we need to avoid overcalibration.



(a) Relative Difference for m1



(b) Relative Difference for buses

Figure 21: RBF interpolation across models

The optimization problem can be seen as a multiobjective problem. Our goal is to minimize two objectives: the ridership relative difference for tram lines (m1 in Lausanne) and for bus lines. We tried to solve this, to see if the numerical results from the interpolations are far from our trial-and-error results. In the first method, we treated the m1 relative difference as the objective function and added a constraint on the bus relative difference, keeping it below a certain threshold (5%). We also tested the reverse approach, using the bus relative difference as the objective and constraining the tram difference. However, it gives worse results. In the second method, we used the interpolated surfaces to find the intersection between the tram and bus surfaces and the z = 0% plane. This intersection represents the point where the model predictions align perfectly with observed data for both modes. Both surfaces are plotted together in the Figure 33, a view of the 0% relative difference can be found in Figure 34.

The first method (36y) provides solutions close to those found through trial and error. We obtained a tram constant of -0.03266 and a bus constant of -0.32727. It is close to the 36j2 model, but with a lower tram constant. The second method (36z) also gave similar results, with a tram constant of -0.03159 and a bus constant of -0.33536. The results for those two optimization techniques can be found in Table 15. From our previous analysis, we argue that these new models over calibrate on the m1 line, the only tram line considered. Indeed, to improve slightly the m1 predictions, they reduce even more the tram constant. However, the bus constant is really close to the one found through trial-and-error.

These results highlight the concept of a Pareto frontier. In a multiobjective problem like this, we aim to find solutions that are not dominated by others. However, there is always a risk of overcalibration in one direction, either favoring tram predictions or bus predictions. It is crucial to consider this trade-off to ensure balanced and practical results for decision-making.

Model	Tram cst	Bus cst	Rel. Diff. m1	Rel. Diff. Bus	Rel. Diff.
36e	-0.210	-0.210	-13.63%	20.18%	0.98%
36j2	-0.053	-0.336	-1.74%	-1.03%	-7.03%
36k2	-0.047	-0.294	0.48%	7.20%	-1.35%
36y	-0.033	-0.327	-0.07%	1.48%	-4.62%
36z	-0.032	-0.335	-0.07%	-0.71%	-6.13%

Table 15: Comparison of Tram and Bus Constants and Relative Differences

In this work, we focus on differentiating tram and bus constants. However, the model could be further refined by calibrating the rail mode as well. Including all three modes would make it harder to find an intersection like the optimal solution in Figure 33. The objective is to find a balance between the different modes without choosing a dominated solution. For MOBi, the emphasis would first be on the train mode, followed by the tram and bus modes.

6.4 Validation of the model

We validate the calibration of the constants in two ways:

1. We do an internal validation, and stay in the Lausanne region. We look at the m2 metro line, which is also a light rail line. Even though, we showed that this line was difficult to predict without taking into account the slope, we still use it as a benchmark. An increase in tram constant should lead to an increase in boardings in the m2 line.

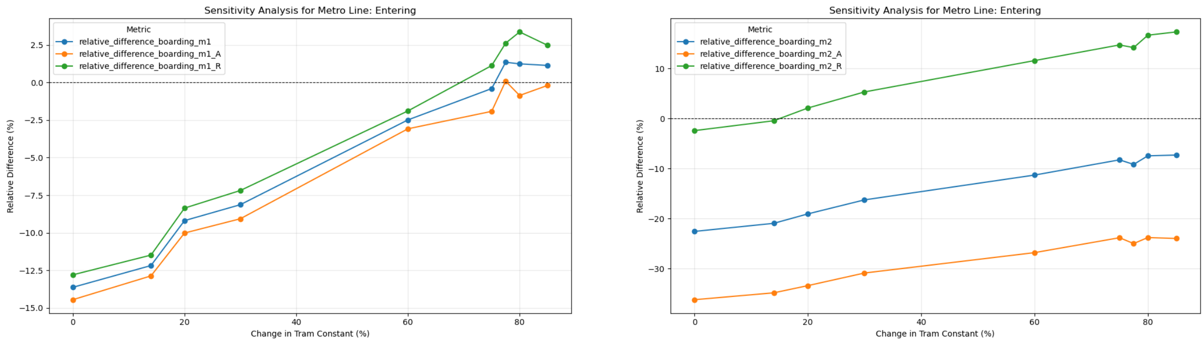
2. We do an external validation. We use the city of Zürich as a validation city. We compare the tram and bus ridership predictions in Zürich against real-world data.

6.4.1 Internal Validation

In the internal validation, our goal is to check if the calibration of the tram constant has an impact on the m2 line. We will compare the different models with the count data for the m2 line.

in Figure 22, we plot the relative difference of boardings for the m1 and m2 lines. Both directions are represented on the same plot. The x-axis represents the increase in the tram constant. The y-axis represents the relative difference in boardings. The “A” Direction for the m1 line is the Flon direction, and the “R” direction is the Renens direction. The “A” direction for the m2 line is the Croisettes direction, and the “R” direction is the Ouchy direction.

We calibrate the tram constant using the results from the m1 line. The best result seemed to be the 36j model, with a 75% increase in tram constant, as can be seen on the left. For the m2 line, we can see that the absolute relative difference is globally (blue curve) decreasing with the increase in tram constant. However, in the Ouchy direction (R), the model now overestimates the number of boardings. This is due to the slope problem we mentioned earlier. In the Ouchy direction, the metro line is going downhill



(a) Relative Difference for m1 (b) Relative Difference for m2

Figure 22: Validation of tram constants

with less people boarding. On the Croisettes direction (A), the model still underestimates by far the number of boardings. However, it goes in the right direction. The model is now closer to the actual data.

