

Dynamic travel assignments of urban multimodal transportation networks: A case study of Amsterdam

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1 INTRODUCTION & SCOPE OF WORK

Urban transportation networks, particularly in large metropolitan cities, are composed of multiple transport modes (i.e., metro, tram, and bus), that are physically interconnected and operationally interdependent (Alessandretti et al., 2023). These Urban Multimodal Transportation Networks (UMTNs) are generally more redundant and may provide greater flexibility relative to single-mode transportation systems (Xu & Chopra, 2023). But their interdependencies may also amplify the impacts of disruptions (Cats & Jenelius, 2015). To be specific, a failure in one segment of one mode may propagate across lines and modes through rerouting, capacity limitations, and operational adjustments, potentially triggering multimodal cascading failures (Su et al., 2014).

Given these complexities, most studies exploring passenger flow dynamics under disruptions have focused on single-mode transport systems (Bi et al., 2024; Henke et al., 2024; Ma et al., 2023). The studies that have performed flow allocation approaches for UMTNs often relied on topological abstractions such as L-space or P-space (Ju et al., 2022; Xu et al., 2024). In the L-space model, the network is represented from a physical perspective, where nodes corresponding to consecutive stations along a route are directly connected, emphasizing infrastructure continuity, whereas the P-space model adopts a logical perspective in which nodes are connected if at least one route directly links them, highlighting accessibility rather than physical adjacency (Alessandretti et al., 2023; Barthélemy, 2011; Sienkiewicz & Hołyst, 2005). Although these models offer insights into network topology and interdependencies, they simplify physical geometry, bidirectional operations, and multimodal transfer structures for UMTNs inducing inaccurately represent specific passenger transfers or dynamic flow allocation. Besides, although research on dynamic flow assignment has advanced, only few studies explore how flow redistribution affects system functionality under disruption conditions in

UMTNs, particularly when network components reach capacity saturation (Zhu et al., 2020). Moreover, existing robustness or resilience assessments often consider link or station capacity limits but do not treat capacity as a dynamic assignment constraint across varying demand levels (Cats et al., 2017; Wang et al., 2023). This limitation reduces the ability to capture secondary congestion due to re-routing, asymmetric flow demand, and cascading effects.

To address these gaps, this study develops a dynamic flow allocation and performance assessment framework for UMTNs evolving supply changes. The proposed approach integrates detailed multimodal network representation with capacity-constrained dynamic flow assignment, enabling the evaluation of changes in system functionality under different demand and disruption conditions. We apply our model to the public transportation network of Amsterdam, The Netherlands.

2 METHODOLOGY

In this study, the methodology consists of four main steps, namely: (i) construction of the UMTNs topology networks; (ii) generation of a dynamic flow allocation model; (iii) assessment of network performance; and (iv) simulations under normal and disruption conditions.

First, we construct the UMTNs as a directed, weighted, and capacity constrained multilayer graph that clearly represents both physical topology and operational entities while providing a unified illustration of metro, tram, and bus networks. These physical-service networks are constructed from OpenStreetMap data (OSM, 2024), with topological correction and ordering used to generate bidirectional baseline networks for each mode. Based on station name equivalence and spatial distance thresholds, bidirectional virtual transfer edges between routes and modes are then established to ensure full network connectivity. The resulting UMTNs consist of nodes and directed edges. Nodes include station nodes where passengers can board and alight, as well as intermediate routing nodes to capture geometric and directional constraints. Each node is uniquely identified by attributes including station name, identifier, transport mode, route affiliation, and geographic coordinates. Besides, edges are classified into service edges and virtual transfer edges. Service edges represent actual transport operations and are subject to capacity constraints. While virtual transfer edges simulate passenger transfers between routes and modes with transfer time penalties, virtual transfer distances minimize transfer movements but without capacity limits (Gao et al., 2025).

