Spatio-temporal Network Accessibility

Transit quality of multimodal public transport systems in cities worldwide

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by

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Preface

This thesis marks the completion of my master degree programme at Delft University of Technology, and reflects my interest and understanding of everything I have learned of multimodal public transport systems.

The research was conducted as part of the master degree programme in Transport, Infrastructure and Logistics at the Faculty of Civil Engineering and Geosciences. During this process, I have benefited from the feedback, support and guidance of several people whom I would like to thank.

I am thankful to Srijith Balakrishnan, my supervisor, for his valuable support, his great suggestions and enthusiasm throughout this research. I also wish to thank Niels van Oort and Jan Anne Annema for their critical and professional perspectives and practical insights that have helped sharpen the relevance and quality of this report.

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Daan van der Klooster
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Summary

This report presents the development and application of a standardized methodology for assessing the accessibility of multimodal public transport systems. As cities around the world face growing pressure to deliver efficient, inclusive, and sustainable mobility, there is a clear need for analytical tools that can evaluate how well transit networks serve diverse populations across both space and time. This is particularly important in multimodal systems, where the overall user experience depends not only on the performance of individual modes, but also on how well these modes are integrated in terms of spatial layout, service availability, and schedule coordination.

Although many existing studies have evaluated public transport accessibility, most of these focus on single modes or static indicators such as travel time and coverage. They often neglect the dynamic, interconnected nature of real-world transit systems, and provide limited insight into how multimodal integration affects system performance. To address these gaps, this research introduces a comparative framework that combines spatial and temporal accessibility metrics using publicly available GTFS data and graph-based network representations.

The primary objective of this research is to design a methodology that enables structured, comparative analysis of multimodal public transport networks. The study applies this methodology to a diverse set of twelve cities and investigates whether the resulting metrics reveal meaningful insights into the spatial and temporal structure, coordination, and operational strategies of their networks. These insights then serve as the foundation for identifying system strengths and weaknesses and developing targeted policy recommendations.

The main research question of this report is:

> *What insights into network accessibility can be gained from a comparative, metric-based analysis of multimodal public transport networks, considering both spatial and temporal dimensions?*

This question is explored through four phases, phases, each addressing a specific sub-question:

1. Identifying standardized spatial and temporal accessibility metrics from existing literature.
2. Constructing a network-based framework that simulates multimodal public transport networks using infrastructure-based and service-based graph representations.
3. Extracting and comparing performance indicators across a set of cities.
4. Classifying networks and translating the results into actionable recommendations for urban transport policy.

The study assesses multimodal public transport systems in twelve cities from five continents, selected on geographical diversity, network complexity and data availability. The four primary transport modes assessed are bus, metro, tram and train. For each city, a typical weekday is simulated during both peak and off-peak conditions.

The analysis of every city is structured along two major dimensions:

- Spatial accessibility, capturing the physical integration and infrastructural density of public transport networks.
- Temporal accessibility, reflecting the service availability and travel efficiency of public transport networks.

A central focus of this study is to systematically examine the relationship between network size, modal diversity, and multimodal accessibility outcomes. Specifically, the research investigates whether a larger network with more transport modes necessarily results in better user experience, or whether strategic network design and operational choices are more decisive. Additionally, the study seeks to

identify how different spatial configurations and temporal operational strategies, such as the distribution of transfer points, timetable coordination, and the balance between direct routing and intermodal transfers, influence accessibility outcomes from a passenger perspective.

To support the metric-based assessment of public transport networks, a comprehensive set of Python scripts was developed to process, analyze and simulate the multimodal networks created from GTFS datasets. This methodology transforms raw timetable data into structured graph representations using various libraries. The infrastructural-based L-space graph representation captions the physical network topology, while the service-based P-space graph models the connectivity between stops based on vehicle movements according to timetables.

The graph representations were extensively adapted to reflect real-world conditions to user experience and in order to capture the interaction between the different transport modes present in the graph. Custom functions were implemented to identify intermodal transfer opportunities, model transfer edges based on walking distances and transfer penalties, and simulate scheduled-based travel times through temporal network attributes. This step has ensured that travel simulation account for typology, service availability, transfer constraints and travel impedance. The modified graphs provided the basis for the shortest path computations, filtered through a custom sampling strategy that respected a maximum transfer limit and time constraints to ensure representative and computational efficient origin-destination data.

The outputs enabled systematic trip simulations, capturing detailed components of generalized travel costs, including in-vehicle time, waiting time and transfer penalties. The resulting datasets structure all simulated trips and their attributes into matrices, each containing detailed multimodal path information that forms the foundation for extracting key accessibility indicators. From there, the spatial and temporal metrics could be consistently computed and compared across all twelve cities. This approach has transformed GTFS data into a powerful performance-based instrument for evaluating public transport systems from a user-centered perspective.

This report reveals that multimodal public transport network performance is shaped by two major interrelated strategic dimensions: spatial structure and temporal operation. From the analysis of the twelve cities, clear patterns have emerged in how systems are organized and operated, which has a direct influence on user experience.

It was found that two main spatial design strategies can be distinguished: centralized connectivity, hub-oriented, hierarchical networks that depend on long single-modal trips, and distributed connectivity networks, with grid-like structures that embrace intermodal transfers as a core operational mechanism. It has been found how the distributed networks consistently outperform centralized networks in terms of spatial accessibility, resilience and utility for passengers, regardless of the overall network size or mode count.

Besides, cities follow three dominant temporal strategies during operations: frequency-focused, relying on high service volumes, coordination-based, prioritizing intermodal timetable synchronization and hybrid/segmented, combining frequency and coordination to varying extents. It is concluded in this research that coordination-based systems offer the most reliable and equitable temporal accessibility. Their performance excels in consistency, equity and passenger experience.

All twelve multimodal public transport systems have been classified into four categories, in order to translate the key findings from the metric extraction into targeted policy recommendations. The typology is grounded in the spatial and temporal performance metrics and reflects how each city organizes, integrated and operates its network. The combination of these insights has resulted into four strategic categories, with each distinct challenges and opportunities.

The analysis has demonstrated that the cities of Berlin, Prague and Singapore show strong spatial cohesion and temporal coordination. Therefore, they are classified as well-integrated networks. This strong network structure also emerges from the networks of Paris, Toronto ad Melbourne. However, these three networks underperform on temporal reliability and synchronization. These are the spatially strong, but temporally weak networks.

Bangkok and New York City have proven to perform operationally strong, especially in centralized areas with high frequency volumes and numerous direct serviced. However, the networks fail to establish spatial equity and intermodal distribution. These networks are classified as efficient, but spatially sparse. At last, the networks of São Paulo, Mexico City, Denver and Valencia turned out to be either underdeveloped or transitional, showing fragmentation, weak coordination and low spatial and temporal consistency.

For all four categories, the accessibility framework provides a structured approach to identify spatial and operational inefficiencies and translate them into practical, context-specific strategies. These recommendations demonstrate that improving network accessibility is not simply a matter of adding capacity. It requires aligning physical infrastructure, service design and operational strategies to support efficient and inclusive urban transport.

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Nomenclature

Abbreviations

Abbreviation	Definition
CPL	Characteristic Path Length
GCS	Giant Component Size
GTC	Generalized Travel Cost
GTFS	General Transit Feed Specification
OD matrix	Origin-Destination matrix
OSM	OpenStreetMap
VoT	Value of Time

Symbols

Symbol	Definition	Unit
A_i	Cumulative accessibility ratio for origin node i	[–]
a_i	Proportion of node ends of type i on one side of an edge	[–]
b_i	Proportion of node ends of type i on the other side of an edge	[–]
$C_D(i)$	Degree centrality of node i	[–]
CPL	Characteristic Path Length, the average shortest path length in the graph	[–]
CPL_{std}	Standardized Characteristic Path Length	[–]
C_T	Mode Coupling Coefficient	[%]
c_{ij}	Generalized travel cost between nodes i and j	[min]
$D_I(i)$	Intermodal degree of node i	[–]
$d(i,j)$	Shortest path distance between nodes i and j in terms of edge count	[–]
E	Set of all edges in the graph	[–]
E_T	Set of all transfer edges in the graph	[–]
e_{ii}	Proportion of edges between nodes of the same category or type	[–]
e_{ij}	Edge connecting nodes v_i and v_j, where $e_{ij} \in E$	[–]
$f(c_{ij})$	Threshold function (1 if $c_{ij} \leq \bar{t}$, 0 otherwise)	[–]
G	Graph defined as $G = (V, E)$, where V is the set of nodes and E is the set of edges	[–]
GTC	Generalized Travel Cost for a single trip	[min]
$\overline{\text{GTC}}$	Average generalized travel cost across all trips	[min]
h	Length of the selected time interval	[h]
IVT_m	Average in-vehicle time for trips starting with mode m	[min]
IVT_t	Total in-vehicle time for a single trip	[min]
IVT%	Weighted contribution of in-vehicle time to average GTC	[%]
i, j	Indices of nodes in the graph	[–]
K_{m_1,m_2}	Number of intermodal transfers from m_1 to m_2	[–]
k_i	Degree of node i, the number of direct connections to node i	[–]
L_T	Transfer edge length	[m]
M	Set of all transport modes in the network	[–]

m	A specific mode from the set of all transport modes M	[–]
N	Total number of valid origin-destination paths in the network	[–]
N_T	Number of transfers in a single trip	[–]
r	Network assortativity, a measure of the relationship between the degrees or attributes of connected nodes	[–]
S	Composite weighted service availability score	[veh/(node·h)]
s_m	Average vehicle movements per node per hour for mode m	[veh/(node·h)]
T	Set of observed intermodal transitions (m_1, m_2)	[–]
T_N	Normalized Transfer Opportunity Indicator	[–]
TRANS_m	Transfer-related impedance for mode m	[min]
TRANS%	Weighted contribution of transfers to average GTC	[%]
$\bar{t}$	Travel time threshold value	[min]
$\bar{t}_{25}$	25th percentile GTC threshold	[min]
$\bar{t}_{50}$	50th percentile GTC threshold	[min]
$\bar{t}_{75}$	75th percentile GTC threshold	[min]
V	Set of all nodes (vertices) in the graph	[–]
$\|V_m\|$	Number of nodes associated with mode m	[–]
V_{total}	Total number of vehicle movements across all modes	[veh]
v_i	The i-th node in the graph, where $v_i \in V$	[–]
v_m	Number of vehicle movements for mode m in time interval h	[veh]
$W_i^{(m_1,m_2)}$	Waiting time for the i-th intermodal transfer from m_1 to m_2	[min]
$\overline{W}_{\text{intermodal}}$	Weighted average intermodal transfer waiting time	[min]
W_j	Weight (e.g., opportunities) at destination node j	[–]
w_m	Relative weight of mode m based on its vehicle movement share	[–]
WAIT_m	Average waiting time for trips starting in mode m	[min]
WAIT%	Weighted contribution of waiting time to average GTC	[%]
Wait_t	Total waiting time for a trip (initial + transfer)	[min]
Walk_t	Total walking time (access, egress, transfers)	[min]
α_{wait}	Valuation/weight of waiting time	[–]
α_{walk}	Valuation/weight of walking time	[–]
β_n	Transfer penalty	[min]
γ	Gamma index, the ratio of total edges to maximum edges in a planar graph	[–]
ρ_D	Degree assortativity, the tendency of high-degree nodes to connect with high-degree nodes	[–]
ρ_M	Mode assortativity, the tendency of nodes to connect with others of the same transport mode	[–]

1 Introduction

This first chapter introduces the topic of spatio-temporal accessibility of multimodal public transport networks and outlines the motivation behind the research. It begins with a discussion of the background and relevance of the study, followed by a definition of the concept of accessibility in the context of this study. The chapter then presents the main research question along with its supporting sub-questions. Finally, it defines the research objective, clarifies the scope of the study, presents the methodology of the research and provides an overview of the report structure.

1.1. Research Background

Population growth and rapid urbanization continue to intensify an increasing demand for efficient, inclusive, and sustainable public transport systems. As cities expand and their populations become more reliant on public services, an essential challenge arises: ensuring that public transportation networks effectively serve diverse populations while maintaining efficiency and accessibility - a priority that is also emphasized by the UN (United Nations, 2024).

One of the most promising approaches to addressing these challenges lies in multimodal public transport systems, which integrate multiple modes of public transit, such as buses, trains, trams, and metros (van Eck et al., 2014). However, the service quality and effectiveness of multimodal public transport systems vary significantly across different cities worldwide (International Transport Forum, 2019). The spatial distribution of transit services, disparities in service frequencies, and the level of coordination between different transport modes contribute to inconsistencies in user experiences (Duran-Micco & Vansteenwegen, 2021). Moreover, ensuring equitable access to multimodal transport is crucial for socially disadvantaged groups that depend on public transportation for their daily mobility needs (Bhavsar et al., 2019).

To effectively assess the accessibility of multimodal public transport systems, it is crucial to understand not only the characteristics and service provision of each mode, but also how their spatial and temporal integration affects the overall accessibility of the public transport network (Patterson et al., 2023). A comprehensive evaluation framework is therefore needed: one that systematically captures the spatial and temporal interactions between public transit modes, reveals network strengths and weaknesses, and provides actionable insights for enhancing system effectiveness and improving user experience. However, existing analyses often overlook the interactions between transport modes, both spatially and temporally.

While extensive research has been performed on the accessibility of public transport networks, much of the existing literature has primarily focused on distinct performances of individual public transport modes. Conventional accessibility studies often assess transport networks by analyzing factors such as travel time, service frequency, or geographic coverage of separate public transport modes independently (Park & Goldberg, 2021). However, these approaches overlook the complex interplay and dependencies that emerge from multimodal public transit systems. The overall quality of these systems is not solely dependent on the individual performance of each public transit mode but is also influenced by how well these modes are integrated both spatially and temporally (Ryan et al., 2023). Limited attention has been paid to the interconnected nature of transit systems in existing literature: lack of service coordination, mismatched schedules, and fragmented infrastructure can create significant accessibility deterioration (Sharifiasl, 2024).

Furthermore, many existing accessibility studies do not incorporate the dynamic nature of transit systems, often relying on static models that assume constant service levels or service availability, thereby failing to capture temporal variations in service quality (Stępniak et al., 2019). As a result, there is limited information available for the complete understanding of how multimodal transport systems function in practice and how the functionality of the system can be evaluated to improve service quality. In conclusion, a different approach, considering both the spatial distribution of transit services and the temporal alignment of transit schedules and the quality of multimodal integration, is recommended.

This report addresses these gaps by developing a comprehensive accessibility assessment framework for evaluating multimodal public transport accessibility. While various studies have explored aspects of network accessibility, there remains a lack of a systematic and universally applicable approach to assess the performance of public transport networks across different cities and contexts. This research responds to that need by proposing a standardized framework that incorporates both spatial and temporal dimensions, capturing the dynamic interplay between public transport modes and evaluating how the quality of their integration affects user experience. The framework applies to publicly available and globally standardized transit schedule data, ensuring its applicability across diverse cities and transport systems. It considers key aspects such as the geographical span of transit networks, temporal fluctuations in service provision, the synchronization of service schedules, the ease of intermodal transfers, and the degree of infrastructural integration.

By examining multimodal public transport systems across various cities worldwide, this research serves the purpose to provide valuable insights into the different aspects that influence accessibility. It will reveal network design choices and operational strategies of various cities, propose strategies for enhancing multimodal coordination, and offer policy recommendations to promote more equitable and efficient public transport solutions. Ultimately, the findings of this study will contribute to sustainable urban development, advancing international collaboration in transport planning, and improving the quality of life for populations in urban environments by ensuring that public transportation systems are not only functional but also accessible for all.

1.1.1. Defining Accessibility

A key challenge at the start of this research is defining the term *accessibility*, as the literature distinguishes between multiple interpretations.

Joyce and Dunn (2009) identify a distinction between *access* and *accessibility*. The term *access*, also referred to as *local accessibility*, concerns the physical or social accessibility of public transport networks. Local accessibility focuses on the proximity of transit stops to users, the physical accessibility of stations and vehicles, and the ease of use for individuals, including elderly and disabled people (Litman, 2024). In this sense, local accessibility relates to the ease of entering the public transport network.

Accessibility, or more specifically *network accessibility*, refers to a broader concept. Geurs and van Wee (2004) define it as “the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s).” While local accessibility describes access to the network itself, network accessibility focuses on the ability of the system to enable efficient movement from origin to destination (Joyce & Dunn, 2009). It includes factors such as the number of reachable destinations, total travel time, the required number of transfers, and the connectivity between public transport modes. These aspects are central to the *quality* of accessibility. In this research, transit quality is defined as the system’s effectiveness in facilitating efficient, reliable, and integrated public transport travel, rather than passenger comfort features such as seating or hygiene.

