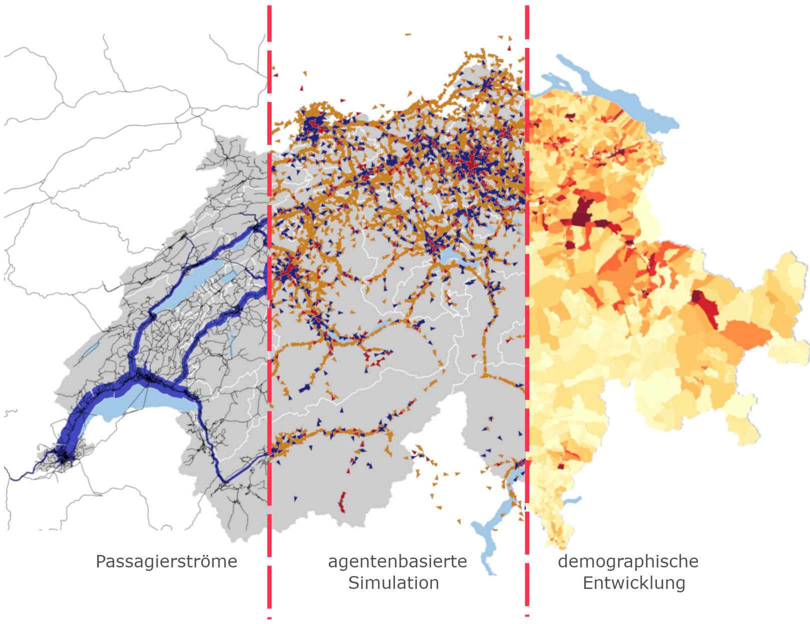

Differentiation of Modal Preferences in Public Transportation

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Abstract

Rail and light rail is 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. The calibration and validation of constants for different modes ensures the model accurately captures modal preferences in SIMBA MOBi, the activity-based, agent-based demand model of the Swiss Federal Railways. The refined model was tested with Lausanne and Zürich data. 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.

Keywords

Tram Bonus, Public Transport, Agent-based Modeling

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1 Introduction

Metro and tram lines are often perceived as superior to buses due to their higher level of service, including greater frequency, reliability, and comfort. Their fixed routes also provide better readability, making them easier to navigate. Additionally, tram lines, unlike buses, are typically separated from traffic, avoiding congestion. This phenomenon, often referred to as the rail or light rail bonus, suggests a preference for rail-based systems over buses, even under similar service conditions.

Despite this widely accepted assumption (Vuchic and Stanger, 1973; Bunschoten *et al.*, 2013), it is difficult to measure and predict this preference with discrete choice models. Stated preference (SP) and revealed preference (RP) surveys struggle to capture the light rail bonus. Differentiating between transport modes remains a challenge. Studies (Ben-Akiva and Morikawa, 2002; Axhausen *et al.*, 2001; Scherer, 2011) give conflicting results. They show that the preference depends on many factors, which makes it hard to isolate in the alternative specific constants (ASCs). However, they agree that a preference exists. More generally, estimating ASCs from choice data is difficult (Ben-Akiva and Morikawa, 2002). A common method is to use aggregate data to calibrate ASCs and match market shares (Train, 2003). In Switzerland, a national stated preference survey is conducted every five years. They tried to isolate the light rail bonus by asking different questions, without success. Differentiation in the next SP survey will not be pursued (Federal Office for Spatial Development, 2024). Still, understanding these preferences is important for transport planning. In Lausanne, a new tram line will open in 2026. Accurate demand forecasts are needed to plan rolling stock and operations.

To address this gap, we use observed count data from the Lausanne's public transport company (tl) to differentiate preferences across public transport modes. This approach enables a calibration of ASCs that better captures real-world modal choices in the SIMBA MOBi agent-based model. The proposed differentiation is tested in Lausanne and externally validated in Zürich. Finally, the new model is applied to a fictive scenario to assess the impact of Lausanne's tram project, isolating the effect of the tram bonus. The SIMBA MOBi model, developed by Swiss Federal Railways (SBB), is an agent-based transport simulation model designed to estimate passenger demand across multiple transport modes. It integrates detailed travel behavior components, including mode choice, schedule, and accessibility constraints. Previous versions of MOBi treated all public transport modes uniformly, without differentiating between bus and tram preferences. Our contribution reviews this approach by introducing calibrated public transport modal differentiation, improving prediction accuracy for both current and future infrastructure planning.