The best model for the m2 lines seems to be the 36k one, with an increase in tram constant of 77.5%.

When we look at the final results, taking into account the tram constant increase and the bus constant decrease, we can see that the results change slightly. We calibrated the bus constant on multiple scenarios of tram constant. Our goal was to look at the interdependence of the two constants. We selected 2 different models that prove to have a good fit for the Lausanne Region, the 36j2 and 36k2. When calibrating the tram constant, 36j with an increase of 75% was the best model. The bus constant was then decreased to get the best fit. The model 36k, when calibrating the tram constant, was already overestimating the boardings in the m1. However, this model was still interesting to look at, since it was the best model for the m2 line. The results are presented in Table 16.

Relative Difference	Base Model	36j2	36k2
Tram Constant	-0.21	-0.0525 (+75%)	-0.04725 (+77.5%)
Bus Constant	-0.21	-0.336 (-60%)	-0.294 (-40%)
Overall (Bus + Tram)	0.98%	7.03%	-1.35%
Overall Bus	20.18%	-1.03%	7.20%
Overall Tram	-24.87%	-15.09%	-12.87%
Over M1	-13.63%	-1.75%	0.48%
Over M2	-30.62%	-21.93%	-19.71%

Table 16: Comparison of models for Lausanne

From this Table 16, we can see that the model 36k2 is the best model for the Lausanne region, looking at the overall relative difference. We will test these models on the Zürich region to see if the calibration is still valid.

6.4.2 External Validation

For external validation, we used open-source data from "Open Data Stadt Zürich", provided by the public transport company VBZ Verkehrsbetriebe Zürich 2023. The dataset includes information on all tram lines and bus lines in Zürich. Unlike in Lausanne, we compare our tram constant on real trams, whereas we looked at metro lines in Lausanne. The data contains details per stop, per line, and per day for 2023, which serves as our reference year. The network can be seen in Figure 32.

To preprocess the data, we focused on working days only. We averaged the boarding counts over the year for each stop. Next, we linked the VBZ stop IDs to DIDOK IDs by matching the stop names. This allowed us to align the VBZ data with our model outputs. Using this processed data, we compared the observed boarding counts with the predicted values from our model. We looked at 13 different tram lines and 24 bus lines in Zürich city center.

This comparison helps assess how well the calibrated model for Lausanne performs in another city with light rail systems.

Relative Difference	Base Model	36j2	36k2
Tram Constant	-0.21	-0.0525	-0.04725
Tram Lines (13 lines)	-11.84%	3.53%	6.69%
Bus Constant	-0.21	-0.336	-0.294
Bus Lines (24 lines)	26.02%	16.84%	27.13%
Excluding Bus Line 31	16.32%	8.79%	18.44%
Overall (Tram + Bus)	-3.04%	5.18%	10.37%

Table 17: Comparison of models for Zurich

On this table, we see that the initial model (MOBi 5 released model) predicts relatively good results, with an underestimation of only 3.04% of boardings. However, if we check the predictions for the bus lines and tram lines separately, we realize it overestimates the bus boardings significantly (+26.02%) and underestimates the tram boardings (-11.84%). These results compensate for each other, but they are far from the actual data. We also found that the model overestimates bus line 31 by a factor of 2. As a result, we excluded this line from the analysis. These findings confirm the need to differentiate the constants across public transport modes.

If we now compare the two models tested, 36j2 and 36k2, we see that model 36j2 performs best for the Zürich region. For the overall results, model 36j2 has a 5.18% relative difference, while model 36k2 has a 10.37% relative difference. Model 36j2 overestimates tram boardings by 3.53% and bus boardings by 8.79%. This is a significant improvement compared to the initial model.

Model 36k2 likely increases the tram constant too much. This could be because, in Lausanne, the m1 and m2 are more like metro lines than tram lines. Metro lines tend to be more often separated from car traffic, while trams might be slower due to congestion. Moreover, trams are in general slower than metros. Additionally, we see that Zürich needs a greater reduction in the bus constant. Therefore, model 36j2, with a 60% decrease in the bus constant, is the best model for the Zürich region.

Based on this external validation, we prefer the 36j2 model. We will now look at the impact of the differentiation of the constants on the network.

6.5 Impact of the differentiation

Compared to the base model, our model now differentiates between tram and bus modes. The tram constant was increased by 75%, and the bus constant was decreased by 60%.