To develop the dynamic flow allocation model, we first generate a set of origin–destination (OD) pairs based on the total number of stations, station identifiers, and topological reachability of the network. During this process, the OD set is designed to cover the network as extensively as possible with a minimal number of OD pairs and is controlled with the same amount for each transport mode. In the case study of Amsterdam, for a single-modal transport network, we uniformly select 1300 OD pairs; for the multimodal transport networks, we ultimately select 3900 OD pairs across modes for comparison with the results of integrating three-layer single-modal networks. Subsequently, the initial demand for each OD pair is randomly generated according to empirical distributions and data reported in previous studies, so as to approximate real-world demand variability. The network topology, passenger travel behavior, initial OD supplies, and edge capacity constraints are then integrated into a unified flow assignment framework. An iterative minimum-cost maximum-flow algorithm is applied to allocate flows under these constraints (Chen et al., 2022; Hamdouch & Lawphongpanich, 2008; Spiess & Florian, 1989). As the algorithm evolves over time, each iteration guarantees feasibility with respect to capacity limits, demand supplies, and bottleneck conditions. To be specific, in each iteration, flows are assigned along the minimum-cost paths in priority, while cumulative costs and allocated flows are continuously recorded. The model outputs include the total assigned flow on each edge, the total travel cost, and cost–flow indicators for each OD pair. Three key conditions are enforced: (1) the total assigned flow on any edge cannot exceed its capacity; (2) the total assigned flow for each OD pair cannot exceed its initial supply; and (3) per-iteration flow assignment along each OD path is constrained by the capacity of its bottleneck edge to ensure path feasibility.

To assess the feasibility of the dynamic flow allocation model under different demand levels, four initial supply scenarios are simulated for each transport mode under normal conditions while keeping the number and composition of OD pairs fixed. In the first and third scenarios,

all OD demands can be fully satisfied, although the supply range in the first scenario is broader than in the third. For example, in the case study of Amsterdam, metro demand ranges from 20 to 42 passengers per hour per OD pair in the first scenario and from 25 to 38 passengers per hour per OD pair in the third. By contrast, the second and fourth scenarios expand the demand ranges based on the first and third scenarios, leading to partially unmet demand after flow assignment. For instance, metro demand ranges are expanded to 20–45 and 25–40 passengers per hour per OD pair, respectively.

After validating the dynamic flow allocation model, targeted disruption scenarios are performed by sequentially removing each edge within each mode. System Serviceability Index (SSI) is then used to evaluate changes in dynamic flow allocation under both normal and disruption conditions (Chen et al., 2024; Franchin & Cavalieri, 2013; Wang et al., 2010), thereby quantifying and comparing the impact of individual edge failures on the system performance of each single and multimodal mode.

$$SSI = \frac{PF'}{PF} = \frac{\sum_{m \neq n \in V} F_{mn}'}{\sum_{m \neq n \in V} F_{mn}} \quad (1)$$

Where PF and PF' represent the total fully allocated passenger flows in the system under normal and disruption conditions, respectively. They are calculated as the sum of the assigned flows over all OD pairs denoted by (m, n) , where both m and n belong to the node set V .

3 RESEARCH OUTCOMES

Using the UMTNs composed of the metro, tram, and bus networks in Amsterdam as a case study, we first construct the multimodal bidirectional topological networks based on OpenStreetMap data. Then the peak-hour interval passenger flows are dynamically assigned under four demand scenarios in both single-mode and multimodal mode to evaluate the feasibility of the proposed dynamic flow allocation model. Figure 1 presents the first-hour results for the full multimodal system in both directions which are highlighted by the P and N-direction, illustrating edge capacity utilization after iterative allocation while satisfying both capacity and OD demand constraints. The specific routes of each transportation mode in both Positive and Negative (P- and N-) directions are described in detail in Table 1 of appendix.