2 Differentiation across public transportation modes

2.1 Motivation for Differentiation

Our goal is to differentiate between public transport modes. As seen from a 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 identify an area where our model accurately reflects reality for comparison. Based on our knowledge of the Lausanne area and previous work on student behavior, we focused the study on Lausanne and its two light rail lines.

The analysis uses passenger count data from Transports publics lausannois (tl) for calibration and validation. This dataset includes boarding and alighting counts across Lausanne's network, averaged over 250 non-holiday weekdays in 2023. The base model, 36e, accounts for student behavior. It includes a specific student parameter for public transport subscriptions and a revised rule for student car availability. This is important for the m1 line, which mainly serves the Dorigny campus (UNIL and EPFL).

Due to Lausanne's metro characteristics, we focus calibration on the m1 line and exclude the m2 line. The m2 line is difficult to model due to its steep slope, which affects travel behavior. The Lausanne train station area also introduces uncertainty, as the model struggles to capture the many multimodal transfers there. These factors make the m1 line a better reference for tram constant calibration.

Table 1 shows that the 36e model performs well overall for Lausanne. However, a detailed analysis reveals that it overestimates bus ridership and underestimates tram (m1+m2) ridership. These errors cancel each other out. To adress this, we propose to differentiate between tram, bus, rail and other modes.

2.2 Methodology

Within MOBi, transportation modes are structured at two levels: the planning stage (MOBi.Plans) and the simulation stage (MOBi.Sim). In MOBi.Plans, agents choose

Table 1: 2023 Boarding difference: tl data vs. base model

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%

between four main modes: Car, Public Transport, Bike, and Walk. In the simulation step, additional modes are added:

- Public Transport.
- Feeder Modes: Access to public transport is possible by walking, cycling, using a car, ride-sharing, or taxi.
- Car-Based Modes: Includes private car travel, ride-sharing, and taxi.
- Non-Motorized Modes: Walking and cycling.

Public transport schedules also classify vehicles into rail, tram (light rail), bus, and other (e.g., cable cars, boats). However, MOBi.Sim scoring does not differentiate between these public transport sub-modes.

The simulation tool for dynamic network modeling is MATSim. MATSim uses an iterative, agent-based approach to optimize daily travel plans based on a scoring function. It evaluates the utility of each travel decision. The utility of an agent's daily plan consists of activity utility and travel disutility:

$$S_{\text{plan}} = \sum S_{\text{activity}} + \sum S_{\text{travel}}. \tag{1}$$

The travel disutility considers marginal utilities of time, cost, and distance, as well as mode-specific penalties. Public transport users face additional penalties for waiting times and transfers.

Our study focuses on preference differentiation. We modify only the alternative-specific constants (ASCs) for tram and bus, keeping all other scoring parameters unchanged. This ensures that the observed differentiation comes from actual user preferences rather than scale effects.

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.

Rieser *et al.* (2018b) 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.

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. It is allocated to ensure sufficient computational power for processing large datasets and running the MATSim mobility simulation. Despite optimizations in the SwissRailRaptor (Rieser *et al.*, 2018a), the iterative nature of the simulation and the detailed representation of the transport network contributes to the runtime.

The calibration of ASCs follows an iterative process using passenger count data from Lausanne and Zürich. Due to computational constraints, we employ a trial-and-error approach to adjust constants, ensuring the model's outputs align with observed boarding patterns. The final calibrated constants reflect empirically observed preferences for tram and bus, allowing for a more realistic representation of modal choices in Swiss urban transport systems.

3 Results and Discussion

The calibration process reveals that increasing the tram constant is necessary to correct the model's underestimation of tram ridership, while decreasing the bus constant helped address its overestimation. The sensitivity analysis and mode results are presented in the Appendix in Figure 3 and 4 and Table 5.

Table 2: Relative difference between tl ridership and model prediction for Lausanne

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%

The final model, 36j2, provided the best balance for accurately reflecting observed public transport usage. Table 2 summarizes key improvements from the calibration. Compared to the base model (36e), 36j2 significantly reduces discrepancies between observed and simulated public transport ridership in Lausanne.

3.1 Key Insights

To ensure the model's robustness for prediction ability, it is tested against Zürich's tram and bus networks using open-source VBZ data (Verkehrsbetriebe Zürich, 2023). The results in Table 3 confirm that excessive increases in the tram constant, which worked well in Lausanne, lead to overestimations in Zürich. Trams operate under different service conditions. This validation step helped refine the calibration, ensuring that the 36j2 model was applicable across different urban contexts. This discovery also highlights the need for corrections in different cities based on tram coverage.