This research examines the structural and operational dimensions of public transport networks, rather than broader definitions of accessibility that incorporate social, economic, or local land-use factors. Therefore, unless otherwise specified, *accessibility* in this study refers specifically to *network accessibility*, understood as a measurable system-level outcome. This interpretation aligns with the research objective of assessing multimodal integration and network performance, and is further elaborated in Section 1.3.

1.2. Research Questions

This study aims to contribute a structured and scalable approach for evaluating the performance of public transport networks in terms of both spatial coverage and temporal service availability. It introduces a comparative methodology based on standardized metrics, drawing on spatial and temporal network properties derived from real-world transit data. The methodology is then applied to a diverse set of twelve cities to investigate whether the resulting indicators reveal meaningful insights into the spatial structure, modal coordination, and operational strategies of their multimodal transport systems. These insights form the foundation for identifying network strengths and weaknesses and developing targeted policy recommendations.

The main research question of this thesis is formulated as follows:

> *What insights into network accessibility can be gained from a comparative, metric-based analysis of multimodal public transport networks, considering both spatial and temporal dimensions?*

In addition, four supplemental sub-questions have been formulated to support the answering of the main research question. These sub-questions are:

1. What are the major spatio-temporal accessibility metrics for public transport networks and how suitable are they for the evaluation of the systems performance?
2. How can real-world multimodal public transport data, combining spatial structure and operational information, be structured to support standardized accessibility analysis across cities?
3. How can the appropriate metrics be applied to evaluate the performance of multimodal public transport networks in terms of accessibility and integration?
4. How can the analysis of multimodal public transport systems' performance provide insights on network planning and recommendations for improving accessibility?

1.3. Research Objective and Scope

The core objective of this research is to evaluate the overall performance of multimodal public transport systems as integrated networks, rather than as isolated modal components. While many cities operate multiple transit modes, such as buses, metros, trams, and trains, their effectiveness as a cohesive system depends heavily on how well these modes are spatially and temporally integrated.

A key focus of this study is to investigate the relationship between network scale, modal diversity, and overall accessibility, defined here as the ease, efficiency, and smoothness with which passengers can travel from origin to destination within the public transport network. By systematically analyzing spatio-temporal integration, this research aims to understand whether "more" (in terms of modes or network size) necessarily translates into "better" accessibility and user experience.

Besides, an important objective is to identify spatial network design and operational strategies that influence multimodal accessibility outcomes. Rather than merely describing network characteristics, the research seeks to reveal how different structural and operational design choices like the distribution of transfer points, the coordination of timetables, and the balance between direct routing and intermodal transferring, shape the actual travel experience from a user's point-of-view.

To achieve this, the research develops a structured representation of public transport networks that combines spatial and temporal dimensions, enabling the extraction of metrics related to multimodal accessibility and intermodality. This representation is organized around two core components:

- Spatial accessibility, which assesses the physical and infrastructural integration of different transport modes within the network
- Temporal accessibility, which focuses on the availability, coordination, and reliability of services throughout the day.

These dimensions are further divided into specific metric categories, each targeting a distinct aspect of intermodal performance.

The scope of this research is limited to analyzing GTFS (General Transit Feed Specification) data for a selection of twelve cities across the world. These datasets are particularly suitable for this analysis, as they provide a standardized and detailed data format for representing both the spatial structure (i.e. stops and routes) and the temporal operations (i.e. timetables, frequencies) of public transport networks. This enables consistent comparison between different cities around the globe. A more detailed explanation on GTFS datasets and their suitability for this research is provided in Section 2.1.

These datasets are processed into network graphs using both L-space (infrastructure-based) and P-space (service-based) network representations. For each city, the analysis is strictly limited to four primary modes of public transport: buses, metros, trams, and trains. These modes were selected because they represent the most prevalent components of urban multimodal systems and are consistently documented within the selected GTFS datasets.

By extracting and standardizing the appropriate metrics from the graph-based network representations, the study enables a systematic comparison of multimodal network performance across urban regions around the globe. The primary focus lies on the supply side of public transport, evaluating structural and operational features rather than user demand or socio-economic dependencies. However, by clarifying how multimodal systems succeed in delivering efficient and accessible transport, the findings aim to support evidence-based recommendations for improving coordination, network planning, and investment in urban mobility.

1.4. Methodology

The methodology of this research is divided into three phases, each corresponding to a key stage in the process of answering the research questions and fulfilling the main objective of the study. These phases include the construction of a spatio-temporal accessibility assessment framework based on a structured review of existing literature and network theory, the generation of graph-based representations of public transport networks based on GTFS data, and the extraction and analysis of accessibility metrics for comparative evaluation across cities.

Phase 1: Theory and framework construction

In the first phase, a structured literature review is conducted to identify the major spatial and temporal metrics used in the analysis of public transport networks. These metrics reflect key aspects of accessibility and multimodal integration, including but not limited to:

- Spatial availability and network topology (e.g., stop coverage, connectivity, degree centrality)
- Temporal availability and service intensity (e.g., trip frequency, waiting time)
- Intermodal connectivity and transfer impedance (e.g., physical distances, timetable synchronization)
- Network efficiency (e.g., shortest paths, generalized travel cost)

A core objective of this phase is to assess how suitable each identified metric is for evaluating multimodal public transport systems of different cities. Metrics are evaluated for their ability to capture the interplay between spatial and temporal characteristics, their interpretability, and their scalability for cross-city comparison.

This review enables the design of the accessibility assessment framework and supports the definition of weighting schemes and penalty factors (e.g., for waiting and transfer times) used in later phases of the analysis.

Phase 2: Graph construction and network modeling

The second phase involves the processing of GTFS Schedule datasets into usable graph-based representations of multimodal public transport networks. This includes several key steps:

- **City selection:** A set of twelve cities is assembled to reflect geographic, socio-economic, and network diversity. Each city must provide GTFS data covering all of the present primary transport modes: buses, metros, trams, and trains. The cities included in this study were selected to ensure cultural en geographical diversity. Their public transport systems vary in size and modal availability, allowing the analysis to assess whether network scale and service volume significantly impact multimodal accessibility. Selection criteria have also focused on data completeness, multimodal coverage, and recency of GTFS datasets. A full explanation of the city selection process is provided in Section 3.1.1.

- **GTFS processing:** Datasets are imported into SQLite databases. SQLite offers a structured and reproducible format for GTFS data handling. Then, the datasets were preprocessed to ensure data completeness, consistency, and the ability to simulate typical weekday operations. For each city, two simulation periods are defined during the temporal filtering: peak hours (07:00–09:00) and off-peak hours (12:00–14:00). This is done to enable temporal performance comparison.
- **Graph construction:** Using the processed data, multimodal transport networks are modeled as graphs in both L-space (based on direct infrastructure connections) and P-space (based on service-based connections). Intermodal transfer opportunities are embedded in the graph to support intermodal analysis.

The resulting graphs form the foundation for extracting spatial and temporal performance indicators in the final phase.

Phase 3: Metric extraction and result analysis
In the final phase, the constructed graphs are analyzed to extract accessibility metrics defined in the accessibility assessment framework. These metrics are designed to capture:

- **Spatial structure:** Physical integration, network connectivity, intermodal topology
- **Temporal dynamics:** Service frequency, waiting time, synchronization quality
- **User experience:** Generalized travel cost and cumulative accessibility
- **Temporal robustness:** Comparative performance during peak and off-peak hours

Metrics are standardized to account for differences in city size and network scale, allowing for cross-comparative analysis. Where applicable, results are weighted by mode-specific vehicle volumes to ensure a balanced representation of multimodal performance.

Phase 4: Network classification
The outcome of the third phase is detailed and metric-based information of multimodal public transport systems across cities, with a focus on identifying structural strengths, integration gaps, and opportunities for improvement. Based on these findings, networks are classified into typologies according to shared patterns in spatial coverage, intermodal integration, service availability, and timetable coordination. This classification reflects the strengths and weaknesses revealed by the standardized metrics and enables the identification of recurring challenges and strategic priorities across different types of networks. The typology serves as a bridge between empirical analysis and policy relevance, forming the basis for targeted recommendations aimed at improving multimodal accessibility and system performance.

1.4.1. Research Process Overview

To further clarify the structure and progression of the research, Figure 1.1 provides a visual summary of the inputs, processes, and outputs for each phase, mapped to the corresponding chapters of the report.

Figure 1.1: Research process overview: inputs, processes, and outputs

1.5. Report Structure

This report is structured as follows: Chapter 2 presents the developed accessibility assessment framework. It explores the theoretical background of GTFS data, network representation methods, and a range of spatial and temporal accessibility metrics used in public transport studies. Then, Chapter 3 describes the multimodal graph construction process. It establishes the foundation needed for the accessibility analysis by detailing the processes of city selection, data cleaning, database creation, and the generation of network graphs. Chapter 4 focuses on simulating passenger movements through the constructed multimodal networks by modeling intermodal transfers, travel costs, and service coordination. Chapter 5 presents the results. It reports and compares the extracted spatial and temporal metrics across the twelve selected cities, and evaluates patterns in multimodal integration, network design and operational strategies. Chapter 6 translates the spatio-temporal network performance into targeted improvement strategies for policy makers. The conclusion of the report is presented in Chapter 7. Finally, the discussion and recommendations for further research are provided in Chapter 8.

2 Spatio-temporal Metrics for Multimodal Accessibility

A framework based on literature and network theory

This chapter establishes the theoretical foundation necessary for evaluating the accessibility of multi-modal public transport systems. It forms the first step of the research process, corresponding to Phase 1 of the methodology: the identification and selection of key spatial and temporal accessibility metrics.

The chapter first introduces GTFS datasets as the primary data source for modeling public transport operations and discusses how multimodal networks can be represented graphically through L-space and P-space graph constructions. Building on insights from the academic literature, a comprehensive set of spatial and temporal performance metrics is then defined, focusing on elements such as physical network structure, service availability, operational efficiency, and intermodal coordination.

Together, these metrics constitute the accessibility assessment framework that enables standardized, comparable analysis of accessibility across different cities. This framework will be directly applied in the subsequent chapters to evaluate the performance of real-world public transport networks and to address the first research sub-question.

2.1. GTFS Datasets

In order to create a database suitable for the public transport system analysis, GTFS datasets will be used. GTFS datasets contain information about transport modes and associated stop locations, routes, schedules and frequencies (General Transit Feed Specification, n.d.) and are made available by governmental agencies and open databases like Mobility Database (https://mobilitydatabase.org/) and Transitland (https://www.transit.land/). GTFS datasets provide detailed insights in public transport system characteristics, like spatial coverage, operational details, mode diversity and mode integration. Therefore, the datasets provide the opportunity to fully assess the systems performance.

2.1.1. Types of GTFS Feeds: Schedule vs. Realtime

One can distinguish two main types of datasets that GTFS provides: GTFS Schedule and GTFS Realtime. GTFS Schedule is a feed consisting of static public transport information based on transit schedules. GTFS Realtime, on the other hand, enables transport agencies to provide dynamic public transport information, including service alerts, real-time vehicle positions, and up-to-date arrival and departure times.

This research uses GTFS Schedule datasets for the examination of multimodal public transport networks in multiple cities. While GTFS Realtime may provide more accurate representations of actual vehicle movements, it is less suitable for this study for several reasons. First, GTFS Realtime is not consistently available across cities and is often of limited extend, making it unsuitable for standardized, multi-city comparison. Second, the GTFS Realtime format is technically designed for live data streaming and operational monitoring, rather than large-scale structural analysis. Its dynamic and unstructured format leads to challenges for reproducible, graph-based modeling of public transport accessibility.

GTFS Schedule, by contrast, offers a globally adopted, standardized, and structured format that reflects planned service provision, which is sufficient and appropriate for modeling everyday operations and comparing network structures and timetables across cities. It aligns with the goal of this research: to assess spatio-temporal accessibility under regular service conditions using consistent and comparable data inputs.

2.1.2. Core Dataset Elements

A GTFS dataset consists of at least six text (.txt) files (usually formatted as a CSV file), with each file containing a different type of information. Table 2.1 presents the names and attributes of the files that are incorporated in a basic GTFS dataset.

Table 2.1: Basic structure of a GTFS dataset

GTFS file	Description
agency.txt	Contains details about the transit agencies that are part of the dataset.
stops.txt	Contains the names, geographical coordinates and identification numbers of stops/stations.
routes.txt	Contains the names, identification numbers and transit modes of routes.
trips.txt	Contains the identification numbers, headlines and directions of individual trips that are assigned to routes.
stop_times.txt	Contains identification numbers of trips and the complementary arrival time, departure time, stop identification and stop sequence of vehicles.
calendar.txt	Defines service availability by day of the week.

GTFS datasets make it possible to visualize and analyze the spatial properties of a public transport network. This involves the geographical arrangement of stops and routes ('routes' refer to the defined spatial pathways that bus and train lines follow, outlining the connections between stop within a transportation network). The 'stops.txt' file contains the geographical coordinates of all stops or stations in a network. The 'routes.txt' file, 'trips.txt' file and 'stop_times.txt' file explain how these stops are connected and form a network.

In addition, GTFS datasets make it possible to extract travel times between stops and stations. GTFS does not report the (average) travel time to traverse an edge directly. The 'stops.txt' file, 'routes.txt' file' and 'trips.txt' file define the possible paths one can traverse to travel between stops. The 'stop_times.txt' file provides the complementary arrival and departure times of vehicles at stops and makes it therefore possible to determine the (average) travel time between consecutive stops on a route. The 'calendar.txt' file allows to explore daily variations of travel times.

2.1.3. Extended GTFS Features

Additionally, a GTFS dataset may contain supplemental files with extra information. The files that are especially relevant for the further progress of this paper are presented in Table 2.2.

Table 2.2: Supplemental structure of a GTFS dataset

GTFS file	Description
calendar_dates.txt	Contains exceptions on the default service availability as presented in 'calendar.txt'.
frequencies.txt	Defines the operational time slots and vehicle headways of vehicles on trips.

The 'calendar_dates.txt' file lists exceptions to standard service schedules, indicating dates on which service availability, schedules, or timetables differ from regular operations. In some feeds, this file covers only holidays or special services, such as school trips operated by agencies without fixed schedules.

In other feeds, however, it provides a complete overview of active and inactive services for each service date, replacing the weekly patterns defined in 'calendar.txt'. Consequently, selecting a representative date for modeling typical transit operations requires close monitoring of the 'calendar_dates.txt' file to ensure that the chosen date reflects standard, everyday service patterns.

Frequency-based GTFS datasets

In the most common format used in GTFS data, transit operations are schedule-based. This means that for every trip in the 'trips.txt' file, there is a link to a detailed timetable in the 'stop_times.txt' file. The latter contains the specific service schedule, including both the arrival and departure times of vehicles at each stop. Some GTFS datasets, however, are not schedule-based but frequency-based, implying that the transit service does not operate according to a fixed timetable but rather according to regular time intervals. GTFS provides these datasets with a 'frequencies.txt' file.

The 'frequencies.txt' file links trips to a vehicle headway, usually expressed in seconds. Additionally, it specifies the time interval during which a particular headway is applied throughout the day. Thus, over adjacent periods of time during the day, vehicle headways, and thereby hourly vehicle volumes, may vary. Frequency-based GTFS datasets also contain a 'stop_times.txt' file, which, however, usually includes very limited information.

Whereas schedule-based GTFS datasets contain accurate information about transit operations throughout the day, frequency-based GTFS datasets need to be expanded: this means that individual trip departure and arrival times have to be artificially generated based on the scheduled vehicle headways (Zervaas, 2014). This expansion can be performed through Python, and the exact procedure is elaborated on in Section 3.2.1.

Generally, these datasets are considered less reliable then schedule-based datasets, because the expansion process might potentially introduce slight distortions in the modeled availability of services, as well as the estimated waiting times, as trips are not directly based on planned vehicle departures. As a consequence, frequency-based datasets might overestimate service regularity and underestimate passenger waiting times.

In conclusion, while frequency-based GTFS datasets enable the inclusion of public transport systems that do not operate on fixed schedules, their use requires careful handling and synthetic reconstruction of data. For this research, these datasets are included only when no schedule-based alternative is available. Also, the limitations of the expansion process should be considered in the interpretation of results.

2.2. Graphical Representation

Before assessing public transport network accessibility, it is essential to establish a consistent representation of the network. In public transport network topology, a graph (G) consists of two sets: a set of *nodes* or *vertices (V)* and a set of *edges (E)*. These are the two fundamental structural elements. Nodes typically represent stations, stops, or hubs where passengers can enter, exit, or transfer between modes. Edges represent the connections between these nodes, corresponding to the routes or route segments that public transport vehicles travel along (Mohmand & Wang, 2014). Together, nodes and edges create a graphical representation of the network, enabling comprehensive analysis.