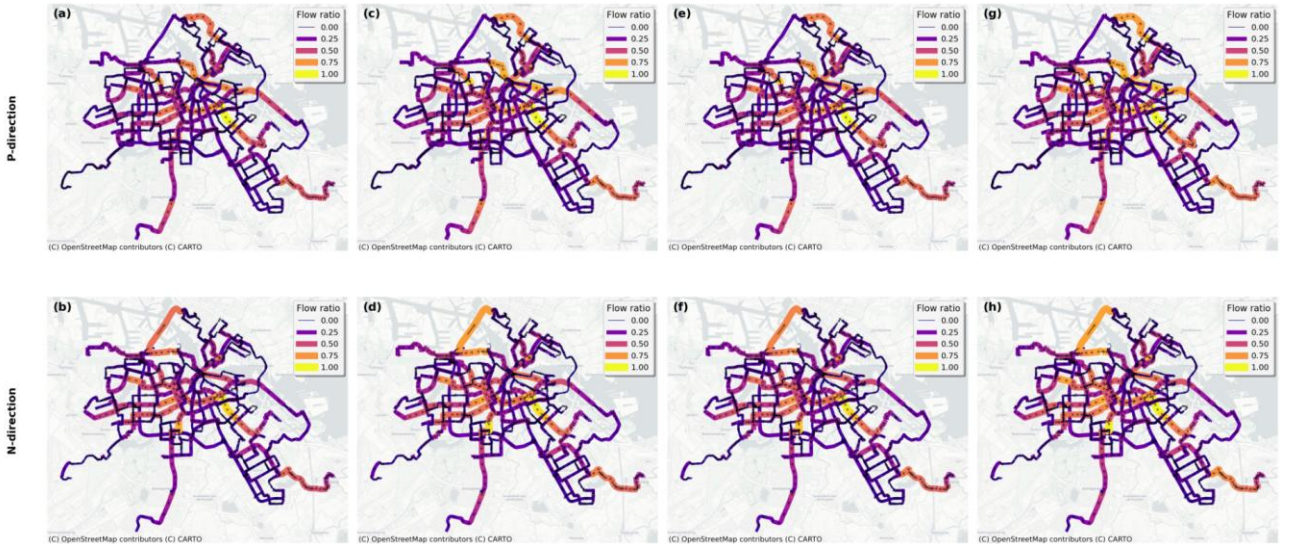


Figure 1 Capacity utilization map of edges in multimodal network under four different demand scenarios with the multimodal mode OD set. Each panel shows P-direction and N-direction flows by row and different demand scenarios by column, and thicker lines with colors closer to one indicate higher utilization.

The results show that, with a fixed OD composition set, high-utilization edges remain consistent across demand scenarios within the same mode and direction, while opposite directions at the same geospatial locations exhibit obviously different usage levels, reflecting peak-hour commuter-oriented directional asymmetry observed in Amsterdam's transit system

(Yap & Cats, 2022; Zhao et al., 2022). The results also show that high-frequency edge usage in the metro network decreases noticeably under multimodal OD selection, with a similar but weaker effect in the tram network, while the bus network experiences an overall increase in utilization and the emergence of new high-frequency usage edges. This highlights modal redistribution effects in the multimodal network and further confirms the dynamic flow allocation model's realism and applicability.

In addition to flow assignments in normal situations, we also evaluated network performance under specific disruptions by sequentially removing each edge from the metro, tram, and bus networks and assessing the resulting changes in system functionality. Figure 2 shows the results for SSI in the first hour under demand scenario 2, comparing the multimodal simulation with the corresponding single-modal case in columns (a) and (b). Although this demand scenario already exhibits oversaturation under normal conditions due to capacity constraints, clear differences emerge between the results of two modeling approaches in two columns. In the single-modal simulations, disruptions to certain critical edges lead to a significant decrease in SSI, indicating a high vulnerability of the system to single-edge failures. These links form localized bottlenecks, and their removal often triggers sharp declines in system performance, which are shown by the dark blue edges in Figure 2. However, in the multimodal simulations, for the same disrupted edge, the SSI value remains high, spatially more uniform and frequently equals to or exceeding one. These difference and SSI values greater than one suggest that the UMTNs adequately allows passenger flow to adaptively reroute to other modes and lines, thereby mitigating the impact of targeted disruptions on the system level. Specifically, in the single-modal case, edges with an SSI value greater than 1 reflect that removing the particularly restricted edge can locally alleviate system capacity constraints. The SSI values greater than one in the multimodal case, exhibits a systematic improvement driven by cross-modal rerouting and capacity-constrained flow redistribution, highlighting that the proposed dynamic flow allocation model can capture the behavior of adaptive path rerouting and its improvement on the system resilience. Moreover, the findings emphasize that the robustness of multimodal urban transportation systems not only relies on the topological redundancy but also comes from demand-driven, capacity-constrained cross-modal flow redistribution.