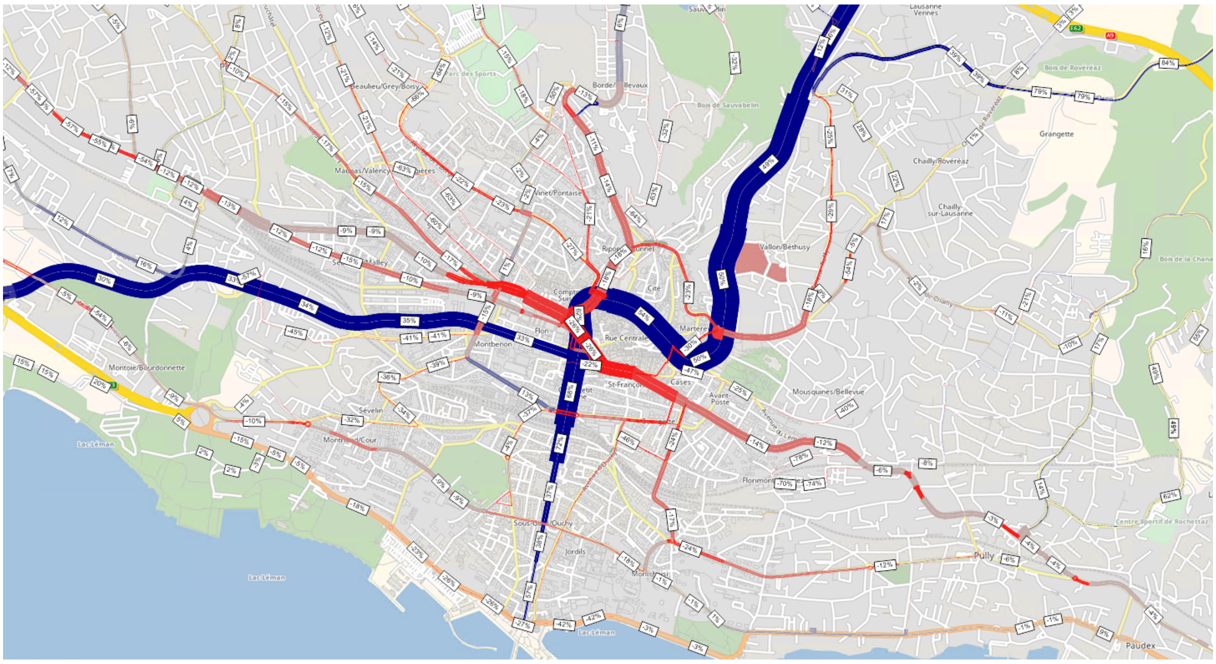


Figure 23: Lausanne network in Visum

When we compare the initial model (36e) with the final model (36j2), we see that the model now predicts between 12% and 60% more boardings in the tram mode, shown in blue in Figure 23. In Lausanne, the results are easy to interpret, as the two metro lines are clearly visible in blue. For the bus mode, the model predicts fewer boardings, shown in red. However, we can observe the effects of transfers from bus to tram. On the east side, bus lines 6 and 41 show more boardings due to transfers at Sallaz. It was one of the assumption we made, that the tram mode would attract users also using bus mode for their journey. However, we can also see what happens in competitive routes: On the west side, bus lines 17 and 18, which run parallel to the m1 line, show fewer boardings. The agents now prefer the tram mode (m1) over the bus mode.

Figure 24 compares the initial model in Zurich with the final one, calibrated with differentiated constants. The model now predicts more boardings in the tram mode (blue) and fewer in the bus mode (red).

Since we calibrated the constants of the different modes, we need to check the impact on the modal split. The modal split is the distribution of trips between different transport modes. Here, we check which mode was most used for each trip, based on distance and the principle of territoriality. This modal split includes all trips performed in

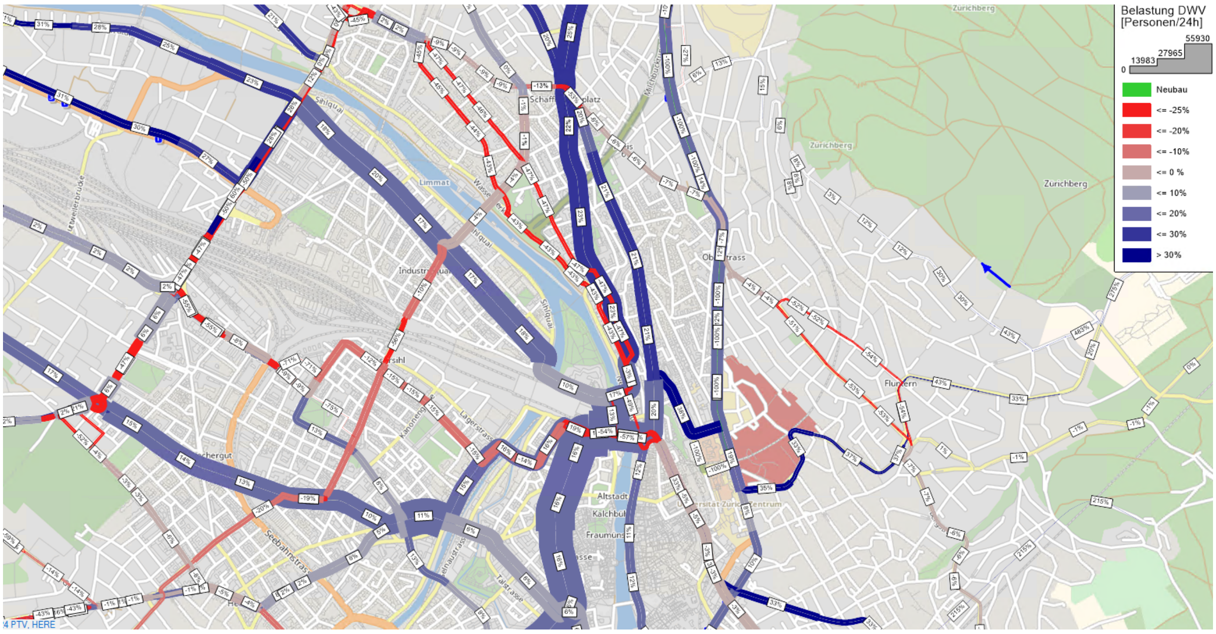


Figure 24: Zurich network in Visum

the region, not just trips originating in Lausanne. Unfortunately, we do not have the real modal split for Lausanne, as it is a difficult metric to obtain. In Office fédéral de la statistique / Office fédéral du développement territorial 2023, a similar modal split was computed for the Lausanne agglomeration in 2021. Based on the principle of territoriality, the public transport share was 17.6%. However, this number could be underestimated due to the impact of Covid-19. Our numbers may also differ since our borders are not the same as the agglomeration definition. Still, we can compare the results between different models. The results are presented in Figure 25 and Figure 26.