Table 3: Relative difference between VBZ ridership and model prediction for Zürich

Model	Tram cst	Bus cst	Rel. Diff. Tram	Rel. Diff. Bus	Rel. Diff.
36e	-0.210	-0.210	-11.84%	16.32%	-3.04%
36j2	-0.0525	-0.336	3.53%	8.79%	5.18%
36k2	-0.04725	-0.294	6.69%	18.44%	10.37%

Applying the calibrated model to Lausanne improved results. The new tram and bus constants corrected biases in ridership predictions. The interaction between tram and bus constants highlights important network effects. A higher tram constant shifts demand from bus to tram along competing corridors. It led to higher ridership and more intermodal transfers, reinforcing the importance of tram services as network connectors.

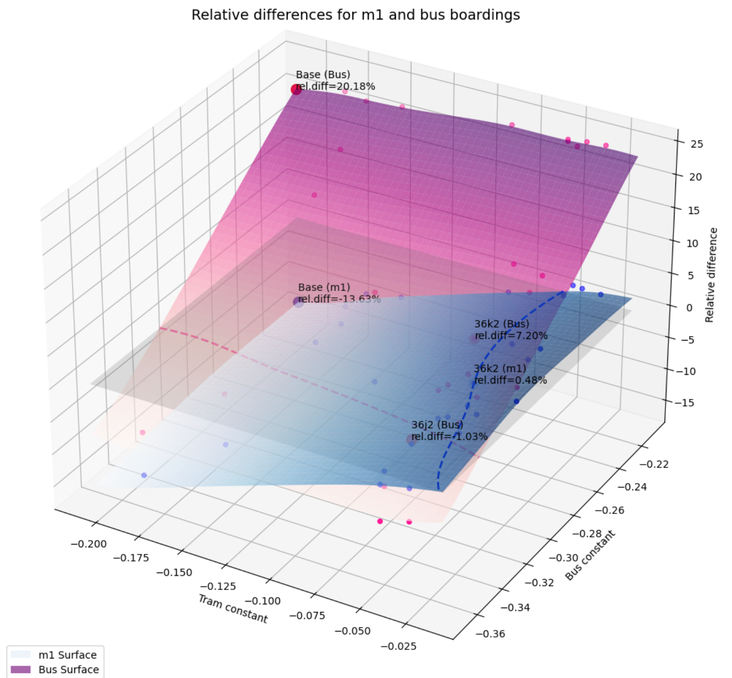
Despite these changes, the overall modal split stays stable. Figure 7 shows a small drop in public transport share, with a rise in walking and minor changes in car and bike use. Figure 8 confirms this trend for commuting trips. Public transport remains essential for work and education travel.

Figure 9 shows a higher share of tram and rail trips and fewer bus boardings. This confirms that tram improvements shift demand from buses but keep a balanced network-wide impact. Table 5 shows a slight decline in total public transport use by time and distance traveled. This is mostly due to the shift to faster tram services.

3.2 Interaction of constants

Changing the tram constant affects bus boardings and vice versa. To illustrate this, we use radial basis function (RBF) interpolation. Figure 1 shows the impact of tram and bus constants on ridership predictions. The x-axis represents the tram constant, the y-axis the bus constant, and the z-axis the relative difference in predictions in Lausanne.

Figure 1: RBF interpolation across models (both m1 and bus objectives)



A high tram and bus constant overestimates ridership, while low values underestimate it. The goal is to find values near the z = 0% plane, where predictions match observed data. We approach the problem as a multiobjective optimization. The goal is to minimize relative differences for both tram and bus. Using interpolated surfaces, we find the best constants by identifying the intersection of the tram and bus surfaces with the z = 0% plane. This highlights the trade-off in balancing both objectives. Figure 10 shows this intersection.

The result in Table 4 aligns closely with trial-and-error calibration. The method finds a tram constant of -0.0316 and a bus constant of -0.335 (36z), close to model 36j2 but with a lower tram constant. However, since the only proxy for the tram constant is the m1 line, this solution overcalibrates on the m1. We achieve very good values for the m1 but with poor generalization ability. This result highlights 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.