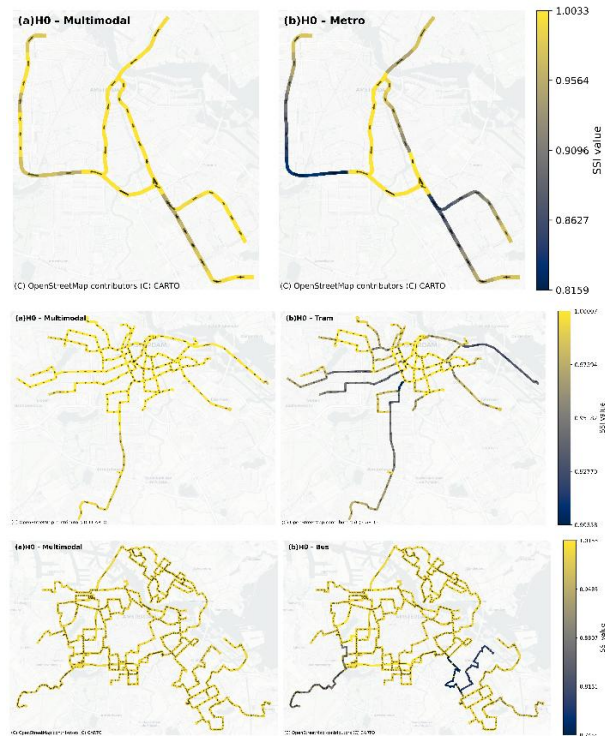


Figure 2 The results for SSI of targeted disruption conditions in the first hour and P-direction under demand scenario 2. The upper row shows the results for the metro network in the multimodal and single-mode simulation. The middle row shows similar rows for the tram network. The bottom row shows the results for the bus network.

REFERENCES

- Alessandretti, L., Natera Orozco, L. G., Saberi, M., Szell, M., & Battiston, F. (2023). Multimodal urban mobility and multilayer transport networks. *Environment and Planning B: Urban Analytics and City Science*, 50(8), 2038–2070. (29 citation(s)).
<https://doi.org/10.1177/23998083221108190>
- Barthélemy, M. (2011). Spatial networks. *Physics Reports*, 499(1), 1–101. (2128 citation(s)).
<https://doi.org/10.1016/j.physrep.2010.11.002>
- Bi, W., Schooling, J., & MacAskill, K. (2024). Assessing flood resilience of urban rail transit systems: Complex network modelling and stress testing in a case study of London. *Transportation Research Part D: Transport and Environment*, 134, 104263. (1 citation(s)). <https://doi.org/10.1016/j.trd.2024.104263>
- Cats, O., & Jenelius, E. (2015). Planning for the unexpected: The value of reserve capacity for public transport network robustness. *Transportation Research Part A: Policy and Practice, Resilience of Networks*, 81, 47–61. (127 citation(s)).
<https://doi.org/10.1016/j.tra.2015.02.013>
- Cats, O., Koppenol, G.-J., & Warnier, M. (2017). Robustness assessment of link capacity reduction for complex networks: Application for public transport systems. *Reliability Engineering & System Safety, Special Section: Applications of Probabilistic Graphical Models in Dependability, Diagnosis and Prognosis*, 167, 544–553.
<https://doi.org/10.1016/j.ress.2017.07.009>
- Chen, L., Kyng, R., Liu, Y. P., Peng, R., Gutenberg, M. P., & Sachdeva, S. (2022). Maximum Flow and Minimum-Cost Flow in Almost-Linear Time. *2022 IEEE 63rd Annual Symposium on Foundations of Computer Science (FOCS)*, 612–623. (205 citation(s)).
<https://doi.org/10.1109/FOCS54457.2022.00064>
- Chen, X., Ma, S., Chen, L., & Yang, L. (2024). Resilience measurement and analysis of intercity public transportation network. *Transportation Research Part D: Transport and Environment*, 131, 104202. <https://doi.org/10.1016/j.trd.2024.104202>
- Franchin, P., & Cavalieri, F. (2013). 18—Seismic vulnerability analysis of a complex interconnected civil infrastructure. In S. Tesfamariam & K. Goda (Eds), *Handbook of*

Seismic Risk Analysis and Management of Civil Infrastructure Systems (pp. 465–514e). Woodhead Publishing. <https://doi.org/10.1533/9780857098986.4.465>