According to Lezoray and Grady (2012), the i-th node in graph *G* can be denoted as $v_i \in V$, while the edge connecting the two nodes v_i and v_j as $e_{ij} = \{v_i, v_j\} \in E$. As a consequence follows the definition of graph $G = (V, E)$, with $|V|$ and $|E|$ respectively being the total number of nodes and edges present in the graph. Figure 2.1 shows example nodes v_1 and v_2, that are connected by edge e_{12}.

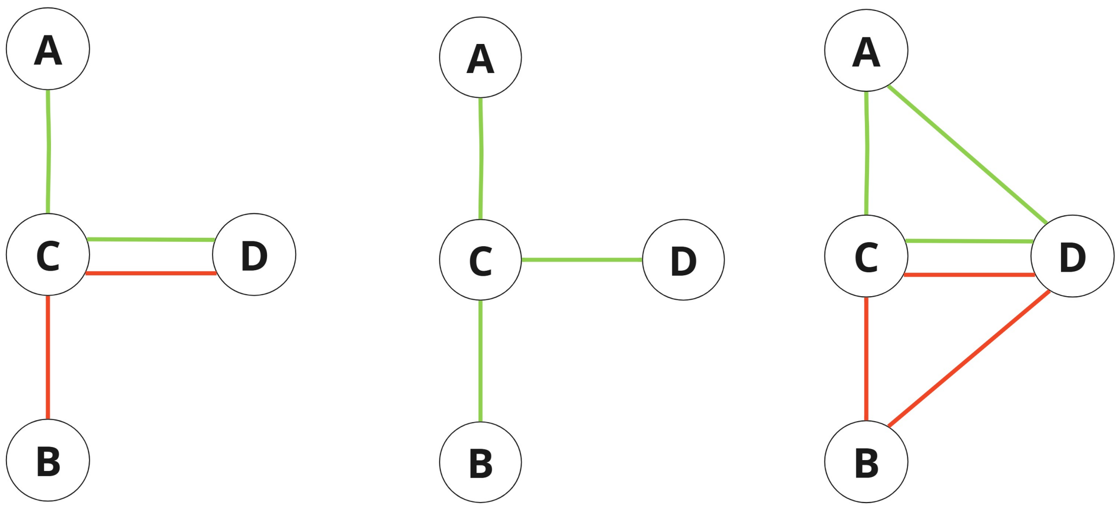
Figure 2.1: Two nodes connected by an edge

There are multiple ways to construct a complete network representation *G* from a given set of nodes and edges. Luo et al., 2019 distinguish between two primary approaches: the Space-of-Infrastructure

(L-space) representation and the Space-of-Service (P-space) representation.

- In L-space representation, nodes represent stops and stations, with an edge linking two nodes if they are directly connected by an infrastructural segment, such as a railway track or roadway.
- In P-space representation, the focus shifts from modeling infrastructure to modeling direct service connectivity. Nodes still represent stops or stations, but edges are created between nodes when they share at least one common route. This means that a node is connected to all stops that can be reached directly, without requiring a transfer between routes or modes.

The different representations are illustrated in Figure 2.2. Figure 2.2a shows a network fragment, where routes are represented by red and green lines. Figure 2.2b demonstrates how this fragment would appear in L-space, while Figure 2.2c shows its P-space representation.



(a) Real-world route representation **(b)** L-space representation **(c)** P-space representation

Figure 2.2: Three network representations

2.3. Network Topology

Network topology defines the structural characteristics of public transport networks. The associated metrics examine how the underlying topology and layout support intermodal interaction and integration. A well-structured network facilitates smooth transitions between modes, reduces travel impedance, and enhances overall accessibility. To capture the different dimensions of topological performance, this section introduces three subcategories: physical integration, infrastructural integration and intermodal integration.

2.3.1. Physical Integration

This metric category focuses on the spatial effort required for intermodal transfers. It refers to the physical impedance passengers should overcome before being able to perform intermodal transfers. This section will outline how this process is described in existing literature and how the physical integration will be assessed in the accessibility assessment framework.

Impedance related to *intramodal* transfers (i.e., transfers that occur within the same mode and station area) is excluded from this category, as detailed data on internal station layouts or walking times within station areas is not included in GTFS datasets by default. Assumptions related to intramodal transfer impedance are discussed in Section 4.3.4, but they are not considered part of this metric category.

Literary Background

Daniels and Mulley (2013) state that the mode of public transportation is the most significant factor influencing individuals' willingness to overcome physical impedance. Their findings suggest that people are generally willing to walk longer distances to access higher-order public transport services, such as rail, where station spacing is usually wide. A study by Van der Waerden et al. (2024) supports this finding, confirming that service frequency and walking route quality significantly affect willingness to walk.

Amirah et al. (2021) endorse the commonly used 400-meter threshold as a guideline for acceptable walking distance to public transport. However, they emphasize the essential role of walking impedance (e.g. crossings, physical barriers, and walkway connectivity) which can significantly reduce the effective threshold for many public transport commuters. Rijsman et al. (2019) found a median walking feeder distance of 380 meters for public transit users.

El-Geneidy et al. (2014) support these insights, emphasizing again that willingness to walk is highly mode-dependent. Their study also acknowledges the 400-meter rule of thumb by using empirical travel behavior data to generate variable walking distance thresholds based on mode of transportation. In a temporal context, this threshold may be translated to an average of five minutes of walking time, as also reflected in the transit planning literature (Institute for Transportation and Development Policy, 2023).

In conclusion, these findings suggest that the willingness to walk for public transport is highly context-sensitive, adapting both service attributes and spatial integration.

Metrics

The total number of intermodal transport opportunities is an important indicator for the physical integration of the different modes of transportation. Therefore, the number of intermodal transfer opportunities E_T in the graph is the first metric that will be added to the accessibility assessment framework.

It should be noted that this metric is highly sensitive to network size: larger public transport networks are expected to have more transfer opportunities. Therefore, it is necessary to standardize this metric in order to allow direct comparison between different network. This is done by adding two new metrics: the Normalized Transfer Opportunity Indicator T_N represents the number of transfer opportunities per node in the graph. Besides, the Mode Coupling Coefficient C_T is defined by the share of nodes that facilitates at least one transfer opportunity.

In order to assess the physical integration of the network, it is not only the number of transfer opportunities that counts. It is also important to examine the impedance that is associated with those intermodal transfers. Therefore, the fourth metric in this category is the intermodal transfer edge length statistic L_T: from all the transfer opportunities in the graph, the average length will be determined and reported, as well as its standard deviation, minimum value and maximum value. An 'intermodal transfer edge' is how a an intermodal transfer opportunity is represented in the graph. Its exact definition and properties will be elaborated on in Section 4.1.

2.3.2. Infrastructural Integration

This category focuses on evaluating the overall connectivity of the network structure. It captures to what extent the presence and layout of existing stops and transport infrastructure enable smooth intermodal traffic operations. Four metrics have been selected to be part of this category.

Degree centrality

To assess the network accessibility of the Pakistani railway network, Chatterjee (2015) used the node degree as one of the indicators. The *degree* (k_i) of node i is defined as the number of nodes directly connected to that node, indicating the number of direct connections that node has. Consequently, in multimodal public transport networks, degree serves as an important indicator for identifying multimodal hubs and is a valuable measure of intermodal transfer potential (Buijtenweg et al., 2021).

Node degree is considered a local accessibility indicator: an indicator measured at the node level rather than at the network level (Cats, 2017). Therefore, it cannot be directly used to compare different public transport networks. Standardized degree values must first be established, along with a clear understanding of how these values reflect the performance of the network as a whole.

Lee (2025b) demonstrates how node degree can be standardized. The standardized value, known as *degree centrality* ($C_D(i)$), is calculated using Equation 2.1, where $|V|$ represents the total number of nodes in the graph.

$$C_D(i) = \frac{k_i}{|V| - 1} \tag{2.1}$$

To facilitate comparison of degree centrality values across different cities, this study adopts the method proposed by Wang et al. (2024), which involves reporting the mean, standard deviation, and the minimum and maximum values observed within the graph.

The degree is added to the accessibility assessment framework as it is a strong indicator for capturing the local connectivity of the public transport network, as well as exploring its multimodal integration potential. Additionally, it will contribute to gaining insight into the complexity of the network.

Degree Assortativity

The degree centrality is a powerful indicator for exploring hierarchical structures within a network. Newman (2002) expanded on this concept by introducing network assortativity (r). Assortativity, in general, refers to the tendency of nodes to connect with other nodes that share similar properties (Noldus & Van Mieghem, 2015). The most commonly used form in literature is degree assortativity (ρ_D), which describes the tendency of high-degree nodes to connect with other high-degree nodes.

Thedchanamoorthy et al. (2014) provide a detailed explanation of the mathematical definition of degree assortativity, describing it as a Pearson correlation that measures the relationship between the degrees of connected nodes. Consequently, degree assortativity takes on a value between -1 and 1. The mathematical formulation, as stated by Lee (2025a), is presented in Equation 2.2, using average node degree values.

$$\rho_D = \frac{\langle k_i k_j \rangle - \langle k \rangle^2}{\langle k^2 \rangle - \langle k \rangle^2}. \tag{2.2}$$

The calculation of degree assortativity may result in three possible outcomes, each with a distinct interpretation:

- Positive assortativity ($\rho_D > 0$) – nodes tend to connect with others that have a similar degree.
- Negative assortativity ($\rho_D < 0$) – nodes tend to connect with others that have a different degree.
- Neutral assortativity ($\rho_D \approx 0$) – no significant correlation between the degrees of connected nodes.

To explore the structure and hierarchy of a public transport network, degree assortativity serves as a valuable indicator. It can reveal hub and clustering patterns, provide insight into how centralized or distributed a network is, and help understand node interactions within a multimodal context. For these reasons, degree assortativity is included in the accessibility assessment framework.

Characteristic Path Length

Cats (2017) identifies the average shortest path length or Characteristic Path Length (CPL) as one of the most important metrics for assessing network efficiency. Mohmand and Wang (2014) present a suitable way to apply this metric to public transport networks. They define the CPL as the average number of edges traversed to get from one node to another. The mathematical formulation of this definition is given in Equation 2.3, with $d(i,j)$ being the shortest path between nodes i and j.

$$\text{CPL} = \frac{1}{|V|(|V| - 1)} \sum_{i,j \in V} d(i,j) \tag{2.3}$$

It should be noted that the CPL of a public transport network is highly influenced by the size of graph G (e.g. the number of nodes and edges present in the graph). Instinctively, large cities with large public transport systems will have longer CPL's. Therefore, it is necessary to standardize the CPL in order to enable network comparison. The concept of characteristic path length was popularized by Watts and Strogatz (1998), who found out that typically the CPL increases logarithmically with $|V|$. For that reason, Newman (2010) suggest standardizing CPL by dividing by $log(|V|)$. Therefore, for network comparison, the standardized CPL will be calculated as stated in Equation 2.4.

$$\text{CPL}_{\text{std}} = \frac{\text{CPL}}{log(|V|)} \tag{2.4}$$

What makes the CPL a strong indicator is that a short CPL indicates a high connectivity between all nodes in the graph. Additionally, the CPL provides interesting insights for both L-space and P-space graph representations. In L-space, where edges represent physical infrastructural connections like roads or railway segments, a short CPL suggests that stations are densely interconnected. In P-space, where edges represent service connections (e.g., shared train or bus lines), a short CPL indicates highly prevalent direct services. In a multimodal context, a short CPL signifies the presence of multiple transfer points that enable efficient transfers between modes of transport. As a result, the CPL of a city's public transport network is a strong indicator of its multimodal efficiency, and therefore it is added to the accessibility assessment framework.

Gamma Index

The last spatial indicator that is added to this category is the *network connectivity*, also denoted as the *gamma index* (γ). According to Scott et al. (2006), the gamma index is defined as the ratio between the total number edges and the maximum number of edges in a planar graph. Its mathematical definition can be found in Equation 2.5.

$$\gamma = \frac{|E|}{3(|V|-2)} \tag{2.5}$$

In L-space graph representation, the gamma index can be interpreted as the likelihood that a road or rail segment is present between any pair of nodes. A higher value indicates a more dense and more integrated graph (Cats, 2017), making it valuable for the accessibility assessment framework. In P-space representation, the index is a useful tool to assess the redundancy of services. A high gamma index in P-space indicates the presence of multiple shared routes, which improves the accessibility of multiple modes of transportation. Additionally, it suggest that passengers have more options to transfer between nodes and so it indicates higher multimodal network efficiency. The gamma index serves as a strong indicator of high-quality intermodal operations. It is particularly valuable for evaluating the integration and redundancy of both infrastructure and services within a multimodal system, making it an important addition to the accessibility assessment framework for assessing multimodal transport networks.

2.3.3. Intermodal Integration

This category explores how well different transport modes are spatially connected within the network. Two metrics have emerged from literature that will be used to assess the intermodal integration of different modes of transport.

Intermodal Degree

Buijtenweg et al. (2021) define *degree* as the number of nodes directly connected to a given node, reflecting the number of direct connections it maintains. While this captures local connectivity, this study aims to analyze not only the extent of a node's connections, but also its role in facilitating interaction between different modes of public transport. In this context, assessing how a node enables access to multiple modes becomes essential for evaluating multimodal integration.

Li et al. (2023) conceptualize multimodal public transport systems as multilayered networks, where each mode forms a distinct layer, and transfer opportunities are represented by interlayer edges. This concept is elaborated on by Aleta et al. (2016), who introduce the concept of the *overlapping degree*, defined as the number of layers (i.e., modes) in which a node is present, indicating its multimodal significance.

Building on these ideas, this research introduces the *intermodal degree* ($D_I(i)$): the number of unique transport modes directly accessible from node i. This measure has a minimum value of 1 (representing access only to the node's own mode) and a maximum value equal to the total number of modes in the system. Like degree centrality, it functions as a local accessibility indicator, and its distribution (mean, standard deviation, minimum, and maximum) is reported at the network level. The intermodal degree is a key metric for identifying the transfer potential of individual nodes. At the network level, it serves as a spatial indicator of intermodal integration, helping assess how different modal subsystems are connected and highlighting critical intermodal transfer hubs. It forms an important addition to the degree centrality, as it not only shows how well connected nodes in the graph are, but also report on the modal diversity of those connections.

Mode assortativity

In subsection 2.3.2, network assortativity was defined as the tendency of nodes to connect to other nodes with similar properties (Buijtenweg et al., 2021). In the literature, degree is often used as the parameter to calculate assortativity, but this is not necessary. Newman (2002) states that the assortativity of a network can also be determined using any categorical attribute, including transport mode. For categorical attributes, the assortativity is formulated as shown in Equation 2.6. In this equation, $\sum_i e_{ii}$ represents the proportion of edges between nodes of the same type, whereas $\sum_i a_i b_i$ represents the expected proportion of same-type connections under random mixing.

$$r = \frac{\sum_i e_{ii} - \sum_i a_i b_i}{1 - \sum_i a_i b_i} \tag{2.6}$$

Building on this concept, the *mode assortativity* (ρ_M) is introduced, defined as the tendency of nodes to be connected to nodes of the same transport mode. This is a strong indicator of spatial network integration, as it directly shows how the different single-mode subgraphs are connected to each other.

Similar to degree assortativity, mode assortativity may take on three types of values:

- Positive mode assortativity ($\rho_M > 0$) – nodes tend to connect with other nodes of the same mode.
- Negative mode assortativity ($\rho_M < 0$) – nodes tend to connect with nodes of different modes.
- Neutral assortativity ($\rho_M \approx 0$) – there is no significant correlation between the modes of connected nodes.

Generally, networks are expected to have positive mode assortativity: nodes primarily tend to connect with nodes of the same mode. However, mode assortativity remains a highly suitable measure for assessing intermodal integration at the network level. Moreover, it enables direct comparison between different public transport networks.

2.4. Operational Efficiency

While spatial structure defines the physical accessibility of a transport network, the actual experience of passengers is also shaped by the temporal dimension. This includes the availability, frequency, and coordination of services throughout the day. This section introduces a set of indicators that assess the operational performance of public transport networks, reflecting how efficiently they function in practice. Because a network's ability to move passengers from origin to destination efficiently depends not just on infrastructure but also on how well services are timed and synchronized, operational efficiency is considered a proxy for temporal accessibility. By analyzing this dimension, the framework captures how dynamic service conditions influence user experience and network functionality.