Table 4: Relative difference between tl ridership and model prediction for Lausanne

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%
36z	-0.032	-0.335	-0.07%	-0.71%	-6.13%

4 Application in the Lausanne case

This section evaluates the impact of differentiating public transport constants on a new tram project in Lausanne. The tram will connect Flon to Croix-Péage via Renens Gare. The first section, Flon to Renens, will open in 2026 (tl tramway lausannois, 2024). The tram competes with both trains and buses. A train already connects Renens to Lausanne, and several bus lines serve this corridor but are at capacity. The tram will have a dedicated lane, offering faster travel (Christian and Keystone-ATS, 2021).

To test the impact, we created a fictive scenario using the 2023 synthetic population and current transport network. We added the new tram line (projected for 2030) with its schedule, stops, and a 6-minute frequency. The goal is not to predict long-term usage but to analyze how differentiating transport constants affects the model.

We compare two models: the base model (36e) and the best calibrated model (36j2) with the effect of the tram bonus.

Figure 2: Daily boardings analysis

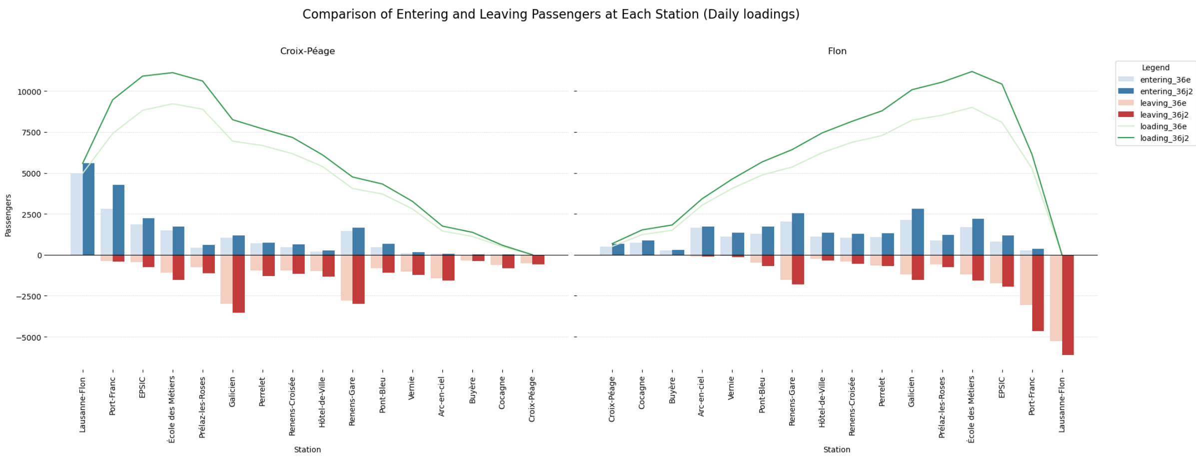


Figure 2 shows daily boardings. Model 36j2 predicts 19,800 boardings in the Croix-Péage direction and 20,900 in the Flon direction. On average, ridership is 24.8% higher than in model 36e, which does not differentiate tram and bus.

Morning peak hour (7:00-8:00) results in Figure 11 show higher flow toward Flon, with 2,370 boardings compared to 1,530 toward Croix-Péage. The tram's 3,000 passengers per hour capacity is not exceeded. Model 36j2 predicts 22% more boardings toward Flon and 14% more in the other direction. In the evening peak (17:00-18:00), the flow is more balanced, with 2,350 boardings toward Croix-Péage and 2,280 toward Flon (Figure 12). In the evening, the tram serves not only commuters returning home but also leisure and other activities. The increase over model 36e is larger in the evening (27%), likely due to the tram's influence on leisure and non-work trips.

This case study confirms that differentiating tram and bus constants significantly affects predictions. The results validate our approach and provide insights for transport planning in Lausanne.

5 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 market share data, like passenger counts, to explain this preference.

The focus was on the Lausanne public transport network. After improving the planning part of the model to better account for students, we assessed 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, more tram transfers 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. However, the model has indirect effects. The tram attracts more users, and the bus attracts fewer. This changes the attractiveness of destinations. In the destination choice model, users prefer destinations accessible by tram. This aligns with the findings of the literature review (Dubé *et al.* (2018) and D. Knowles and Ferbrache (2016)).

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

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.