- Gao, S., Shirazian, S., Ward, P. J., & Koks, E. E. (2025). Understanding the vulnerability of multimodal public transportation networks. *Civil Engineering and Environmental Systems*, 0(0), 1–23. <https://doi.org/10.1080/10286608.2025.2601992>
- Hamdouch, Y., & Lawphongpanich, S. (2008). Schedule-based transit assignment model with travel strategies and capacity constraints. *Transportation Research Part B: Methodological*, 42(7), 663–684. <https://doi.org/10.1016/j.trb.2007.11.005>
- Henke, I., Troiani, G., & Pagliara, F. (2024). An analysis of the vulnerability of road networks in response to disruption events through accessibility indicators specification. *Transportation Planning and Technology*, 47(5), 628–655. (0 citation(s)). <https://doi.org/10.1080/03081060.2024.2329650>
- Ju, Y., Yuan, H., Li, Z., Gan, M., & Chen, Y. (2022). Multilayer structures and resilience evaluation for multimode regional rail transit system. *IET Intelligent Transport Systems*, 16(7), 843–859. <https://doi.org/10.1049/itr2.12179>
- Ma, F., Ao, Y., Wang, X., He, H., Liu, Q., Yang, D., & Gou, H. (2023). Assessing and enhancing urban road network resilience under rainstorm waterlogging disasters. *Transportation Research Part D: Transport and Environment*, 123, 103928. <https://doi.org/10.1016/j.trd.2023.103928>
- OSM. (2024). *OpenStreetMap*. OpenStreetMap. <https://www.openstreetmap.org/>
- Sienkiewicz, J., & Hołyst, J. A. (2005). Statistical analysis of 22 public transport networks in Poland. *Physical Review E*, 72(4), 046127. (379 citation(s)). <https://doi.org/10.1103/PhysRevE.72.046127>
- Spiess, H., & Florian, M. (1989). Optimal strategies: A new assignment model for transit networks. *Transportation Research Part B: Methodological*, 23(2), 83–102. [https://doi.org/10.1016/0191-2615\(89\)90034-9](https://doi.org/10.1016/0191-2615(89)90034-9)
- Su, Z., Li, L., Peng, H., Kurths, J., Xiao, J., & Yang, Y. (2014). Robustness of Interrelated Traffic Networks to Cascading Failures. *Scientific Reports*, 4(1), 5413. (68 citation(s)). <https://doi.org/10.1038/srep05413>

- Wang, N., Wu, M., & Yuen, K. F. (2023). A novel method to assess urban multimodal transportation system resilience considering passenger demand and infrastructure supply. *Reliability Engineering & System Safety*, 238, 109478. <https://doi.org/10.1016/j.ress.2023.109478>
- Wang, Y., Au, S.-K., & Fu, Q. (2010). Seismic Risk Assessment and Mitigation of Water Supply Systems. *Earthquake Spectra*, 26(1), 257–274. <https://doi.org/10.1193/1.3276900>
- Xu, X., Huang, A., Shalaby, A., Feng, Q., Chen, M., & Qi, G. (2024). Exploring cascading failure processes of interdependent multi-modal public transit networks. *Physica A: Statistical Mechanics and Its Applications*, 638, 129576. <https://doi.org/10.1016/j.physa.2024.129576>
- Xu, Z., & Chopra, S. (2023). Interconnectedness enhances network resilience of multimodal public transportation systems for Safe-to-Fail urban mobility. *Nature Communications*, 14(1), 4291. (14 citation(s)). <https://doi.org/10.1038/s41467-023-39999-w>
- Yap, M., & Cats, O. (2022). Analysis and prediction of ridership impacts during planned public transport disruptions. *Journal of Public Transportation*, 24, 100036. <https://doi.org/10.1016/j.jpubtr.2022.100036>
- Zhao, S., Wu, J., Li, Z., & Meng, G. (2022). Train Operational Plan Optimization for Urban Rail Transit Lines Considering Circulation Balance. *Sustainability*, 14(9), 5226. <https://doi.org/10.3390/su14095226>
- Zhu, J.-X., Luo, Q.-Y., Guan, X.-Y., Yang, J.-L., & Bing, X. (2020). A Traffic Assignment Approach for Multi-Modal Transportation Networks Considering Capacity Constraints and Route Correlations. *IEEE Access*, 8, 158862–158874. <https://doi.org/10.1109/ACCESS.2020.3019301>