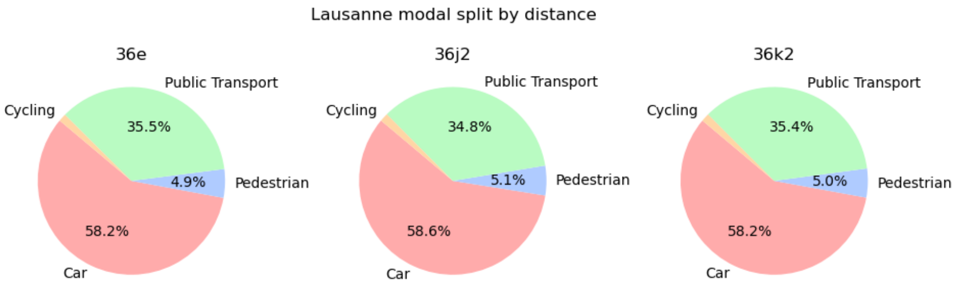


Figure 25: Modal split across models

From Figure 25, we see that the three models have very similar modal splits. The model selected as the best one, 36j2, shows a lower share of public transport modes. This is compensated by an increase in walk mode and slight increases in car and bike modes. Although we cannot compare the results with the real modal split, the model appears consistent across the different versions.

In Figure 26, we show the modal split for commuting only. These include trips starting at home and going to a workplace or educational place, and vice versa. The modal split of/for commuter journeys is similar to that for journeys for all reasons combined.

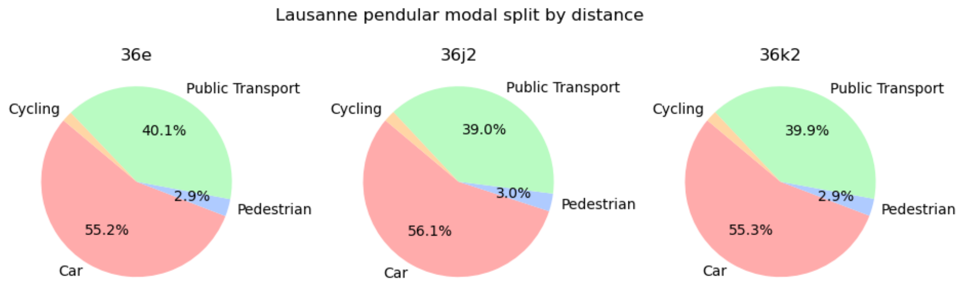


Figure 26: Commuter Modal Split

However, it shows a higher share for public transport and a lower share for pedestrians.

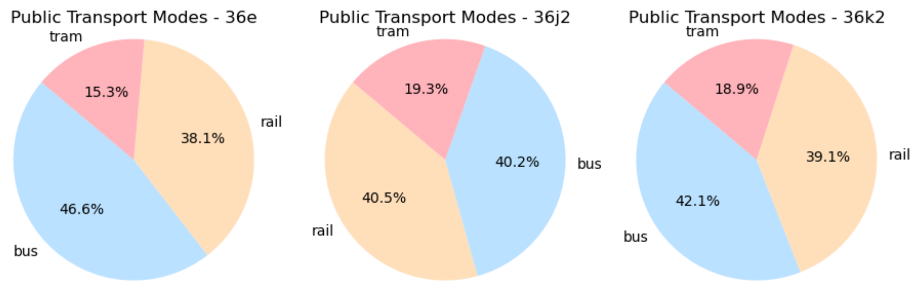


Figure 27: Public transport modal split across models

Regarding the shares of the different public transport modes, namely rail, tram, and bus, we see in Figure 27 that the new models predict more tram and rail boardings, with fewer bus boardings.

Mode	Total Time	Total Km
Pedestrian	1.59%	0.99%
Public Transport	-4.78%	-1.94%
Cycling	8.97%	8.10%
Car	0.71%	0.67%

Table 18: Comparison of Models by Total Time and Total Km

In Table 18, we show the relative difference in mode statistics between the 36e model and 36j2. Similar to Figure 25, the model predicts a decrease in public transport usage for both Passenger Hour Travelled (Total Time) and Passenger Kilometers Travelled (Total Km). Travel time decreases more than distance, which aligns with the prediction of more tram usage than bus usage. Trams are expected to have faster travel times than buses.

There is an important disclaimer. The differentiation can indirectly impact accessibility in the network. A higher constant increases the attractiveness of public transport modes. This lead agents to choose destinations that are better connected by public transport. The accessibility of these zones then improves, since they attract more trips. This change also affects travel time (as seen in Table 18), which is a key factor in accessibility measures. Shorter perceived travel times for public transport increase the accessibility scores for zones served by these modes. As a result, zones near tram lines might become more attractive. To fully analyze this effect, we would need to rerun MOBi plans, but this is beyond the scope of this thesis.

7 Application in the Lausanne case

The goal of this section is to evaluate the impact of differentiating public transport constants on a new tram project in Lausanne. The tram line will connect Flon to Croix-Péage via Renens Gare. The first section, from Flon to Renens, is already in the final phase of construction and will be operational in 2026 (tramway-lausannois 2024). This tram line will compete with both trains and buses. A train line already connects Renens to Lausanne, with a stop at Prilly-Malley. This tram line competes with the train line but can also complement it, as users might take the tram for regional trips to reach the train station. Several bus lines also operate between Flon and Renens. However, they are already at capacity. The tram also promises faster travel due to its dedicated lane (Christian and Keystone-ATS 2021).