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Figure 3: Comparison of m1 line models

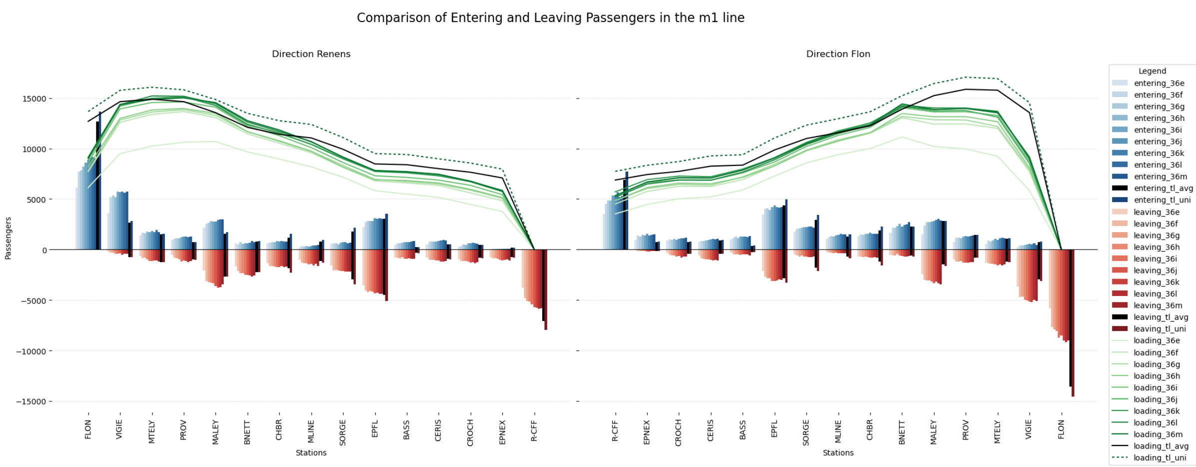

Figure 4: Sensitivity analysis of the different models

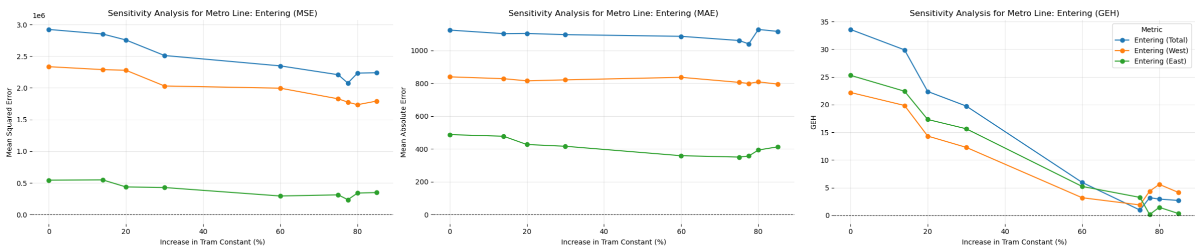