2.4.1. Service Availability

The availability of public transport services serves as an important temporal indicator for network accessibility. Service availability refers to the extent and frequency of public transport services provided to commuters.

Higher service frequencies generally lead to smaller waiting times for passengers. Geurs and van Wee (2004) describe how these reduced waiting times contribute to improved network accessibility of public transport systems. They emphasize that small waiting times not only enhance network efficiency, but also user experiences and accessibility perception.

In their research, Kujala et al. (2018) demonstrate that the temporal component of network accessibility is highly dependent on when and if public transport services are available. It is shown how the lack of (frequent) services may lead to reduced accessibility of opportunities over time. They emphasize that variations in the availability of services expose access imbalances, implying that service availability is an important temporal accessibility constraint.

It can be concluded that the service availability is a strong indicator for the temporal accessibility in public transport networks. Therefore, this category is added to the accessibility assessment framework that is used for the eventual accessibility assessment. The next step is to find a suitable, standardized metric that represents the availability of service throughout the network.

Weighted Service Availability Score

GTFS datasets enable network-wide trip simulations within specific time intervals, using data from the 'trips.txt' file. Each trip corresponds to one scheduled vehicle departure and is therefore a reasonable proxy for service availability. Moreover, this information can easily and directly be extracted from the GTFS datasets. However, simply counting the number of raw trips has two major disadvantages.

The first problem associated with counting the number of trips in the graph, is that, in a multimodal context, all trips are counted treated equally. This would lead to the risk of overestimation of the importance of slow modes with high frequencies (e.g. buses) and underestimation of the importance of fast modes with low frequencies (e.g. trains). Second, the number of trips in the 'trips.txt' file does not directly reflect the actual volume of vehicle movements, especially in frequency-based GTFS datasets, where services are defined by intervals rather than explicit schedules.

Therefore, this research introduces the following approach: the volume of vehicle movements will be extracted from the 'stop_times.txt' file by counting the number of edge traversals (e.g. the number of vehicle arrivals at each stop) in the graph. This method resolves the second limitation by reflecting the true frequency of services throughout the network.

However, this does not completely resolve the first problem: through this method, high frequency modes still dominate. Therefore, it will be necessary to assign weights to the edge traversals, depending on the relative size of the sub-graphs of each mode. This will be done by following these steps systematically:

- Let M be the set of all transport modes in the network (e.g., bus, metro, tram, train), and let $m \in M$ denote a specific mode.
- Let $|V_m|$ be the number of nodes (e.g., stops or stations) in the graph G that are associated with mode m. $|V|$ represents the total number of nodes in the network.
- Let v_m be the total number of vehicle movements (edge traversals) observed or scheduled for mode m in selected time interval h.
- The total number of vehicle movements across all modes is denoted by Equation 2.7.

$$V_{\text{total}} = \sum_{m \in M} v_m \tag{2.7}$$

- The relative weight of each mode, based on its share of vehicle movements, is defined as defined in Equation 2.8. This scaling importance of this scaling factor will be elaborated on in Section 2.4.5.

$$w_m = \frac{v_m}{V_{\text{total}}} \tag{2.8}$$

- To normalize service availability (e.g. enable comparison between networks of different sizes), the average number of vehicle movements per node per hour for each mode is computed according to Equation 2.9.

$$s_m = \frac{v_m}{|V_m| \cdot h} \tag{2.9}$$

  where h is the length of the simulated time interval (in hours).

- Finally, the composite weighted service availability score across the network is computed by taking the weighted sum of s_m across all modes, as is shown in Equation 2.10

$$S = \sum_{m \in M} w_m \cdot s_m \tag{2.10}$$

So, S represent the weighted availability of services, and will therefore be referred to as the *Weighted Service Availability Score*. It represents the total number of vehicle movements in the graph, while taking into account the relative contribution of each mode to the total availability of services. Moreover, it is a standardized parameter that allows direct comparison of service availability for different public transport systems of various sizes, as it accounts for the total number of nodes present in the network. This makes S a complete and suitable indicator for the service availability in the network and is therefore added to the accessibility assessment framework.

2.4.2. Network Efficiency

To determine how efficiently a public transport network can move passengers from their origin to their destination, it is necessary to simulate traffic operations. This involves modeling trips from point A to point B and analyzing the temporal impedance experienced by public transport users.

Luo et al. (2019) suggest proper simulation of passenger trips by using *Generalized Travel Cost* (GTC). GTC is a powerful network efficiency simulation tool that converts different components of a journey (walking time, waiting time, in-vehicle time and transfer time) to *equivalent in-vehicle time*. Opposed to using raw travel time or traveled distance measures, GTC aims to also capture the comfort travelers experience. By implementing the Value of Time (VoT), GTC takes into account both travel time and travel effort, making it an excellent tool to assess network quality of multimodal and transfer-intensive public transport networks (Wardman, 2004).

Construction of GTC starts with the division of a public transport trip into smaller components. Subsequently, these parts are all converted into a single cost metric: equivalent in-vehicle time. Each component of the trip (walking, waiting, in-vehicle travel, and transfer costs) contributes to the perceived impedance of traveling, but not all are experienced equally: passengers tend to perceive waiting and walking as more undesirable than in-vehicle time, especially when service reliability is low (Wardman, 2004). Therefore, the GTC formula assigns specific penalties to each component. Usually, these are based on empirical valuations from stated or revealed preference studies. These weights reflect the relative impedance associated with each component. By determining the GTC for each origin-destination pair of nodes in the graph, a GTC-based Origin-Destination matrix (OD matrix) can be created that contains all 'shortest paths' (e.g. the path with the lowest experienced travel cost).

Equation 2.11 shows the mathematical formulation of the GTC that will be used in this research, based on the formulation by Iseki et al. (2006).

$$\text{GTC} = \text{IVT}_t + (\alpha_{wait} \cdot \text{Wait}_t) + (\alpha_{walk} \cdot \text{Walk}_t) + (\text{N}_T \cdot \beta_n) \tag{2.11}$$

with:

- GTC: Generalized Travel Cost for the trip.
- IVT_t: Total in-vehicle travel time (minutes).
- α_{wait}: Weight or valuation of waiting time.
- Wait_t: Total time spent waiting (initial + transfers, minutes).
- α_{walk}: Weight or valuation of walking time.
- Walk_t: Total walking time (minutes).
- N_T: Number of transfers during the trip.
- β_n: Transfer penalty for transfer n (minutes).

Through application of GTC, it has become possible to effectively simulate origin-destination trips throughout the generated graph, by looking at the experienced travel time by users. It can be considered a strong tool, as it is behaviorally motivated, suitable for multimodal, complex systems and represents the true schedule-based network performance when derived from GTFS datasets (Luo et al., 2019).

It should be noted that access and egress travel (e.g., walking to the first stop, cycling to a station, or using a taxi for the last leg) are not included in the GTC composition analysis. The presented function focuses strictly on internal public transport network components: in-vehicle time, waiting time, and (intermodal) transfer impedance. These reflect the performance of the transit system itself, not the broader door-to-door travel chain.

GTC Composition

Although GTC as a method allows systematical network assessment across different cities and transit modes, by for example taking its system-wide average value, the travel costs of different systems, derived from GTC, may not be *directly* compared. Intuitively, large networks with greater spatial reach will have larger travel costs than smaller, more compact networks, simply because trips are longer on average (Nassir et al., 2016). Therefore, standardization of the values is required. Without standardization, direct comparisons of average GTC between cities risk confusing differences in how networks perform with differences in the size of the cities. Therefore, standardization, adjusting GTC relative to average trip length, urban extent, or expected free-flow travel time, is essential to enable fair cross-city comparisons of operational efficiency and network accessibility.

The aim of this study is to assess the network efficiency of multimodal public transport networks. In order to do so, the value of the GTC itself is not relevant; it is the composition of the GTC that matters the most. That is why the composition of the GTC is the metric that is added to the accessibility assessment framework: the network efficiency of the different public transport systems will not be assessed by the absolute values of the systems average GTC, but by the relative contribution of its components. Notably, all GTC values of trips used to determine the system-wide average GTC (and its composition) are weighted by each mode's share of vehicle movement. This ensures that the more dominant modes of transportation have more impact on the final GTC composition. Section 2.4.5 shall elaborate on why this is necessary for accurate network comparison. This process works as follows:

- First, the relative mode weight w_m is determined, as was described in Equations 2.7 and 2.8.
- Let IVT_m, WAIT_m, and TRANS_m represent the average in-vehicle time, waiting time, and transfer-related cost, respectively, for trips that begin on mode m (The initial mode is used to weigh trips, as the access mode is expected to have the greatest influence on the remaining part of the journey. Disaggregating all modes within a trip would complicate mode attribution and is likely to reduce the interpretability of the results.).
- The average GTC across all trips is calculated, making usage of Equation 2.12.

$$\overline{\text{GTC}} = \frac{1}{N}\sum_{i=1}^{N}\text{GTC}_i \tag{2.12}$$

  where N is the total number of valid origin-destination paths in the dataset. The definition of a 'valid' OD pair will be explained in Section 4.3.5.
- The weighted in-vehicle time contribution to the GTC is calculated by weighting the mode-specific averages through Equation 2.13.

$$\text{IVT\%} = \left(\frac{\sum_{m\in M} w_m \cdot \text{IVT}_m}{\overline{\text{GTC}}}\right)\cdot 100 \tag{2.13}$$

- Likewise, the weighted contribution of waiting time (Equation 2.14 and transfer impedance (Equation 2.15) are given by:

$$\text{WAIT\%} = \left(\frac{\sum_{m\in M} w_m \cdot \text{WAIT}_m}{\overline{\text{GTC}}}\right)\cdot 100 \tag{2.14}$$

$$\text{TRANS\%} = \left(\frac{\sum_{m\in M} w_m \cdot \text{TRANS}_m}{\overline{\text{GTC}}}\right)\cdot 100 \tag{2.15}$$

These percentages allow for an interpretable breakdown of the average GTC into components attributed to in-vehicle time, waiting time, and transfer impedance, while correcting for mode availability across the network. IVT%, WAIT% and TRANS% are the metrics that are eventually presented in the accessibility assessment framework. Note that this approach does not involve the total walking time $Walk_i$ and the valuation of walking time $Walk_w$ as stated in Equation 2.11. Why this is the cased, will be explained in Section 4.3.2.

2.4.3. Temporal Accessibility

As was described in Section 2.4.2, GTC enables the creation of a filled in OD matrix that contains the GTC-based shortest paths between nodes in the graph. Aside from determining the average GTC and its composition, such a matrix provides more GTC-based opportunities for network efficiency assessment.

Using a similar matrix, Verduzco Torres and McArthur (2024) were able to determine the cumulative accessibility of nodes in the graph, which reflects the number of opportunities (i.e. nodes) that can be reached within a specified time threshold. When expressed in standardized form (usually as a percentage) this measure is referred to as the cumulative accessibility ratio (A_i). Mathematically, this parameter is defined by Equations 2.16 and 2.17.

$$A_i = \sum_{j=1}^{n} W_j \cdot f(c_{ij}) \tag{2.16}$$

$$f(c_{ij}) = \begin{cases} 1 & \text{if } c_{ij} \leq \bar{t} \quad \text{(threshold value)} \\ 0 & \text{otherwise} \end{cases} \tag{2.17}$$

Here, i represents the origin node, j is the destination node, W_j is the weight (e.g., number of opportunities) at location j, and c_{ij} is the travel cost (in this case, the GTC) from i to j. The function $f(c_{ij})$ filters destinations based on whether they are reachable within the threshold $\bar{t}$.

The cumulative accessibility ratio A_i is an indicator to measure how smooth and efficient the system is able to transport passengers towards their desired destination. This is especially the case when the ratio is GTC-based. GTC takes into account user experiences, waiting and transfer burdens and other related travel impedance. As a result, the cumulative accessibility ratio offers valuable insights into the real-world efficiency of multimodal transit operations.

However, it is not possible to add the system wide average cumulative accessibility ratio directly to the accessibility assessment framework. The parameter does not allow for direct comparisons between distinct public transport networks. Smaller networks will instinctively always have a higher ratio for a given threshold value than larger public transport networks, simply because it has fewer nodes and edges. Therefore, it is necessary to scale the parameter on the size of the network. This will be done by using percentiles, by following these steps:

- The GTC for every valid OD pair is extracted from the GTC-based OD matrix.
- The 25th, 50th and 75th percentiles of all these OD pairs are determined. The associated GTC value will be used as threshold value for accessibility.
- For each of the threshold values, the number of OD pairs that are reachable within the given GTC value is counted.
- The proportion of OD pairs that is accessible within this threshold value is calculated: this is the cumulative accessibility ratio and it will lie around 25%, 50% and 75% for the associated percentiles.
- For the threshold values that are found, the ratio is taken between the threshold GTC and the maximum GTC found in the graph (the so called network diameter (Cats, 2017)).

A low threshold-diameter ratio suggests that the median GTC is low in comparison to the worst-case GTC. This implies more efficient trips and a strong network core. It does. however also suggest that the

GTC is more sensitive to extreme values. A high threshold-diameter ratio implicates a more uniform distribution of trip GTC, but also implies less efficient operations with a high average GTC system-wide.

Now, the cumulative accessibility ratio is in standardized form, which means that direct comparison between distinct public transport systems has become possible. The cumulative accessibility threshold values of the 25th, 50th and 75th percentile, $\bar{t}_{25}$ $\bar{t}_{50}$ and $\bar{t}_{75}$ and the associated ratios with the network diameter are added to the accessibility assessment framework.

2.4.4. Synchronization

In multimodal public transport systems, transferring between nodes plays a critical role in network efficiency. In order to find out to what extent different public transport systems are able to facilitate smooth intermodal transfers, the mode synchronization will be assessed.

According to Liu et al. (2021), synchronization or transfer coordination serves the purpose of developing timetables with coordinated arrival and departure times of vehicles at transfer stages, in order to create reliable transfers with low transfer waiting times. System-wide synchronized timetables can significantly reduce total travel times for passengers; an effect that has been found greatest for low-frequency modes of transport (Huang et al., 2022). However, timetable synchronization is an intense and complex process. It not only requires feasible time tables, but also incorporates passenger flow patterns and fleet patterns. Therefore, highly advances optimization methods are required (Liu et al., 2023).

Assessing the timetable synchronization of multimodal public transport systems in made possible through the GTC-based OD matrix. This matrix contains the GTC associated with all paths in the graph: this GTC consists of in-vehicle time, walking time, transfer penalties and also the waiting time associated with these transfers. By extracting these waiting times that are associated with intermodal transfers from the trips in the OD matrix, the systems synchronization can be assessed.

Weighted Average Intermodal Transfer Waiting Time

It will be necessary that all intermodal transfer times, once extracted form the OD matrix, are weighted with the modal scaling factors described in Section 2.4.1. This prevents the overestimation of the importance high-frequency modes and prohibits the underestimation of the importance of modes associated with low frequencies. Section 2.4.5 will elaborate more extensively on the true meaning of these scaling factors.

Once the intermodal transfer weighting times are extracted from the GTC-based OD matrix, they are processed as follows: first, the relative mode weight w_m is determined, as was described in Equations 2.7 and 2.8. Then, the weighted average intermodal transfer waiting time (system-wide) is calculated by the formula presented in Equation 2.18.

$$\overline{W}_{\text{intermodal}} = \sum_{(m_1,m_2)\in T} w_{m_1} \cdot \frac{\sum_{i=1}^{K_{m_1,m_2}} W_i^{(m_1,m_2)}}{K_{m_1,m_2}} \tag{2.18}$$

where:

- $\overline{W}_{\text{intermodal}}$ is the weighted average intermodal transfer waiting time.
- T is the set of observed intermodal mode transitions (m_1, m_2) where $m_1 \neq m_2$.
- w_{m_1} is the weight of the source mode m_1
- K_{m_1,m_2} is the number of intermodal transfers from mode m_1 to mode m_2.
- $W_i^{(m_1,m_2)}$ is the waiting time attributed to the i-th intermodal transfer from m_1 to m_2. It is the average duration of an intermodal transfer on the trip.

With this method, it has become possible to gain insight in the mode-specific synchronization quality of a network. Also, the final parameter, the *weighted average intermodal transfer waiting time* allows direct comparison on distinct public transport networks. Therefore, this metric is added to the accessibility assessment framework as a parameter for network synchronization.

2.4.5. Off-peak/Peak Robustness

In the previous sections, several network metrics have been listed that capture the operational efficiency of public transport networks. However, according to the literature, it is not expected that the operational efficiency of the network is at the same level throughout the day.