In testing our model, the goal is to evaluate the impact of differentiating the constants on the network. We proved with simulation and aggregate data that tram modes are more attractive to users than bus modes. The updated model should therefore predict more boardings for the tram line than the previous version. Here, our objective is to quantify this increase and capture the effect of the "tram bonus".

To analyze the impact, we created a fictive scenario. We used the 2023 synthetic population and the current transport network, adding the new tram line to Croix-Péage. This scenario is fictive, as no tram currently exists on this route. Although it does not reflect the predicted 2030 population, when the final tram section is expected to open, it provides valuable insights into the effects of differentiating public transport constants. The goal is not to predict long-term boardings but to test the model on the existing network. The fictive scenario integrates the tram line with a new schedule, stops, and frequency. The tram is supposed to run every 6 minutes with a capacity of 300 passengers per tram.

We compared two models: the base model (36e) and the best model (36j2). Model 36j2 was chosen because it performed the best in Zürich with similar tram lines. Model 36k2 was also a good model, however, it probably was overcalibrated on the m1. Comparing our results with model 36e, we are sure to isolate the effect of the "tram bonus".

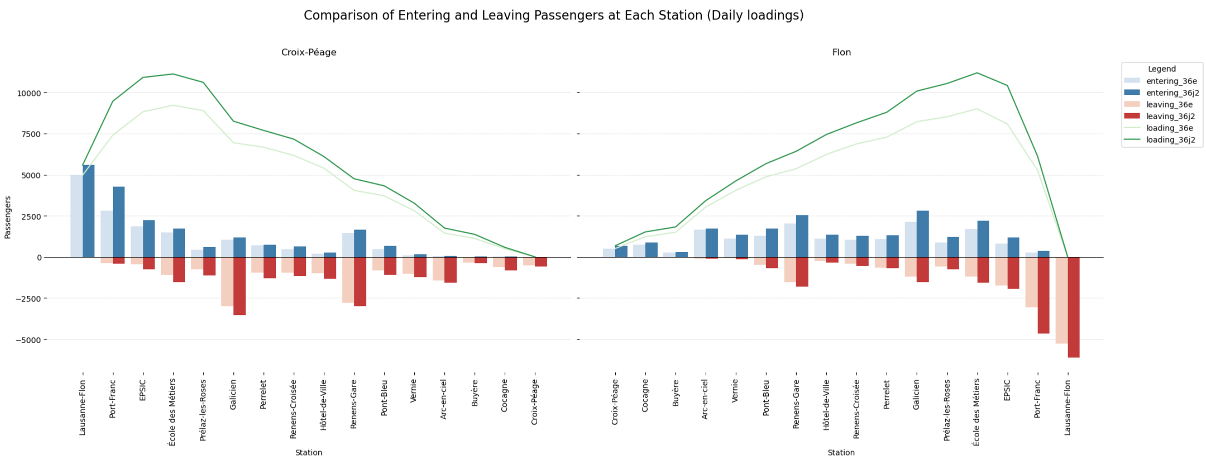


Figure 28: Daily boardings analysis

The comparison focuses on daily boardings, as shown in Figure 28, both overall and per stop and direction. Model 36j2 predicts more than 19,800 daily ridership on the tram in the Croix-Péage direction and over 20,900 in the Flon direction. The results are balanced between the two directions. On average, this model predicts 24.8% more ridership than the base model, which considers the tram line as general public transport without differentiating modes. The difference is significant.

We also analyze peak hours to understand commuter behavior. Morning peak hour (7:00 to 8:00) results are shown in Figure 29, and evening peak hour (17:00 to 18:00) results are in Figure 30. During the morning peak, the Flon direction is busier, with 2,370 predicted boardings compared to 1,530 in the Croix-Péage direction. The tram's capacity of 3,000 persons per hour is not exceeded at any stop. Model 36j2 predicts 22% more ridership in the Flon direction and 14% more in the other direction compared to the base model.

In the evening peak hour, the results are more balanced, with 2,350 boardings predicted in the Croix-Péage direction and 2,280 in the Flon direction. In the evening, the tram serves not only commuters returning home but also leisure and other activities. The difference with the base model is larger than in the morning, with a 27% increase in predictions, mainly due to mode change. This may be even greater with agent replanning, since the tram line increases the attractiveness of activities nearby.

The objective was to determine if differentiating tram and bus constants leads to significantly different predictions. This case study validates our approach and shows its potential for supporting transport planning decisions in Lausanne. It provides results that could help decision-makers plan future transport networks more effectively.