Table 1-1. The routes' name list in both P- and N- direction of Amsterdam metro network

Metro	
P-direction	N-direction
Metro 50: Gein => Isolatorweg	Metro 50: Isolatorweg => Gein
Metro 51: Centraal Station => Isolatorweg	Metro 51: Isolatorweg => Centraal Station
Metro 52: Noord => Zuid	Metro 52: Zuid => Noord
Metro 53: Centraal Station => Gaasperplas	Metro 53: Gaasperplas => Centraal Station
Metro 54: Centraal Station => Gein	Metro 54: Gein => Centraal Station

Table 1-2. The routes' name list in both P- and N- direction of Amsterdam tram network

Tram	
P-direction	N-direction
Tram 1: Amsterdam Muiderpoortstation => Amsterdam Osdorp De Aker	Tram 1: Amsterdam Osdorp de Aker => Amsterdam Muiderpoortstation
Tram 12: Amsterdam Centraal Station => Amsterdam Amstelstation	Tram 12: Amsterdam Amstelstation => Amsterdam Centraal Station
Tram 13: Amsterdam Centraal Station => Amsterdam Geuzenveld	Tram 13: Amsterdam Geuzenveld => Amsterdam Centraal Station
Tram 14: Amsterdam Centraal Station => Amsterdam Flevopark	Tram 14: Amsterdam Flevopark => Amsterdam Centraal Station
Tram 17: Amsterdam Centraal Station => Amsterdam Osdorp Dijkgraafsplein	Tram 17: Amsterdam Osdorp Dijkgraafsplein => Amsterdam Centraal Station
Tram 19: Amsterdam Sloterdijk => Diemen Sniep	Tram 19: Diemen Sniep => Amsterdam Sloterdijk
Tram 2: Amsterdam Centraal Station => Amsterdam Nieuw Sloten	Tram 2: Amsterdam Nieuw Sloten => Amsterdam Centraal Station
Tram 24: Amsterdam Centraal Station => Amsterdam VUmc	Tram 24: Amsterdam VUmc => Amsterdam Centraal Station
Tram 25: Amstelveen Westwijk => Amsterdam Station Zuid	Tram 25: Amsterdam Station Zuid => Amstelveen Westwijk
Tram 26: Amsterdam IJburg => Amsterdam Centraal Station	Tram 26: Amsterdam Centraal Station => Amsterdam IJburg
Tram 3: Amsterdam Westergasfabriek => Amsterdam Flevopark	Tram 3: Amsterdam Flevopark => Amsterdam Westergasfabriek
Tram 4: Amsterdam Station RAI => Amsterdam Centraal Station	Tram 4: Amsterdam Centraal Station => Amsterdam Station RAI
Tram 5: Amstelveen Stadshart => Amsterdam Eerste Marnixdwaarsstraat	Tram 5: Amsterdam Eerste Marnixdwaarsstraat => Amstelveen Stadshart
Tram 7: Amsterdam Azartplein => Amsterdam Slotermeer	Tram 7: Amsterdam Slotermeer => Amsterdam Azartplein

Table 1-3. The routes' name list in both P- and N- direction of Amsterdam bus network