Table 5: Comparison of Models by Total Time and Total Km

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%

Figure 5: Lausanne public transport network, 2023

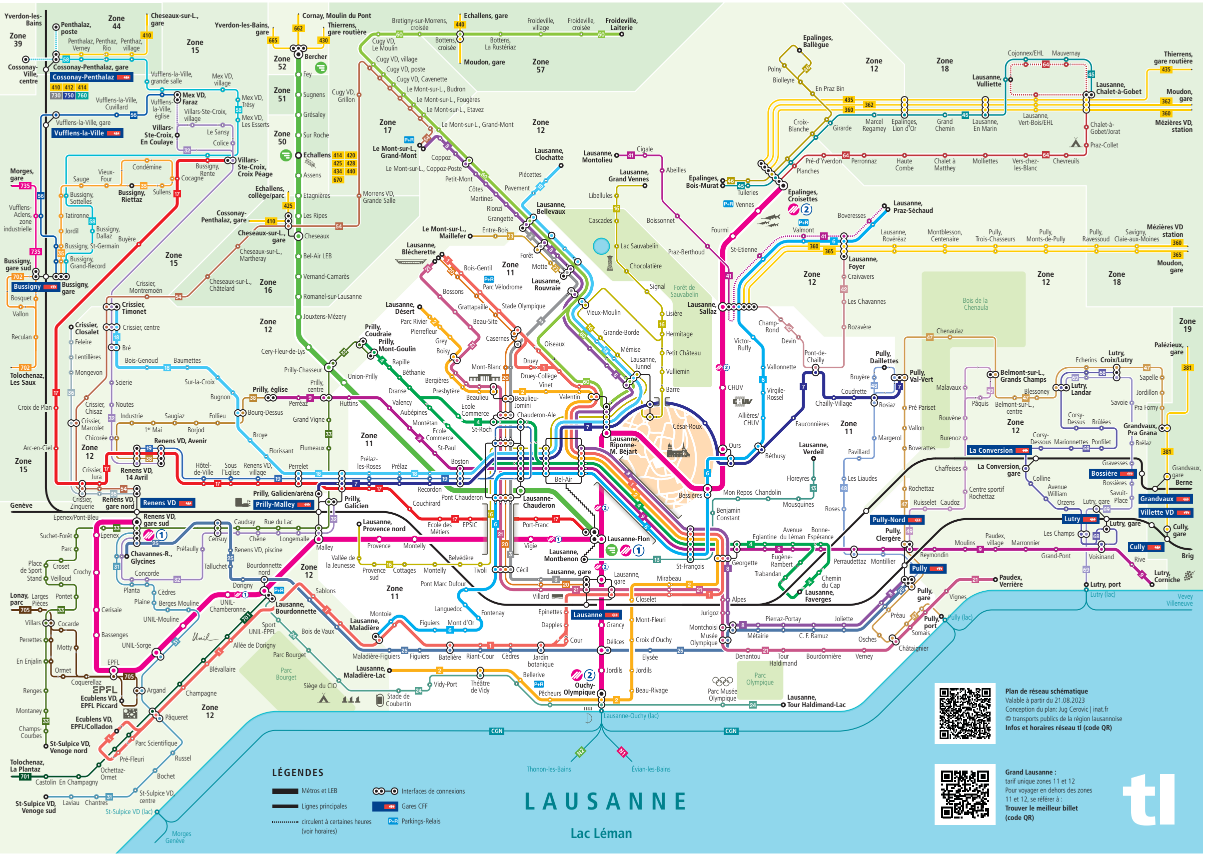

Figure 6: Zurich public transport network