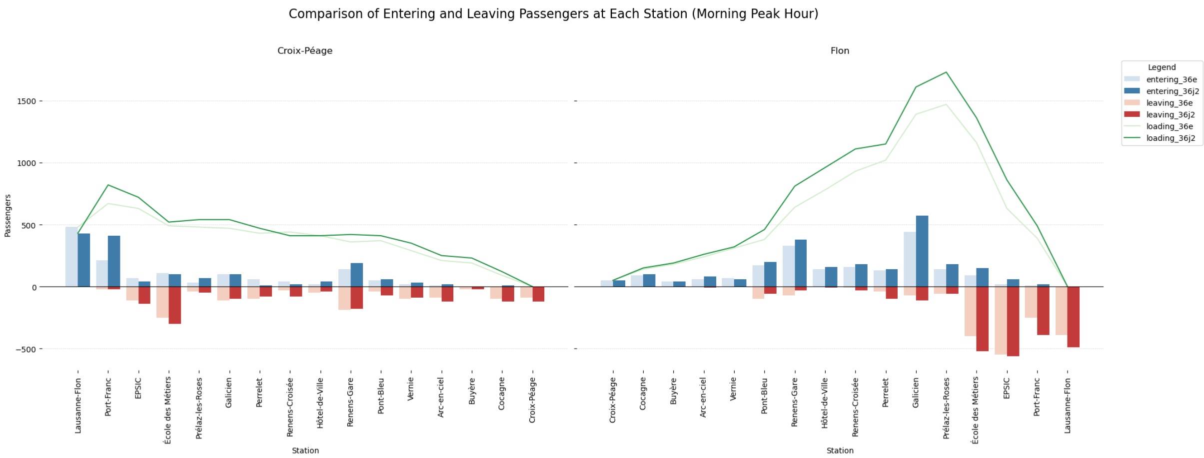


Figure 29: Morning Peak Hour analysis

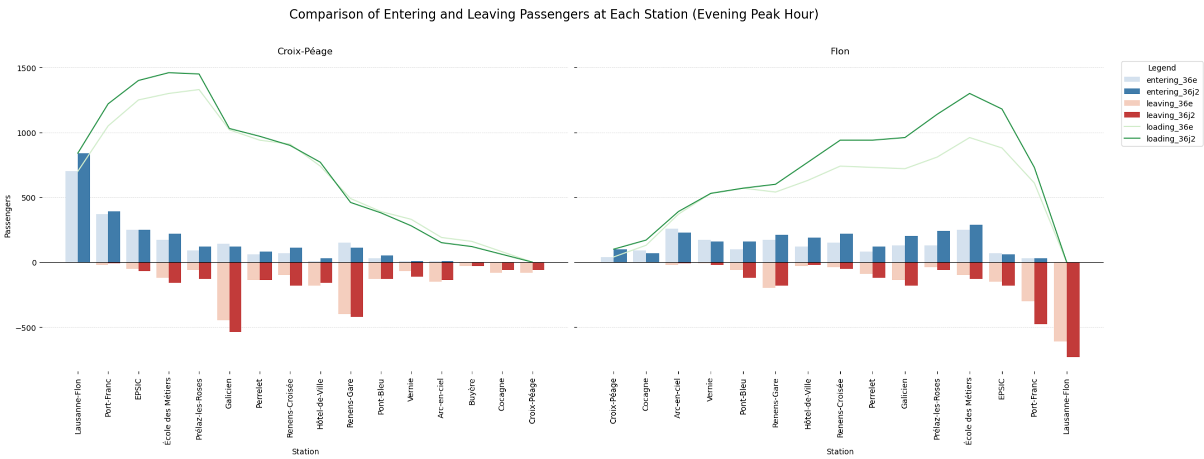


Figure 30: Evening Peak Hour analysis

8 Conclusion

The goal of this project was to differentiate modal preferences in public transportation. The preference for light rail is widely accepted. However, no choice model has isolated the rail bonus with certainty using SP/RP surveys. In this work, we used passenger count to explain this preference.

We first analyzed the current state of the MOBi.sim model. The focus was on the Lausanne public transport network. The model did not predict accurately for students. Students were underrepresented and did not use public transport enough. Enhancements, such as adjusting car availability and revising subscription models, improved predictions. After improving the planning part of the model to better account for students, we reassessed the situation. The MOBi.sim model showed discrepancies between observed and simulated data. Buses were overestimated, and trams were underestimated. These effects canceled each other, making the results appear balanced overall. It proved the necessity for differentiating public transport modes. We kept the same scale parameters for time and cost across modes but adjusted the constants. We first calibrated the tram constant. It needed to be increased by 75% to achieve a good fit. Next, we calibrated the bus constant. It needed to be decreased by 60%. The two constants were interdependent. Increasing the tram constant led to an increase in bus boardings. The calibration was validated internally in the Lausanne region and externally in Zürich. This differentiation of public transport modes has both direct and indirect impacts on the transport model. The direct impact is on tram and bus boardings. The model now predicts more tram boardings and fewer bus boardings. It correctly reflects the competition between these two modes. The overall modal split is also slightly affected, with changes in walking and car use. Passenger hours and kilometers traveled are slightly impacted. Public transport use decreases, while cycling increases.

Using this new model, we analyzed predictions for a new tram project in Lausanne. More than 20% of new passengers are predicted in this scenario compared to the base model. The differentiation of the constants significantly impacts the results.

However, the model has wider effects. The tram attracts more users, and the bus attracts fewer. This changes the attractiveness of destinations, potentially reshaping trip distributions across the network. In the destination choice model, users prefer destinations accessible by tram. This aligns with the findings of the literature review (Dubé, Legros, and Devaux 2018 and D. Knowles and Ferbrache 2016). In future work, rerunning MOBi plans with differentiated constants could result in a different accessibility matrix. Some corridors with trams may become more attractive, while others may become less. Then, agents may reallocate their trips to areas with better public transport connections. This creates an indirect effect, where scoring constants reshape accessibility patterns and, then, travel behavior.

The current model still has some limitations. Our analysis showed that the light rail bonus might vary across different regions in Switzerland. This could be due to differences in vehicles, ranging from those closer to metros to those closer to trams. It could also depend on the network and the extent of tram coverage. Regional corrections might improve the model. Despite this, the model is a strong starting point for differentiating public transport modes.