Bus		
P-direction	N-direction	
Bus 15: Amsterdam Station Zuid => Amsterdam Station Sloterdijk	Bus 15: Amsterdam Station Sloterdijk => Amsterdam Station Zuid	
Bus 18: Amsterdam Slotervaart => Amsterdam Centraal Station	Bus 18: Amsterdam Centraal Station => Amsterdam Slotervaart	
Bus 21: Amsterdam Geuzenveld => Amsterdam Centraal Station	Bus 21: Amsterdam Centraal Station => Amsterdam Geuzenveld	
Bus 22: Amsterdam Station Sloterdijk => Amsterdam Muiderpoortstation	Bus 22: Amsterdam Muiderpoortstation => Amsterdam Station Sloterdijk	
Bus 231: Amsterdam Abberdaan => Amsterdam Station Sloterdijk	Bus 231: Amsterdam Station Sloterdijk => Amsterdam Abberdaan	
Bus 267: Amsterdam Riekerpolder => Amsterdam Sloten	Bus 267: Amsterdam Sloten => Amsterdam Riekerpolder	
Bus 34: Amsterdam Olof Palmeplein => Amsterdam Noorderpark	Bus 34: Amsterdam Noorderpark => Amsterdam Olof Palmeplein	
Bus 35: Amsterdam Olof Palmeplein => Amsterdam Molenwijk	Bus 35: Amsterdam Molenwijk => Amsterdam Olof Palmeplein	
Bus 36: Amsterdam Station Noord => Amsterdam Station Sloterdijk	Bus 36: Amsterdam Station Sloterdijk => Amsterdam Station Noord	
Bus 369: Schiphol Airport => Amsterdam Station Sloterdijk	Bus 369: Amsterdam Station Sloterdijk => Schiphol Airport/Plaza	
Bus 37: Amsterdam Station Noord => Amsterdam Amstelstation	Bus 37: Amsterdam Amstelstation => Amsterdam Station Noord	
Bus 38: Amsterdam Station Noord => Amsterdam Buiksloterham	Bus 38: Amsterdam Buiksloterham => Amsterdam Station Noord	
Bus 40: Amsterdam Muiderpoortstation => Amsterdam Amstelstation	Bus 40: Amsterdam Amstelstation => Amsterdam Muiderpoortstation	
Bus 41: Amsterdam Amstelstation => Amsterdam Station Holendrecht	Bus 41: Amsterdam Station Holendrecht => Amsterdam Amstelstation	
Bus 43: Amsterdam Centraal Station => Amsterdam Borneoeliland	Bus 43: Amsterdam Borneoeliland => Amsterdam Centraal Station	
Bus 44: Amsterdam Station Bijlmer Arena => Diemen Noord	Bus 44: Diemen Noord => Amsterdam Station Bijlmer Arena	
Bus 461: Amsterdam Gustav Mahlerplein => Amsterdam Gelderlandplein NO	Bus 461: Amsterdam Gelderlandplein NO => Amsterdam Gustav Mahlerplein	
Bus 463: Amsterdam Bolestein => Amsterdam Gelderlandplein Noord	Bus 463: Amsterdam Gelderlandplein Oost => Amsterdam Bolestein	
Bus 464: Amsterdam De Boelelaan/De Klencke => Amsterdam Gelderlandplein NO	Bus 464: Amsterdam Gelderlandplein NO => Amsterdam De Boelelaan	
Bus 47: Amsterdam Station Bijlmer Arena => Amsterdam Station Holendrecht	Bus 47: Amsterdam Station Holendrecht => Amsterdam Station Bijlmer Arena	
Bus 48: Amsterdam Centraal Station => Amsterdam Houthaven	Bus 48: Amsterdam Houthaven => Amsterdam Centraal Station	
Bus 49: Weesp Station => Amsterdam Station Bijlmer Arena	Bus 49: Amsterdam Station Bijlmer Arena => Weesp Station	
Bus 61: Amsterdam Osdorplein => Amsterdam Station Sloterdijk	Bus 61: Amsterdam Station Sloterdijk => Amsterdam Osdorplein	
Bus 62: Amsterdam Station Lelylaan => Amsterdam Amstelstation	Bus 62: Amsterdam Amstelstation => Amsterdam Station Lelylaan	
Bus 63: Osdorp De Aker => Amsterdam Station Lelylaan	Bus 63: Amsterdam Station Lelylaan => Osdorp De Aker	
Bus 65: Amsterdam KNSM Eiland => Amsterdam Amstelstation	Bus 65: Amsterdam Amstelstation => Amsterdam KNSM Eiland	

Bus 66: Amsterdam IJburg => Amsterdam Bijlmer Arena	Bus 66: Amsterdam Bijlmer Arena => Amsterdam IJburg
Bus 68: Amsterdam Henk Sneevlietweg => Amsterdam Riekerpolder	Bus 68: Amsterdam Riekerpolder => Amsterdam Henk Sneevlietweg
Bus 245: Amsterdam Molenwijk => Schiphol Zuid (One-way route in the early morning)	
Bus 246: Amsterdam Oostelijke Eilanden => Schiphol Zuid (One-way route in the early morning)	
Bus 247: Amsterdam Bos en Lommer => Schiphol Zuid (One-way route in the early morning)	