According to Geurs and van Wee (2004), the temporal component of network accessibility consists of two key aspects. The first is the frequency component, which refers to variations in service availability. The second aspect is the demand component; it is stated that public transport demand fluctuates throughout the day, primarily driven by commuting patterns and recreational trips. To fully assess the operational efficiency of a public transport network, Stępniak et al. (2019) emphasize the need to analyze variations in service frequencies and travel times across different time periods, such as peak and off-peak hours.

Therefore, the difference in operational efficiency during peak hours and during off-peak hours is the final category that will be added to the accessibility assessment framework. This difference will be examined by calculating the values of the metrics associated with the operational efficiency as described in the previous paragraphs. This means that the simulation of trips, the service availability analysis and the generation of the GTC-based OD matrix will be performed for two different time intervals on the simulation date selected from the GTFS dataset.

Weighted Values

According to Eriksson et al. (2023), fluctuations in performance between peak and off-peak hours are largely associated with the number of vehicles in operation. While GTFS datasets do not include detailed information on vehicle volumes, differences between peak and off-peak conditions can be estimated by analyzing the number of edge traversals, as discussed in Section 2.4.1. However, making direct comparisons between peak and off-peak conditions involves certain risks.

These risks arise from the varying sizes of the sub-graphs associated with different modes of transportation within a network. Generally, the bus network represents the largest sub-network in terms of nodes and edges, followed by the light-rail network, and finally the heavy rail network. It is typically assumed that the number of vehicles in operation is proportional to the size of their respective sub-networks. Based on this assumption, the need for mode scaling factors becomes apparent: one additional train operating during peak hours has a significantly greater impact on network efficiency than one additional bus, simply because it operates within a much smaller sub-graph.

Furthermore, adding vehicles to the network reduces average waiting times. However, the impact of one extra train on reducing waiting times should be greater than that of one extra bus. This is why weighted averages should be used when analyzing service availability, GTC composition, and timetable synchronization. These weights allow for more accurate comparisons; not only between distinct public transport networks, but also between peak and off-peak conditions within the same network.

Off-peak/Peak Performance Ratios

As was stated before, the metrics associated with the operational efficiency of the network will be calculated for two different scenarios: peak conditions and off-peak conditions. The metrics that will be calculated for both scenarios are:

- The Weighted Service Availability Score
- The waiting time component of the GTC (by absolute value, not as a percentage).
- The Weighted Average Intermodal Transfer Waiting Time

The other temporal metrics are not expected to vary significantly between peak and off-peak periods. Since GTFS Schedule data does not account for real-time factors such as congestion or delays, in-vehicle times are likely to remain largely consistent across both simulations. Similarly, the total transfer burden is also assumed to remain stable, as the underlying structure of the network graph does not change between time intervals.

When all values are determined, the ratio between the off-peak values and all the peak values will be calculated. These ratios serve the aim to give an impression on to what extent the network is able to maintain its operational efficiency associated with peak conditions during off-peak conditions. This is what will be called the *Off-peak/Peak Robustness*, the final temporal indicator that will be added to the accessibility assessment framework.

2.5. Accessibility Assessment Framework

This chapter has presented an overview of the use of GTFS datasets in analyzing public transport networks. The relevance of GTFS Schedule data that offers a standardized format for the modeling of the spatio-temporal characteristics of multimodal networks has been explained, highlighting how the possibility of comparative analysis can be established. The chapter also discussed the various mandatory and optional files in GTFS datasets and their main functions and purposes, as well as the differences between scheduled-based and frequency-based datasets.

Moreover, this chapter introduced two graphical representations of multimodal networks: L-space and P-space, which serve as the foundation for network accessibility assessment. Together, these elements form a robust framework for evaluating the performance and integration of public transport systems. Finally, a set of both spatial and temporal network metrics, along with their scientific foundations drawn from the literature, has been presented. These metrics form the accessibility assessment framework that enables a comprehensive assessment of a network's ability to efficiently transport passengers. The complete framework is summarized in Table 2.3.

Table 2.3: Accessibility assessment framework

Metric Category	Metric	Symbol	Unit
Spatial indicators			
Physical integration	Number of Intermodal Transfer Edges	E_T	[-]
	Normalized Transfer Opportunity Indicator	T_N	[-]
	Mode Coupling Coefficient	C_T	[%]
	Transfer Edge Length Statistic	L_T	[m]
Infrastructural integration	Degree Centrality Statistic	$C_D(i)$	[-]
	Degree Assortativity	ρ_D	[-]
	Characteristic Path Length (L-space)	CPL^L_{std}	[-]
	Characteristic Path Length (P-space)	CPL^P_{std}	[-]
	P-space Gamma Index	γ^P	[-]
Multimodal integration	Intermodal Degree Statistic	$D_I(i)$	[-]
	Mode Assortativity	ρ_M	[-]
Temporal indicators			
Service Availability	Weighted Service Availability	S	[veh / (node·h)]
Network Efficiency (GTC-based)	Average GTC	$\overline{\text{GTC}}$	[min]
	Average In-Vehicle Time	IVT%	[%]
	Average Waiting Time	WAIT%	[%]
	Average Transfer Penalty	TRANS%	[%]
Temporal Accessibility	25th Percentile Threshold Value	$\bar{t}_{25}$	[min]
	50th Percentile Threshold Value	$\bar{t}_{50}$	[min]
	75th Percentile Threshold Value	$\bar{t}_{75}$	[min]
Synchronization	Weighted Avg. Intermodal Transfer Wait Time	$\overline{W}_{\text{intermodal}}$	[min]
Off-peak/Peak Robustness	Off-Peak operational performance	[-]	[%]

With the completion of the accessibility assessment framework, the first sub-question of this study - *"What are the major spatio-temporal accessibility metrics for public transport networks and how suitable are they for the evaluation of the system's performance?"* — is answered. The next chapters will apply this framework to analyze real-world transport networks and extract insights on multimodal accessibility.

2.5.1. Discussion on the Accessibility Assessment Framework

The accessibility assessment framework established in this report provides a comprehensive foundation for evaluating the spatio-temporal accessibility and integration of multimodal public transport networks. However, it is important to reflect critically on its scope, objective, and limitations.

Objective and Strengths

The primary goal of the framework is to enable consistent, supply-driven evaluation of multimodal networks, using information that is extractable from GTFS datasets. The framework allows cross-city comparison based on infrastructural layout, intermodal integration, service availability, and generalized travel costs. These are key aspects that directly influence network accessibility from the user perspective.

Through this standardized, GTFS-based approach, the framework captures:

- The spatial cohesion and infrastructural density of the networks.
- The intermodal integration (transfer opportunities and transfer impedance).
- The operational efficiency across time and space
- The temporal robustness (service variations and service synchronization)

It is particularly suited for answering a key research objective: assessing how different network designs and operational strategies impact urban public transport accessibility.

Metrics and Factors Excluded from the Framework

Multiple potential variables were deliberately excluded from the framework. This section briefly discussed these metrics and reveals why they did not make it to the final assessment framework.

Several network indicators traditionally used in public transport network analysis, such as betweenness centrality, closeness centrality, and the node clustering, were deliberately left out of the final accessibility framework. Although these metrics offer valuable theoretical insights, they tend to overlap strongly with degree centrality, which was selected as the primary local connectivity indicator.

High-degree nodes in most cases also exhibit high closeness centrality, as they are better connected to the rest of the network, and similarly tend to appear more often on shortest paths, a property reflected by high betweenness centrality values. Including all of these measures would lead to redundancy, as they each express similar accessibility dynamics from different perspectives. Degree centrality was favored because it is the most direct and interpretable measure for assessing local accessibility across different systems. Besides, it has a clearer link to intermodality than the other metrics (Cats, 2017; Mohmand & Wang, 2014).

Other excluded metrics are the network diameter, directness, meshedness, and efficiency. These metrics tend to overlap with more robust metrics that are already included in the framework. Besides, these metrics are less meaningful in the context of multimodal public transport based in GTFS datasets (Cats, 2017). Network diameter is highly sensitive to extreme values and can not represent typical spatial structuring as well as the characteristic path length. Network directness depends on highly accurate route geometry data, which are not typically included in GTFS datasets. Besides, it is less relevant for evaluating operational accessibility in dense urban network environments. Network meshedness and network efficiency are not very meaningful to capture multimodal service network performance and also show overlaps with other metrics that are included in the framework. Therefore, these indicators were omitted in favor of a more focused and interpretable set of accessibility metrics.

GTFS datasets describe scheduled services rather than service usage. This makes GTFS not suitable for assessing public transport networks from a demand point-of-view. Passenger load factors and vehicle occupancy are not included in the network analysis, as GTFS datasets do not provide this type of information. Similarly„ socio-economic factors and land-use accessibility indicators, such as access to employment opportunities or income-sensitive analyses, were left out of the framework to maintain a focus on supply-side performance without requiring complex external datasets. Fare policies and pricing accessibility were not included, as they vary widely across cities and ore not consistently provided in GTFS data. Finally, subjective quality metrics, such as perceived comfort or perceived safety, were excluded because they cannot be objectively quantified within the available datasets. Although integrating demand-side indicators, socio-economic metrics, and subjective factors would be valuable for a complete network performance assessment, the focus of this research is kept solely on supply-side. This includes characteristics that can be consistently extracted from GTFS, ensuring comparability across different urban environments.

Limitations

Despite the frameworks strengths, it also shows some notable limitations that are a consequence of leaving out the previously described indicators.

- The framework does not measure actual passenger flows. As a result, only potential accessibility is reflected, not real-life user experience.
- Temporal variations are captured via averages and generalized travel costs, but extreme conditions (like rush-hour congestion or night service gaps) are only partially reflected by the framework.
- Penalties regarding waiting times, walking times and tranfer are modeled with generalized assumptions from literature, which does not reflect individual preferences or cultural variability.

Thus, the framework is best interpreted as diagnosing network potential, not the real-world user experience.

Relative Importance of Variables

The accessibility assessment framework is built on carefully selected indicators that are scientifically grounded. However, it is important to note that its primary objective is to offer a structured, comparable overview of multimodal network characteristics across different cities, rather than to deliver absolute or definitive judgments about the network performance. Throughout this research, the framework will be used to reveal general patterns in spatial structure, intermodal integration and operational strategies, providing meaningful indications of how different systems are designed and managed, rather than relying on individual metrics to draw hard conclusions. It is the combination of indicators that will be used to reveal structural and operational tendencies and strategic choices from different networks. Small variations in metrics across the different networks are less critical than the overall constellation of values in the framework.

Besides, not every parameter is weighted equally when it comes to the interpretation process. Every indicator contributes to qualifying and characterizing the network accessibility, but some of the included metrics offer more decisive insights into the network design structure and operational strategy than others. Every metric helps to build a comprehensive understanding of the overall network performance, but not every metric will directly be translated into an actionable policy recommendation by the end of the research. Policy conclusions are preliminary drawn from those metrics that, when combined, most clearly highlight network strengths, weaknesses or other strategic possibilities for improvement.

3

Constructing Multimodal Graphs

From GTFS dataset to graph-based network representation

This chapter describes the second phase of the research process: the construction of standardized graph-based representations of multimodal public transport systems. Building upon the theoretical framework defined in Chapter 2, this phase prepares the foundation needed to extract spatial and temporal accessibility metrics from GTFS datasets.

The first part of the chapter introduces the selection of a diverse and representative set of cities used as case studies in this research. This selection emphasizes the need for variation in socio-economic, cultural, and transport system characteristics to support robust comparative analysis.

The second part of the chapter outlines a generalizable and case-agnostic methodology for collecting, cleaning, and processing GTFS Schedule datasets into structured databases. This method is designed to be applicable to any urban public transport system for which high-quality GTFS data is available. Special attention is given to ensuring that each dataset reflects complete and realistic weekday transit operations, irrespective of the specific city context.

Finally, the chapter details the standardized modeling approach used to create L-space and P-space network graphs. These graph representations capture the spatial structure and operational dynamics of multimodal public transport systems, and serve as the operational input for the metric extraction and comparative analysis conducted in the next phase.

3.1. Data Collection and Preparation

In order to be able to extract the metrics from the theoretical framework presented in Chapter 2 from GTFS datasets, extensive processing and adaptation of these datasets is necessary. This will be done by translating the datasets into integrant, workable databases. From the databases, the visual graph representations in L-space and P-space as described in Section 2.2 will be created. When these graphs are altered in such a way that they represent complete multimodal public transport networks with attributes that represent real life spatio-temporal dependencies, it will become possible to extract the metric from the theoretical framework described in Section 2.5.

3.1.1. City Selection Criteria

Before deciding on the necessary data preparation and processing steps, it is important to first identify which datasets will be used. The objective of this research is to evaluate the multimodal integration and overall network accessibility of public transport systems in cities around the world, with the goal of outlining policy recommendations that can improve system performance.

A key part of this process is conducting a comparative analysis between cities to uncover common strategies and similarities in network structure and operational characteristics. To support this, it is preferable to select a diverse set of cities. The selection should aim to include cities that vary in terms of geographic location, cultural background, population size, available transport modes, and the overall scale of their public transport networks. This diversity enables meaningful comparisons and helps to highlight differences that may be relevant for both analysis and policy development.

Sources

This research is reliant on GTFS datasets that are publicly available online, mostly published by transport agencies or authorities. In order to retrieve suitable datasets, two major suppliers of GTFS feeds were used: Mobility Database (MobilityData, 2024) and Transitland (Interline Technologies LLC, 2024). Both organizations collect, qualify and publish GTFS datasets of cities all over the world. The feeds published on these websites differ in data quality, completeness and currentness: some feeds are updated and republished multiple times per week, other feeds are published incidentally without updates.

Availability and Suitability

It is important to establish clear criteria for the conditions a published dataset must meet in order to be considered suitable for this research. The following dataset requirements have been defined:

- The dataset should include public transport schedules from the period following the COVID-19 pandemic. In practice, this means that the schedules in the GTFS dataset must be dated later than April 2022.
- The dataset must allow for the extraction of a 'typical date': a weekday that reflects regular transit operations. This date should therefore not fall on a weekend, a national holiday, or within a period affected by major scheduled disruptions.
- As this research aims to assess the network quality of multimodal public transport systems, each city dataset must include more than one mode of transportation.
- The dataset must include all public transport modes available in the city's network. So, if a city's system includes buses, light rail, and heavy rail used for urban transport, all of these modes should be included in the dataset. Additionally, no relevant transport agency must be excluded.
- All relevant files, as described in Section 2.1, should be present in the dataset.

In total, datasets from 52 cities around the world were downloaded and thoroughly analyzed for completeness and data quality. This analysis involved evaluating whether the data was up-to-date, reliable, and user-friendly.

Definitive Set of Cities

The selection of cities followed a two-stage process. First, an extensive screening of 52 public GTFS datasets was conducted to ensure technical suitability. Datasets were excluded if they lacked multimodal coverage (e.g. only buses available), showed data irregularities (e.g., very large variations between consecutive days), or were outdated (e.g., based on schedules from before 2022). This process canceled out 22 cities.

After the technical filtering, a second selection stage was carried out to ensure diversity in geography, socio-economic context, and transport system characteristics. From the approximately 30 remaining candidates, a final set of cities was assembled to maximize variation in global location, population size, and network scale. This variation is important to enable one of the key research objectives: assessing the relationship between network size, modal diversity, and intermodal efficiency. By including cities with different levels of multimodality and network complexity, it becomes possible to explore whether larger or more extensive networks necessarily lead to better integration and accessibility outcomes.

Figure 3.1 presents a flowchart summarizing the full sequence of steps conducted during the city selection process.

1. Initial Dataset Collection
52 public GTFS feeds from cities all around the globe
↓
2. Technical Filtering
Exclude datasets lacking multimodality, recent data, or showing irregularities
(e.g., outdated schedules, data gaps, inconsistent modes)
↓
Remaining Candidates: 30 Cities
↓
3. Strategic Selection
Ensure diversity in geography, population size, and network characteristics
↓
Final Selection: 12 Cities
See Table 3.1

Figure 3.1: Two-stage filtering process for city selection

From the 52 analyzed datasets, a final selection of 12 cities was made. These cities all provide complete, processable, and reliable GTFS data feeds and are therefore considered suitable for the subsequent analysis in this research. A detailed overview of the selected cities in alphabetical order is presented in Table 3.1.

Table 3.1: The twelve selected cities in alphabetical order

Bangkok	Paris
Berlin	Prague
Denver	São Paulo
Melbourne	Singapore
Mexico City	Toronto
New York City	Valencia

The final set of cities includes locations spread across five different continents. In addition, the selected cities vary in terms of population size, socio-economic characteristics, cultural background, public transport network structure, and available transport modes. This diversity makes the set a strong and representative sample of urban public transport systems worldwide. An extensive overview of the datasets used and the associated sources can be found Appendix A.