This work improves public transport predictions in MOBi.sim. It demonstrated the existence of a light rail or rail bonus using market share data. The case study showed that accurate public transport predictions are essential for planning new projects. We hope that this work will help decision makers in the public transport sector.

Appendix

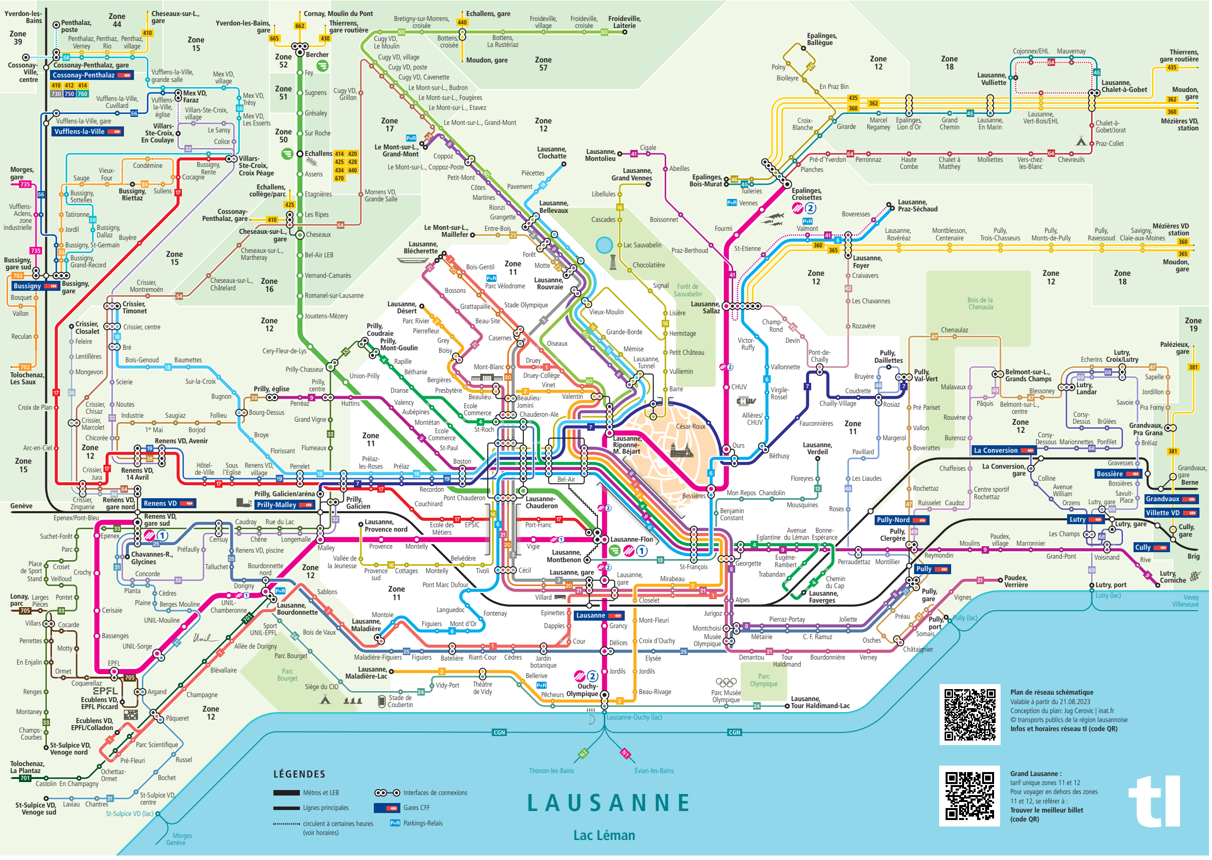