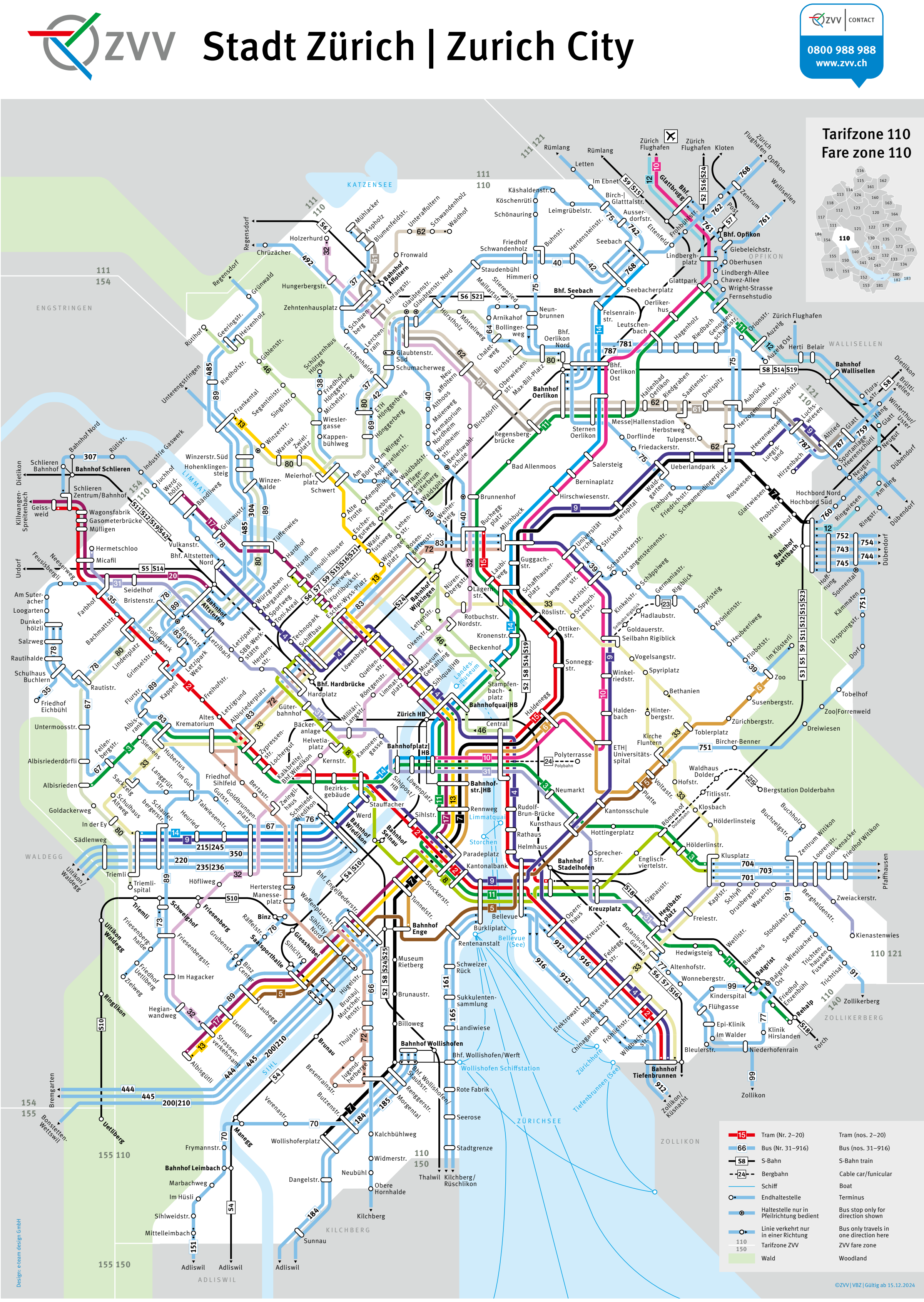

Figure 7: Modal split across models

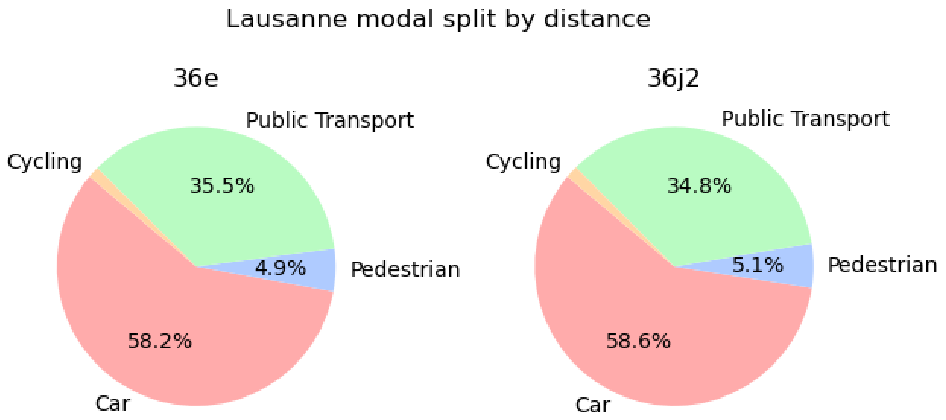

Figure 8: Pendular Modal Split

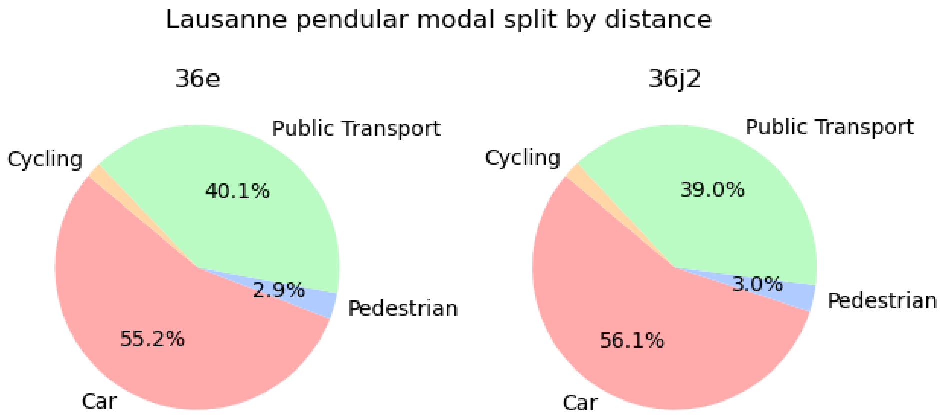

Figure 9: Public transport modal split across models