3.2. Data Import and Preprocessing

This section outlines the steps taken to transform raw GTFS Schedule datasets into structured and consistent databases suitable for network modeling and analysis. The goal is to ensure that a raw dataset accurately represents the real-word public transport operations of the associated network. Key processes include converting text-based GTFS files into SQLite databases, merging feeds from multiple agencies where necessary, expanding frequency-based schedules, and selecting a representative service day. These steps are essential for generating coherent multimodal graphs and enabling the extraction of standardized accessibility metrics.

3.2.1. SQLite Database

As described in Section 2.1, GTFS datasets typically consist of text (.txt) files that use commas (,) as delimiters. This format can complicate data filtering, data processing, and data analysis. Therefore, all files are imported into SQLite databases (one distinct database per network). These databases organize the information into tables, making it easier to read, check for irregularities, and perform modifications (SQLite Consortium, 2025). Additionally, using SQLite simplifies iterating through the different files.

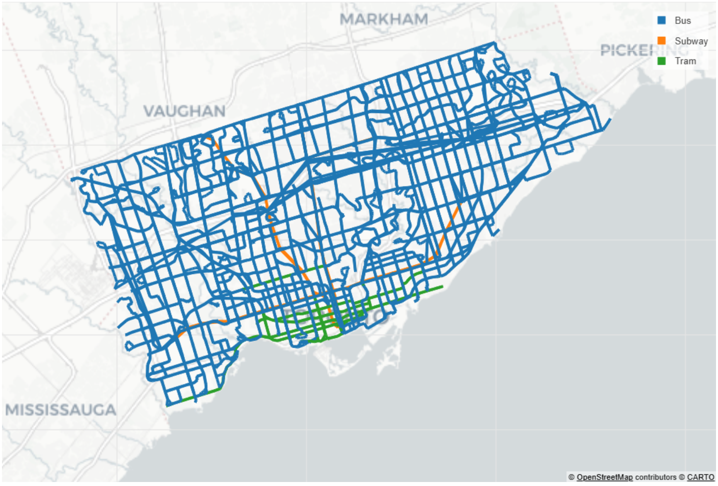
For this research, the GTFS datasets corresponding to the selected case study cities were imported into SQLite databases using Python, based on the script published by Dakad (2019). However, the procedure is generalizable and can be applied to any GTFS Schedule dataset.

Complete and Partial Feeds

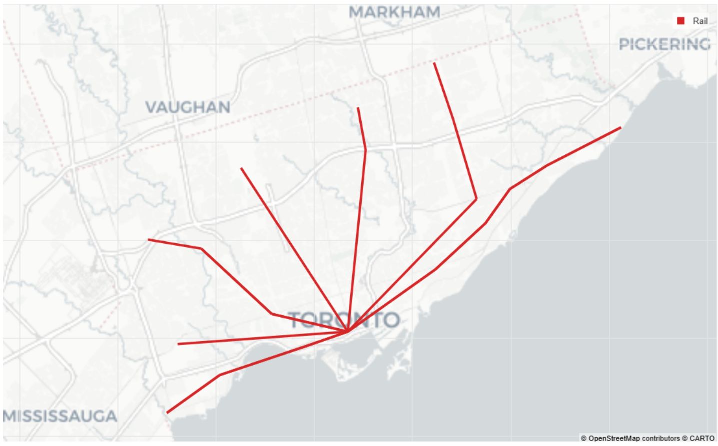
Mobility Database and Transitland are platforms that collect and publish GTFS datasets, which are usually made publicly available by governmental institutions or transit agencies. In most cases, these feeds are integrated datasets that consolidate all GTFS information for multiple agencies, meaning only one GTFS dataset needs to be downloaded and imported into an SQLite database.

However, this is not always the case. In some urban areas, separate GTFS feeds are published by different transit agencies. In these cases, additional effort is required to obtain and integrate multiple datasets into a single SQLite database to ensure consistency. Datasets must be selected carefully to ensure that they cover overlapping periods of service and can be merged into a coherent representation of the full public transport network.

An example of this integration process is illustrated for the city of Toronto in Figure 3.2. For Toronto, the data for bus, subway, and tram services are provided by the Toronto Transit Commission (TTC), as shown in Figure 3.2a, while the commuter rail services are provided by GO Transit in a separate GTFS feed, shown in Figure 3.2b. These separate datasets were combined into a single SQLite database, resulting in a complete multimodal representation of Toronto's public transport system (Figure 3.2c).



(a) Bus, subway and tram network in Toronto (TTC)



(b) Railway network in Toronto (GO Transit)

(c) Complete multimodal network

Figure 3.2: Combination of transit agency dataset for Toronto.

Frequency-based Datasets

The next step in preparing the data is the expansion of frequency-based datasets. As explained in Section 2.1.3, a distinction can be made between schedule-based GTFS datasets and frequency-based GTFS datasets. The main difference between these two types of feeds lies in the presence of the 'frequencies.txt' file and the contents of the 'stop_times.txt' file: schedule-based datasets include detailed stop and arrival times for all vehicle movements across the network, whereas frequency-based datasets rely on headway information and require expansion by calculating additional arrival and departure times based on the headways defined in the 'frequencies.txt' file.

This expansion is performed using a Python script based on the framework published by Afimb (2020), which artificially generates stop times for each trip by interpolating departures within the defined time windows.

Although the expansion process introduces modeled values rather than actual scheduled times, it preserves the intended frequency structure of services and allows for consistent integration into the graph modeling process. This enables frequency-based datasets to be used alongside schedule-based datasets in a standardized and comparable way. The specific datasets requiring this expansion are listed in the concluding section of this chapter (Section 3.4).

3.2.2. Date Extraction

Before it is possible to go over to the next step, the generation and visualization of the graphs, one final data preparation step must be completed: the extraction of a suitable date for simulating transit operations.

As described in Section 3.1.1, the date used for simulation should be a 'typical weekday' reflecting regular scheduled operations, and must be no earlier than April 2022. The suitability of a date for simulation is determined based on the number of trips assigned to that day in the dataset. To identify such dates, a script based on the query published by Jannis and contributors (2023) was applied to the SQLite database. This script enables calculating the number of trips scheduled per day in the 'calendar.txt' file.

The query returns a table listing the number of trips scheduled per day over a 30-day period, providing 30 potential options for selecting a representative service day. An example of such an output is shown in Figure 3.3, illustrating the first 10 options generated from one of the case study datasets (Paris, October 2024).

	service_date	num_trips
1	2024-10-01	142282
2	2024-10-02	142086
3	2024-10-03	142274
4	2024-10-04	148853
5	2024-10-05	96136
6	2024-10-06	63843
7	2024-10-07	142755
8	2024-10-08	142185
9	2024-10-09	142580
10	2024-10-10	142753

Figure 3.3: Example output of potential service dates from SQLite query

From the 30 available options, the *fourth highest* trip count is selected as a rule of thumb (unless the corresponding day falls on a weekend), in order to avoid extreme values while still capturing a typical busy weekday.

However, not all datasets exhibit clear daily variation in the number of trips, as illustrated by the Paris example in Figure 3.3. This largely depends on the size and quality of the GTFS feed. In some cases, only minor differences exist between weekdays and weekends, or weekend trips may be absent entirely. In such situations, a standard weekday is selected manually. For datasets showing little or no variation over a longer period of time, preference is given to dates close to the dataset's publication date, to ensure reliability. The final simulation dates selected for the case study cities are listed in Appendix A.

3.3. Generating Multimodal Graphs

With a complete database and a suitable date selected for the simulation of transit operations, it is now possible to convert the data into a multimodal public transport L-space graph using Python. This section provides a detailed explanation of the graph generation process. The corresponding Python function is included in Appendix B: this script is based on an GTFS processing script from the TU Delft GitLab repository but was substantially extended to enable multimodal support, spatial and temporal filtering, and enhanced node/edge annotations (De Ruijter, 2023). What follows is a step-by-step description of the data processing and graph construction procedure.

3.3.1. Temporal Filtering

First, the operational network must be defined for a specific time interval. GTFS datasets include all scheduled trips over a range of days and times, making it essential to precisely define the time window to be used for simulation. This time window functions as a time-specific snapshot of the network, capturing all relevant spatial and operational characteristics as they exist in real-world conditions during that period.

The simulation date was determined in the previous step, as described in Section 3.2.2. With this date as input for the Python function, all trips occurring on that specific day can be extracted from the SQLite database. The next step involves selecting a time interval during which transit services will be simulated.

As outlined in Section 2.4.5, this research aims to evaluate network operations under both peak and off-peak conditions. Therefore, two distinct time intervals have been defined, resulting in two separate graphs:

- 07:00 to 09:00 (Peak conditions)
- 12:00 to 14:00 (Off-peak conditions)

Graphs representing peak conditions are generally expected to be more extensive than those representing off-peak conditions. That is why in this study's application, the peak-period graph is generated first for each city and is used for the spatial component of the analysis as well as the initial network efficiency simulation. The off-peak graph is then generated solely for the purpose of comparing temporal accessibility characteristics with the peak-period graph. It is assumed that the spatial structure of the network remains unchanged between these two periods.

Only the trips that occur within the specified time interval will be considered by the Python script during the simulation process. With the necessary data now extracted and filtered, the next step can begin: the creation of the graph's nodes.

3.3.2. Graph Nodes

For each mode of transportation present in the dataset, a separate sub-graph is generated. These sub-graphs will later be merged into a single, unified multimodal graph. The process begins with the creation of graph nodes, based on the information stored in the 'stops' table of the SQLite database. A node is created for every stop in the database, each enriched with the necessary attributes.

For illustration purposes, an example node (Porte de Vincennes, Paris) with all its associated attributes is shown in Table 3.2. It shows the attributes of the first metro station of the Paris graph.

Table 3.2: Node attribute dictionary of Porte de Vincennes, Paris

Attribute	Value
`node_id`	0
`latitude`	48.84700773108863
`longitude`	2.4108049967015006
`name`	Porte de Vincennes
`mode`	Subway
`original_ids`	IDFM:463012, IDFM:22077, IDFM:24396, IDFM:26534, IDFM:460560, IDFM:460563, IDFM:28371

The list of attributes consists of its index or identification number of the node, its position on the globe, its name and the mode it is associated with. The 'original ID' refers to the largest fully connected sub-graphs the node belongs to.

Based on the cities position on the globe, the first part of the spatial filtering takes place: stops that are too from from the city center (retrieved from LatLong.net (2025)) are removed, as well as all trips and services that are associated with them. The full spatial filtering of the graph will be finished when the edges are created.

3.3.3. Graph Edges

The construction of edges in the multimodal transport network is completed for the L-space graph model at first. This means that edges represent infrastructural connections between consecutive stops. These connections reflect the physical stop-to-stop sequences encoded in the transit system. The core table used for edge generation is 'stop_times' table, which specifies the ordered list of stops for each trip. Consecutive stop pairs within a trip define the connections through edges.

Every edge that is created has an attribute dictionary assigned to it. An illustrating example of how such a dictionary looks, is presented in Table 3.3, which contains all attributes of the first edge of the Paris graph.

Table 3.3: Example attribute dictionary of an edge

Attribute	Value
`source node`	0
`destination node`	1
`direction_id`	`{1: 215}`
`headsign`	`{La Défense (Grande Arche): 215}`
`duration_avg`	101.5813953488372 seconds
`n_vehicles`	215
`d`	1104 meters
`route_I_counts`	`{IDFM:C01371: 215}`
`mode`	Subway

The attribute dictionary defines the characteristics of each edge in the L-space graph. It explicitly identifies the two nodes the edge connects. The 'direction_id' indicates the number of trips operating in the direction of the edge (e.g., outbound or inbound). The 'headsign' attribute provides a breakdown of destination labels and the number of trips using the edge to reach each destination.

Additionally, the dictionary includes the average travel time (duration_avg) required to traverse the edge, calculated from scheduled departure and arrival times in the 'stop_times' table. The 'n_vehicles' field counts the total number of vehicle trips serving this edge within the specified time interval. The 'd' attribute represents the physical distance of the edge, derived either from the route geometry or approximated from stop coordinates. The 'route_I_counts' dictionary lists all route identifiers that include this edge and the number of associated trips. Finally, the mode attribute specifies the transport mode to which the edge belongs.

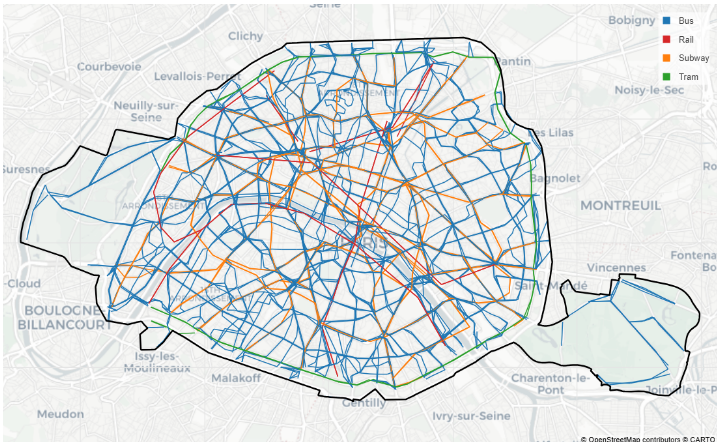
3.3.4. Spatial Filtering

With the completion of the node and edge generation for every mode and the merging of all the sub-graphs, graph G is now complete. However, a couple of extra steps are undertaken in order to prepare the graph for further analysis. At first, the complete spatial filtering of the graph is performed in two steps.

City Boundaries

As was described in Section 3.3.2, nodes too far away from the city center were already removed from the graph before creating the edges. Now, the exact area of interest for each city needs to be defined. This is done by extracting the city boundaries from OpenStreetMap (OSM) data (OpenStreetMap, 2024). All nodes and connected edges that are positioned outside of the defined city boundaries are excluded from the final graph. How this works in practice is shown in Figure 3.4, with Figure 3.4a showing the initial unfiltered Paris graph and Figure 3.4b showing the final graph filtered by the city boundaries (city boundaries are highlighted in black).

(a) Unfiltered Paris graph



(b) Filtered Paris graph

Figure 3.4: Spatial filtering through city boundaries visualized

Merging Nodes

In most cases, a GTFS dataset contains significantly more stops in the stops.txt file than the actual number of physical stations. This can occur for various reasons. For example, multiple stop entries may refer to the same physical location, such as “Station X Northbound” and “Station X Southbound.” It is also possible that inconsistencies in spelling or formatting, such as “Station A - B” and “Station A-B” result in duplicate entries.

To ensure the resulting graph realistically reflects the structure of the multimodal public transport network, these redundant stops must be consolidated. This is achieved by merging excessive or duplicate nodes into single nodes, along with their associated edges. The merging process is carried out in two rounds:

1. Round 1: for each sub-graph, all nodes located within a 50-meter radius of one another are merged, regardless of their names. This captures duplicate stop entries that share the same physical location.
2. Round 2: nodes are filtered based on name similarity to identify cases where station names include platform numbers, mode identifiers, or minor typographical differences. Nodes within a 500-meter radius and with at least 75% name similarity are merged.

By merging nodes that are nearly identical in terms of location and/or name, a clean and realistic multimodal network graph is produced, better suited for accessibility and performance analysis.

3.3.5. Sanity Check

One final step remains before the L-space graph is fully complete: the sanity check. This step, inspired by the procedures included in the open-source GTFS graph processing script by De Ruijter (2023), ensures that the generated graph is structurally valid and consistent with the real-world transport network. The sanity check consists of three components:

- Detection of isolated islands: the graph is examined for 'island nodes'. These are nodes that are not connected to any other node. All island nodes are removed from the final graph.
- Self-loop removal: The graph is first checked for self-loops. These are edges where the destination node is the same as the origin node. These may arise during the node-merging process and are clearly undesirable for operational simulations. Any identified self-loops are removed from the graph.
- Invalid edge duration check: The graph is inspected for edges with invalid durations: durations less than or equal to zero. Such edges can disrupt the trip simulation process and must be removed.

There is one additional component of the sanity check apart for the three previously mentioned components: the determination of the Giant Component Size (GCS) of the graph. However, this final step will not be performed yet. At this stage, the graph only consists of separate sub-graphs (one per mode of transportation), which makes examining the intermodality of the graph not possible yet. The determination of the largest strongly connected component will therefore be performed in a later stadium. This process will be elaborated on in Section 4.1.2.

3.3.6. L-space Graph

With all these steps completed, the result is a complete, realistic, and functional L-space graph representation. It consists of nodes and edges with simulated trips between 07:00 and 09:00 on the selected date, and is fully prepared for further analysis. An example of a fully processed and cleaned L-space graph representation of Paris, with all nodes and edges clearly visible can be seen in Figure 3.5.