Figure 31: Lausanne public transport network, 2023

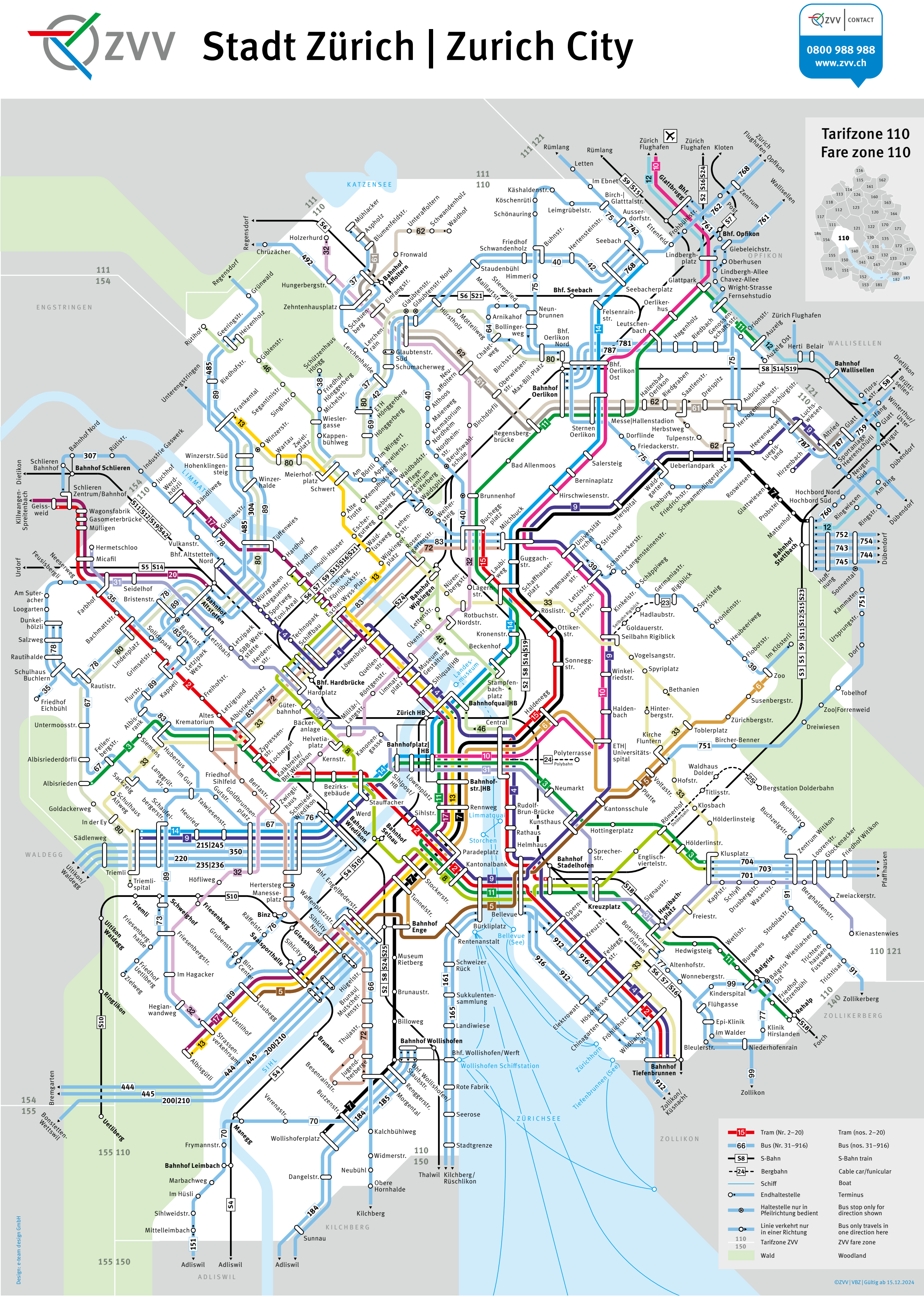


Figure 32: Zurich public transport network

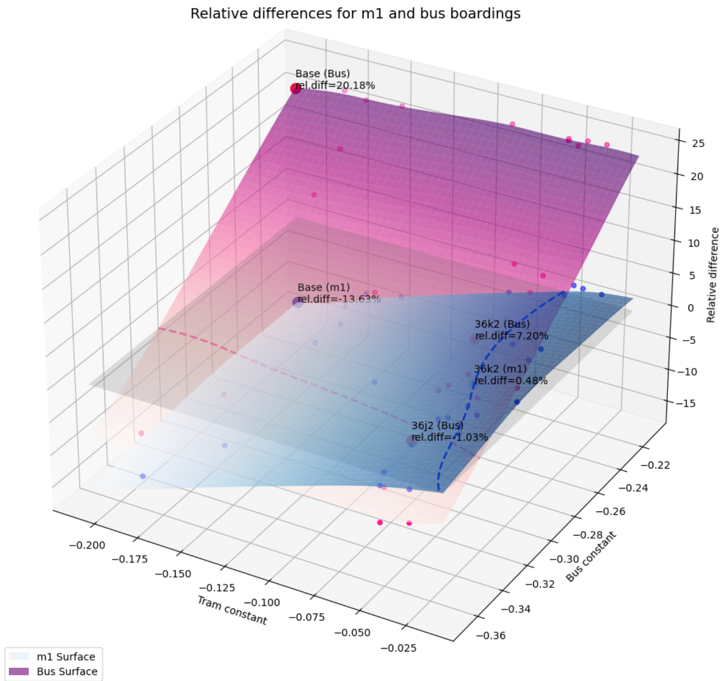


Figure 33: RBF interpolation across models (both m1 and bus objectives)

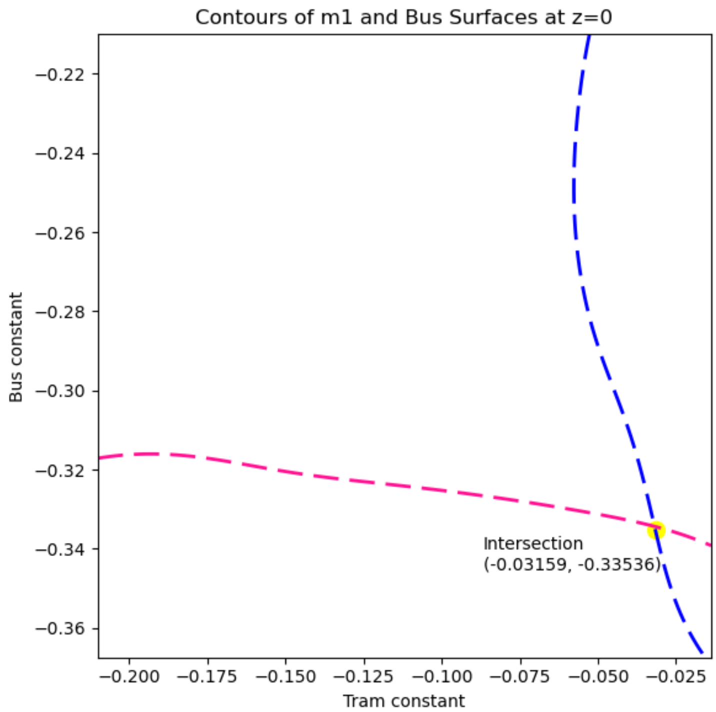


Figure 34: View of the z=0 plan

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