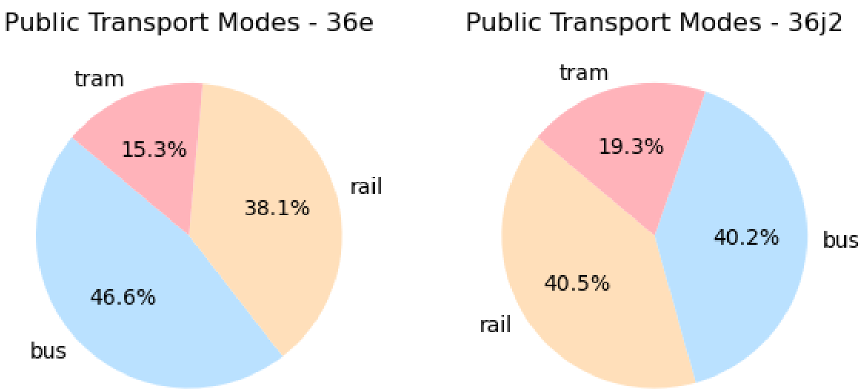

Figure 10: View of the z=0 plan

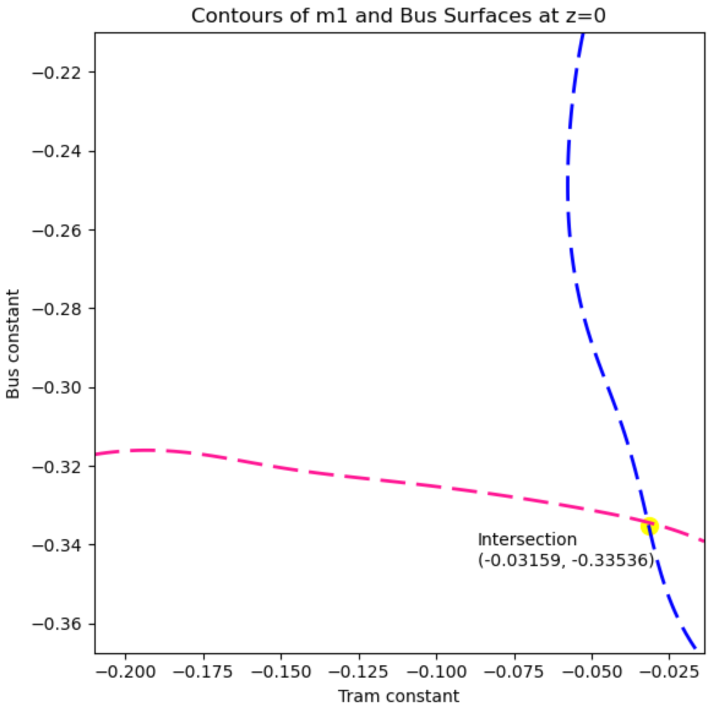

Figure 11: Morning Peak Hour analysis

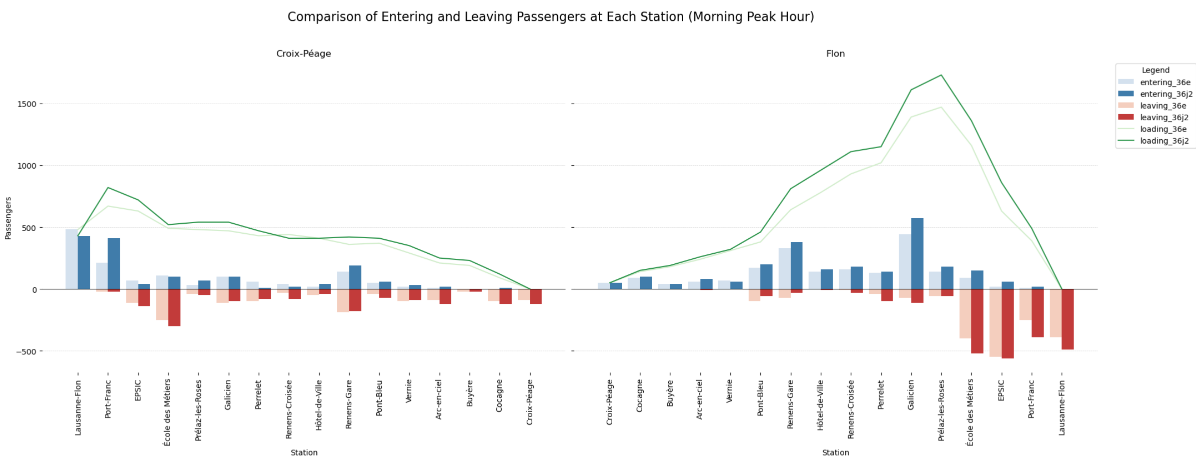

Figure 12: Evening Peak Hour analysis