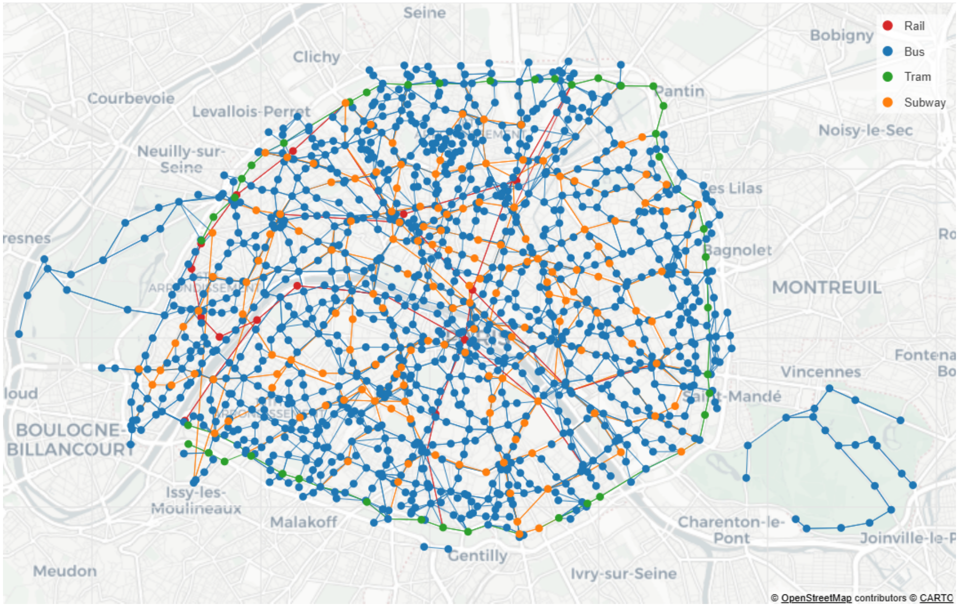


Figure 3.5: Complete L-space graph of Paris

It is important to emphasize that the graph shown in Figure 3.5 represents four separate sub-graphs: one for each mode of transport. At this stage, there is no interaction or integration between the different modes, as no connections (edges) exist between nodes belonging to different transport modes.

3.3.7. P-space Graph

With the completion of the L-space graph, it becomes possible to construct a corresponding P-space graph, in which edges no longer represent physical infrastructure but instead represent direct service-based connectivity. In P-space, the set of nodes V remains unchanged (each node still corresponds to a stop). However, the set of edges E changes.

To transform the L-space graph into P-space, Python creates an edge between any two nodes that are connected via a path in the L-space graph, where all intermediate edges belong to the same route and direction. These shared routes are identified using the 'route_l_counts' dictionary embedded in the attributes of L-space edges, which records the number of vehicle trips associated with each 'route_id'.

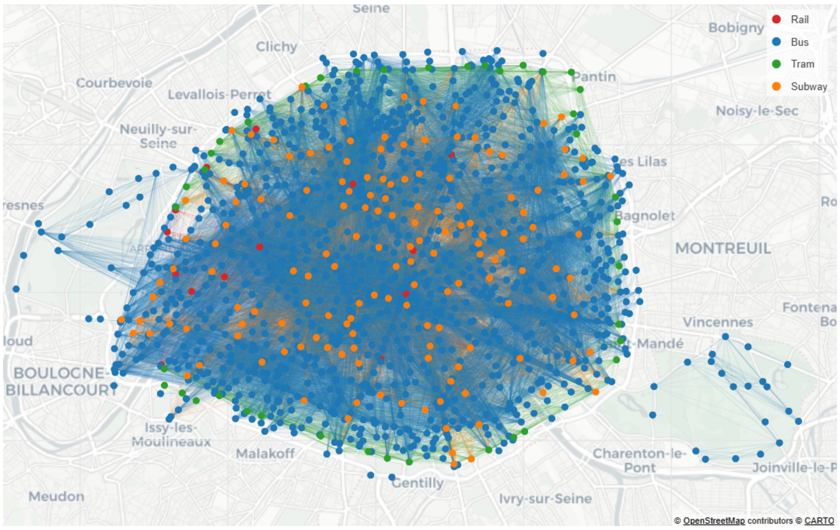
This transformation results in a fully connected subgraph for each route-direction pair. The attributes assigned to all the edges in the P-space graph are listed in Table 3.4 for illustration purposes. The table demonstrates all attributes of one edge from the Paris network P-space representation.

Table 3.4: Example attribute dictionary of an edge in P-space

Attribute	Value
`source node`	0
`destination node`	69
`veh`	`{'IDFM:C01679': {1: 31.0}}`
`avg_wait`	0.967741935483871
`mode`	Tram

Similar to the edges in L-space, the edges in P-space contain the source node and destination node as attributes, as well as the mode the edge is associated with. Additionally, 'veh' represents the average number of vehicles that move between the two nodes per hour. The average waiting time, 'avg_wait', is defined as the time a passenger traveling from node A to node B (without having to transfer) is expected to wait, expressed in minutes. It is important to note that this waiting time is based on the average headway of vehicles on the route: it is assumed that the average waiting time equals the average vehicle headway, divided by 2. This represents a simplified estimation of waiting time. However, it is important to keep in mind that the network simulations are based on GTFS Schedule data, which is purely timetable-based. This justifies the decision to take the average waiting time as half of the average headway: 'perfect circumstances' without delays or disruptions are assumed. Section 4.3.4 elaborates on how this simplified network representation is accounted for during shortest path simulations.

As an example, the final result of the P-space graph for Paris in peak conditions can be found in Figure 3.6a. Every edge in this graph represents a direct service connection. It becomes clear that P-space graphs are much denser than L-space graphs: the set of edges E has expanded significantly. To get a better understanding of the true structure of a P-space graph, the same graph of the Paris public transport network is shown in Figure 3.6b. However, in this figure, the colors of the edges are not determined by the mode they are associated with, but by the route they belong to.



(a) Complete P-space graph of Paris

(b) P-space graph with edge color by route

Figure 3.6: P-space representation of Paris public transport network

3.4. Concluding Remarks

This chapter presented the methodological steps required to transform raw GTFS datasets into coherent and standardized multimodal transport networks, suitable for comparative accessibility analysis. Through a structured process of city selection, data preprocessing, and graph construction, a consistent modeling framework was established for twelve diverse urban transport systems worldwide.

By incorporating both spatial and temporal attributes, such as network topology, operational schedules, and intermodal connectivity, the resulting L-space and P-space graphs offer a realistic and flexible platform for evaluating network accessibility.

To summarize the complete data processing and modeling workflow, the general framework is presented in Figure 3.7.

1. GTFS Import (including SQLite database creation)

↓

2. Data Adjustment (if applicable)

Merge multiple agency feeds / Expand frequency-based datasets

↓

3. Date Extraction

↓

4. Graph Construction

↓

5. Spatial Filtering

↓

6. Sanity Check

↓

7. L-space and P-space Output

Figure 3.7: Workflow for standardized data preprocessing and graph construction

While the methodology is designed to be fully generalizable and applicable to any urban GTFS dataset, it will now be systematically applied to the twelve selected case study cities.

In four of these cases - Melbourne, New York City, Toronto, and Valencia - multiple agency datasets were merged to construct a complete citywide network. In four others - Bangkok, Mexico City, São Paulo, and Singapore - frequency-based GTFS feeds required expansion to generate complete scheduled operations.

With the multimodal graph models prepared for each city, the study is now ready to move into the next phase: the extraction and analysis of spatial and temporal accessibility metrics, applying the theoretical framework introduced in Chapter 2.

4

Trip-Based Simulation of Multimodal Systems

Modeling transfers, travel impedance, and multimodal interaction

This chapter marks the third phase of the research process, focusing on simulating passenger movements through the constructed multimodal public transport networks. Building upon the graph-based representations developed in Chapter 3, this phase models real-world operational dynamics by integrating intermodal transfers, travel impedance, and service coordination into the network structure.

The chapter first describes the modeling of intermodal transfer edges, which connect separate modal sub-systems into integrated multimodal networks. Next, the concept of Generalized Travel Cost (GTC) that forms the basis for simulating trip experiences between origin and destination pairs is applied to the system, accounting for in-vehicle time, waiting, walking, and transfer penalties. A customized method for sampling origin-destination pairs and calculating GTC-weighted shortest paths is presented, enabling scalable analysis across large networks.

Finally, the chapter outlines how the simulated networks and OD matrices are used to extract both spatial and temporal accessibility metrics. These outputs provide the empirical foundation for answering the main research question: evaluating and comparing the accessibility of multimodal public transport networks in cities worldwide.

4.1. Modeling Intermodal Transfers

Both the L-space graph and the P-space graph generated through the process outlined in Chapter 3 consist of distinct sub-graphs, each representing a separate sub-system corresponding to a specific mode of transportation. These sub-systems operate independently, without any existing connections between them.

To assess the network as an integrated whole, particularly in terms of interaction between modes and the system's level of intermodality, it is essential to connect the sub-graphs. This is achieved by introducing connections at locations where intermodal transfers are possible. In other words, additional edges must be added to the graph: the so-called intermodal transfer edges.

4.1.1. Transfer Feasibility

In order to determine the exact locations of the intermodal transfer edges, it is necessary to determine how far passengers are willing to walk for making an intermodal transfer. This study's application will endorse the rule of thumb that was described in Section 2.3.1: it is assumed that passengers are willing to walk 400 meters maximum for public transport, and that they are willing to walk the same distance to perform an intermodal transfer. It is expected that this chosen threshold value will lead to outbalanced results: it is expected that enough transport opportunities will emerge from the graph to enable a realistic, integrated examination of the multimodal system, but that it limits the influence of walking as a mode of transportation that is introduced in the system. The implementation of intermodal transfer edges into the graph is executed through a Python function that can be found in Appendix C.1. The process consists of three steps:

- For every node, it is determined how many nodes associated with a different mode of transport are located within a threshold of 500 meters Euclidean distance. This is in order to speed op the computational time of the model. The 500-meter threshold is set 20% higher than the final walking distance limit to account for real-world travel impedance between two points. The node pairs that match this condition are labeled as 'potential transfer edges'.
- For every potential transfer edge, the walking distance between the two nodes is determined making usage of OpenStreetMap data (OpenStreetMap, 2024). The actual intermodal transfer are created only if this walking distance is equal or less than 400 meters.
- OSM also determines the time it takes on average to traverse the intermodal transfer edge by walking. This edge attribute is used for the performance of a sanity check that is used for the examination of all intermodal transfer edges for excessive walking times. Edges with an average walking time that exceeds six minutes are removed from the graph.

Eventually, this process leads to a set of transfer edges being created all over the graph.

As an illustration, an example of how this looks in practice can be found in Figure 4.1. This figure shows an enlarged fragment of the Paris multimodal system, showing how the intermodal transfer edges connect nodes associated with different modes of transport.

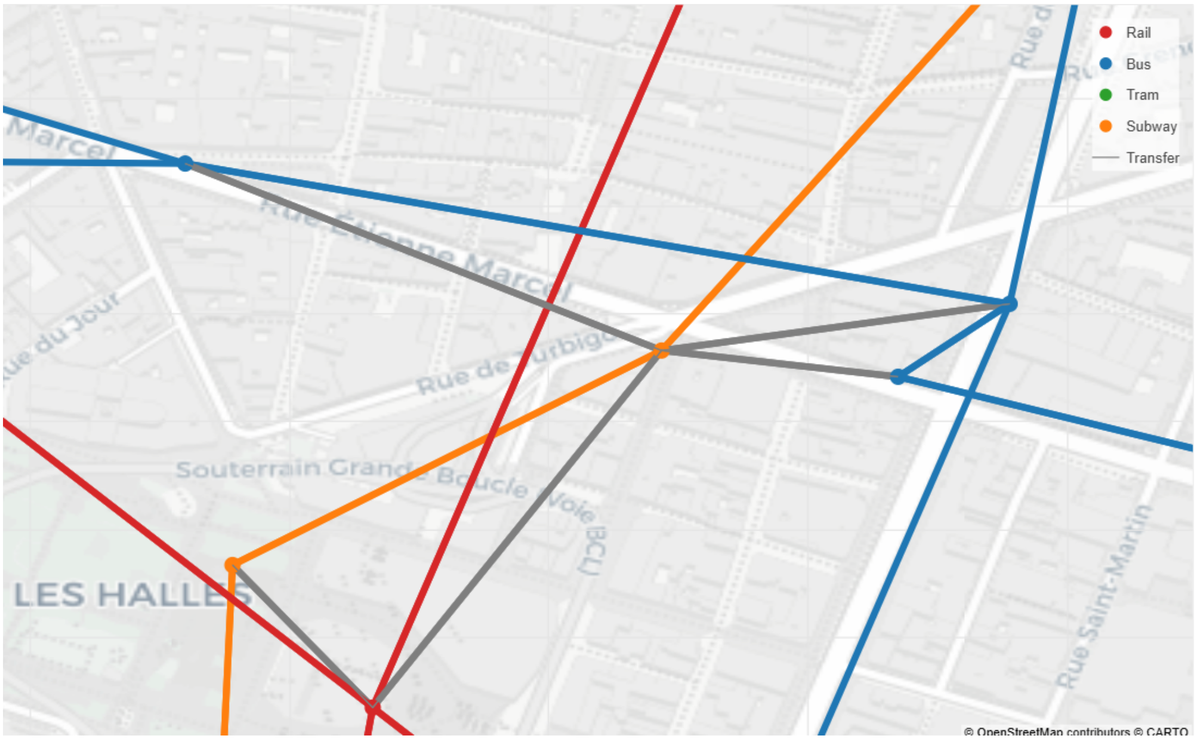


Figure 4.1: Enlarged fragment of the Paris network, demonstrating intermodal transfer edges

Like all regular edges, also the transfer edges have a set off attributes assigned to them. The attributes of an example transfer edge from the Paris multimodal system are listed in Table 4.1.

Table 4.1: Example attribute dictionary of a transfer edge in Paris

Attribute	Value
source node	6
destination node	425
type	'transfer'
length	113.4
travel_time	53.15

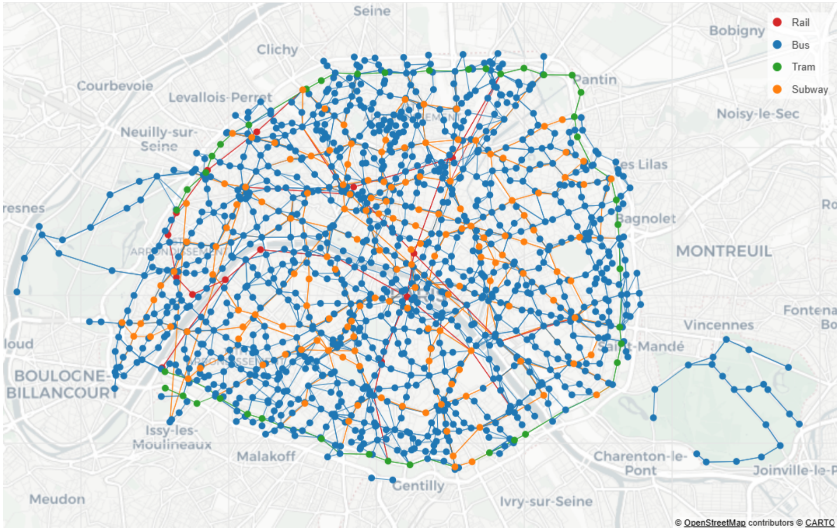
Like any regular edge, the transfer edges have a source node and a destination node. Additionally, they have the label 'transfer', which will play an important role in the trip simulation process. The length of the edge equals the walking distance associated with it and the travel time equals the average time it takes to traverse the transfer edge by foot. The intermodal transfer edges are created in the L-space graph first, then they are also copied to the P-space graph.

4.1.2. Giant Component Size

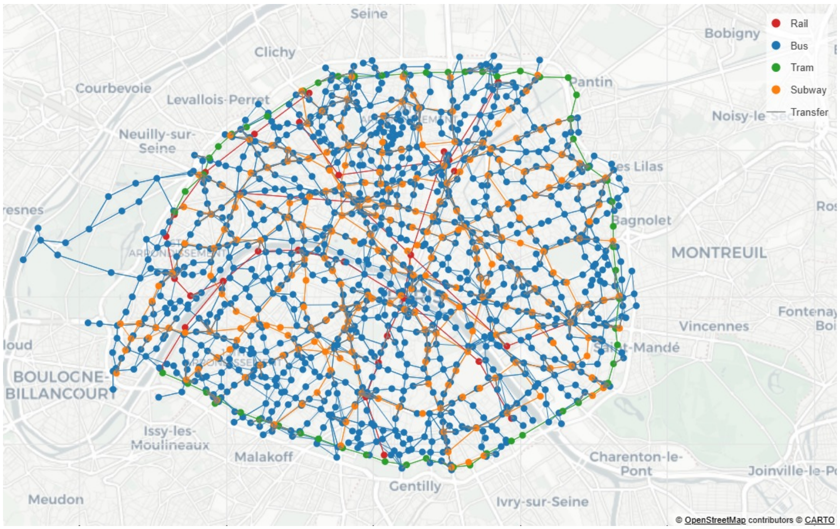
With the intermodal transfer edges added, the four sub-graphs are now fully connected, resulting in a comprehensive and integrated graph of the multimodal public transport system. This integrated structure enables the assessment of intermodal connectivity and interaction. However, one final step is required before the graph is ready for analysis: determining the Giant Component Size (GCS).

Ezaki et al. (2024) define the Giant Component Size as the largest fully connected sub-graph within a multimodal transport network. For trip simulations based on an OD matrix, it is essential to work with a strongly connected graph, which means that all nodes are reachable from one another. Any isolated nodes or segments of transit infrastructure that are disconnected from the main system must therefore be removed. Only the largest strongly connected component, the Giant Component, will be retained for further analysis. Note that a disconnected component may refer not only to nodes or groups of nodes that are structurally isolated (i.e. not connected to the Giant Component by any edges) but also to nodes that are technically connected by edges on which no trips occur within the selected time frame. In both cases, these components are considered functionally disconnected and are excluded from further analysis. The Giant Component can be retrieved using the Networkx library in Python (Hagberg et al., 2008).

This final refinement is illustrated using the example of Paris. The initial L-space graph is shown in Figure 4.2a, while Figure 4.2b displays the resulting Giant Component after intermodal transfer edges have been added and all disconnected components have been removed.



(a) Initial L-space graph



(b) Giant Component

Figure 4.2: Determination of the largest strongly connected component

4.2. Final Simulation Graph

With the successful construction of both L-space and P-space graph representations, the multimodal public transport network is now fully modeled and ready for trip simulation and further analysis. These graphs incorporate spatial layout, modal diversity, and time-specific operations, forming a coherent and standardized foundation for extracting accessibility metrics. As a result, the second sub-question — *How can real-world multimodal public transport data, combining spatial structure and operational information, be structured to support standardized accessibility analysis across cities?"* — can now be considered answered. The next step involves applying these graphs to extract spatial and temporal indicators that evaluate network performance.

4.2.1. Structural Layout

The graph representations generated under peak conditions (07:00–09:00) will be used for the spatial component of the analysis. It is assumed that the structural layout of the network, defined by its stops, routes, and modal connections, remains constant throughout the day. Therefore, peak-period graphs are considered representative of the network's full capacity and are most suitable for comparative analysis. Using these graphs ensures that the spatial metrics reflect the system's maximum service availability and intermodal integration potential.

4.3. Generalized Travel Cost

With the completion of both the L-space and P-space graphs, it is now possible to simulate real-world network operations. As outlined in Section 2.4.2, this will be achieved by generating the Generalized Travel Cost (GTC) of the graph, and apply it on an Origin-Destination (OD) matrix. The mathematical formulation of the GTC function was previously introduced in Equation 2.11 and is restated below for reference.

$$GTC = \mathrm{IVT}_t + (\alpha_{wait} \cdot \mathrm{Wait}_t) + (\alpha_{walk} \cdot \mathrm{Walk}_t) + (\mathrm{N}_T \cdot \beta_n) \tag{2.11}$$

The GTC function will be applied to every OD pair in the customized OD matrix to determine the GTC-weighted shortest path from the origin node to the destination node within the multimodal public transport system. The following sections elaborate on the calculation procedure.

4.3.1. GTC Components

The GTC-function is composed of four key components: in-vehicle time, waiting time, walking time, and transfer penalties. The parameters themselves were defined theoretically in Chapter 2. Now will follow a brief description of how each parameter is operationally retrieved from the graph-based representations.

- **In-vehicle time (IVT_t)** is retrieved from the `duration_avg` attribute of the L-space graph edges.
- **Waiting time ($Wait_t$)** is extracted from the `avg_wait` attribute of the P-space graph edges and is multiplied by waiting time burden parameter α_{wait}.
- **Walking time ($Walk_t$)** is based on the `travel_time` attribute of the intermodal transfer edges in the L-space graph and is multiplied by a walking time burden parameter α_{walk}.
- **Transfer penalties** are counted based on the number of route transfers and intermodal transfers along a path, and expressed as fixed penalty values per transfer type.

Together, these four components form a comprehensive cost function that reflects the true impedance experienced by passengers traveling through a multimodal public transport system.

4.3.2. Burden Parameters

Appropriate values for all burden parameters in the GTC function must be selected to ensure realistic and meaningful results. The values used in this study are derived from relevant literature and reflect commonly accepted estimates of perceived burdens associated with waiting, walking, and transferring. The selection process and justification for each burden parameter value are detailed in the following section.

Waiting Time Burden Parameter

Three sources were consulted in order to determine the value for waiting time burden parameter α_{wait}.

- Webb et al. (2025) state that the perceived burden multiplier for waiting time should at least be equal to 2.
- According to Psarros et al. (2011), the value lies between 1.75 and 2.5.
- Nielsen et al. (2021) also use 2 for waiting burden parameter.

In conclusion, this research assumes a waiting time burden parameter of 2, meaning that one minute of waiting time is perceived as equivalent to two minutes of in-vehicle travel time. This value reflects the higher perceived burden of waiting compared to riding. As a consequence, the contribution of the waiting time to the overall GTC will be augmented. As a result, cities with less synchronized services will show higher values emerging from the GTC function.

Walking Time Burden Parameter

This research aims to evaluate the interactions between modes of transportation within multimodal public transport systems. As such, it is assumed that the perceived burden of walking time between different modes depends on the specific modes involved (Daniels & Mulley, 2013). Based on this, a walking time burden parameter (α_{walk}) of 1 is applied, meaning walking time is treated as equivalent to in-vehicle time. The additional perceived burden of walking is instead accounted for through mode-specific transfer penalties.

It is important to note that walking time to the origin node is not included in this analysis. This study focuses on assessing how effectively the system supports smooth operations within the network, starting from the origin node and ending at the destination node.

Transfer Penalties

The pure transfer penalty, the perceived burden of making a transfer, has been reported to range between 15.2 and 17.7 minutes according to Garcia-Martinez et al. (2018). This study also highlights that intermodal transfers tend to be perceived more negatively by passengers than route transfers within the same mode.

Similarly, Douglas and Jones (2012) estimate the transfer penalty to lie between 10 and 20 minutes, noting that the value is mode-dependent. Transfers to trams and buses are typically perceived as more negative, due to greater uncertainty in scheduling and punctuality associated with these modes. In such cases, penalties can reach up to 20 minutes. On the other hand, transfers to trains and subways are generally considered less problematic, as these modes are perceived to be more reliable and the station areas of these modes often feature infrastructure like escalators and elevators, reducing the physical impedance. In these cases, route transfer penalties usually range between 7 and 10 minutes.

Based on the findings of Garcia-Martinez et al. (2018) and Douglas and Jones (2012), transfer penalties were determined for this study. Both studies indicate that the perceived burden of a transfer typically ranges between 10 and 20 minutes, with an average around 15 minutes. Factors influencing the perceived penalty include walking distance, transfer uncertainty, schedule reliability, and mode change discomfort. In this research, the baseline transfer penalty was set at 15 minutes, and adjusted upwards or downwards depending on the specific characteristics of the modes involved, following the patterns described by these authors. The resulting transfer penalty values used in this study are summarized in Table 4.2.

Table 4.2: Transfer penalties by mode combination, based on Garcia-Martinez et al. (2018) and Douglas and Jones (2012)

Route transfers			
From mode	*To mode*	*Value [min]*	*Explanation*
Bus	Bus	18	High due to unpredictability of schedules
Tram	Tram	12	Moderate due to higher reliability street-level transfers
Subway	Subway	7	Low due to high frequencies and higher reliability
Rail	Rail	9	Slightly higher than subway due to longer walking times
Intermodal transfers			
From mode	*To mode*	*Value [min]*	*Explanation*
Rail	Tram	15	Mode change increases perceived effort
Tram	Rail	15	Symmetrical perception of tram-rail transfers
Rail	Bus	19	Higher because of unpredictable bus schedules and long walking time
Bus	Rail	17	Slightly higher due to long walking time
Tram	Bus	14	Transfers are usually same floor, bus is disliked more
Bus	Tram	12	Usually same floor transfers
Subway	Rail	15	Stations might have complex designs, level changes often necessary
Rail	Subway	15	Symmetrical penalty for mode change
Subway	Tram	15	Surface transfer increases perceived burden
Tram	Subway	15	Symmetrical perception of tram-subway transfers
Bus	Subway	15	Mixed reliability; moderate penalty
Subway	Bus	17	Bus services are perceived as less reliable

While these values are grounded in literature and reflect reported perceptions of transfer burden, the exact magnitude of perceived inconvenience may vary between individuals, cities, or trip contexts. As such, the final values selected for this study remain somewhat arbitrary within the empirically supported range. To assess the robustness of the results, a sensitivity analysis was conducted (see Section 4.3.3), which demonstrates that although changes in these parameters influence the absolute GTC values, the overall distribution of travel cost components and comparative conclusions remain stable. This indicates that the accessibility assessment is robust under reasonable variation in the burden parameters.

Notably, Nielsen et al. (2021) emphasize that subsequent transfers are perceived as increasingly negative by passengers. Evidence suggests an increase in perceived penalty of up to 20 percent for each additional transfer. To account for this in the GTC function used in this research, an additional pure transfer penalty of 3 minutes is applied for every transfer beyond the first transfer, regardless of whether it is a route transfer or intermodal transfer.

4.3.3. Sensitivity Analysis

In order to make sure the GTC results and the conclusions drawn from them are robust, a sensitivity analysis was performed. The aim of this analysis is to assess how variations in burden parameters (waiting burden parameter, transfer penalty and extra transfer penalty) affect the resulting GTC values and the GTC composition. This is important because these parameters, while based on relevant scientific literature, may vary across user groups and individuals.

The results of the sensitivity analysis are presented in Table 4.3. Three scenarios of the Paris sampled OD matrix (see Section 4.3.5) were compared: the baseline case using literature-derived parameters previously described, a low-penalty scenario with reduced parameters, and a high-penalty scenario with increased parameters. Each scenario's average GTC and the distribution of travel components (in-vehicle time, waiting time, transfer cost, and transfer walking time) were analyzed.

Table 4.3: Sensitivity of GTC composition to parameter variations

Scenario	Waiting Burden	Transfer Penalties	Extra Transfer Penalty (min)	Avg GTC (min)	IVT %	Waiting %	Transfer %	Transfer Walking %
Baseline	2.0	Baseline	3	70.29	26.1%	9.8%	49.9%	14.3%
Low Penalty	1.75	Baseline -5 min	2	56.26	32.3%	12.3%	40.6%	14.9%
High Penalty	2.5	Baseline $+5$ min	4	86.21	21.3%	7.9%	54.8%	15.9%

This sensitivity analysis demonstrates that adjusting the penalty parameters influences the absolute magnitude of the average GTC: lower penalties decreased the average GTC by approximately 20%, while higher penalties increased it by about 23%. However, the relative contribution of each component did not differ drastically across scenarios: the transfer burden consistently accounted for the largest share of perceived travel costs.

These findings support the use of the baseline penalty values adopted in this research. Even though the magnitude of the GTC is sensitive to the chosen penalty parameters, the overall composition of travel costs and the comparative interpretation of network performances across cities worldwide remain robust. Therefore, the chosen parameters provide a realistic basis for the assessment of multimodal public transport system accessibility. It is not expected that slight changes in the adapted transfer penalties will have significant consequences on the results the GTC-based trip simulations will reveal.

4.3.4. Model Assumptions and Limitations

The GTC function, while useful for estimating generalized travel effort, has several limitations that must be acknowledged to ensure reliable interpretation of the simulation results. These are briefly discussed below.

As described in Section 3.3.7, the average waiting time in the P-space graph is approximated as half the average vehicle headway. This assumption is justified by the ideal conditions represented in GTFS Schedule datasets, where delays and disruptions are not included. To partially compensate for this simplification, it is assumed that both the waiting burden parameter and transfer penalties account for small delays, with mode-specific transfer penalties reflecting the varying degrees of scheduling uncertainty among different modes.

Additionally, walking times within the station area are not included in GTFS datasets. These times are generally longer for subway stations and railway stations compared to trams and buses, and may vary depending on station size and layout. In this study, it is assumed that both the waiting burden parameter and transfer penalties also account for these walking times.

It is important to keep in mind that the GTC function is not intended to provide an exact measure of travel time, but rather a balanced estimation of both travel time and perceived travel effort. Its purpose is to support the evaluation of network efficiency by capturing all facets of public transport use, rather than serving as a precise timetable-based model.

4.3.5. Sampled OD matrix

With the mathematical construction of the GTC function complete, the final step is to determine the appropriate size of the OD matrix to which the function will be applied. This section elaborates on the methodology used for that purpose.

The maximum size of the OD matrix is directly dependent on the number of nodes in the graph, denoted by $|V|$. In theory, the matrix could contain up to $|V| \times (|V| - 1)$ OD pairs. For large multimodal graphs consisting of several thousand nodes, this results in OD matrices with millions of entries. Computing GTC values for every pair in such a large matrix would be extremely time-consuming and computationally expensive. Therefore, a customized and optimized method was developed to reduce computational load while still ensuring valid and representative results.

Transfer Limit

A full OD matrix includes trips that, in practice, may not be realistic. Since this study does not account for door-to-door movements (i.e., no access or egress trips are modeled), some shortest paths could involve a high number of transfers despite the presence of transfer penalties. In reality, passengers are unlikely to accept an unlimited number of transfers during a trip. Moreover, including OD pairs that involve an excessive number of transfers could distort the analysis of network efficiency.

To address this, a transfer limit was introduced. Only OD pairs requiring three or fewer transfers - whether route or intermodal - are considered valid. These are referred to as valid OD pairs. Any OD pair that exceeds this threshold is excluded from the final OD matrix used in the analysis.

Sample Size

By excluding excessively long OD pairs, the potential size of the OD matrix is already significantly reduced. Furthermore, since the GTC-weighted OD matrix is used to calculate system-wide averages, it is not necessary to compute the shortest path for every valid OD pair. It is assumed that a sample of 5% of all valid OD pairs is sufficient to yield reliable average GTC results. Thus, the goal is to compute the GTC-weighted shortest paths for 5% of the total valid OD pairs.

To determine the exact sample size of the GTC-weighted OD matrix for any given graph, a Python-based method was developed. The key steps of this procedure, implemented in the script provided in Appendix C.2, are as follows:

Step 1: First, the maximum possible number of OD pairs is calculated for each graph. To estimate what percentage of those pairs are valid (i.e., include no more than three transfers), Python is instructed to generate 10,000 valid OD pairs randomly. During this process, it also records the number of attempts required to reach that number. The estimated percentage of valid OD pairs is then calculated as the ratio between 10,000 and the total number of attempts made.

Step 2: Based on this estimated percentage of valid pairs and the 5% sampling rule, the desired number of valid OD pairs to include in the final analysis is determined.

Step 3: Python then randomly generates OD pairs again until the desired number of valid pairs is reached. To keep the process efficient, two boundary conditions are applied:

- A maximum of 2,000,000 attempts to find valid OD pairs.
- A maximum processing time of 60 minutes.

If either limit is reached before the desired sample size is met, the OD pair set obtained up to that point is accepted as sufficiently representative for reliable GTC-based analysis. The details of all final OD matrices of all twelve cities can be found in Appendix D.

4.3.6. GTC Output

With the final size of the OD matrix determined, it is now possible to determine the GTC-weighted shortest paths between the OD pairs. This is done making usage of Yen's shortest path algorithm (Yen, 1971). The result is a custom-sized OD matrix with each entry containing a dictionary with all relevant information concerning the generated shortest path. An example of a such a shortest path, coming from the Paris public transport network OD matrix, can be found in Table 4.4.

Table 4.4: Example attribute dictionary of a multimodal path

Attribute	Value
`path`	[5, 510, 936, 145, 799, 1140]
`GTC`	66
`in_vehicle`	12
`waiting_time`	6
`transfer_travel_time`	4
`n_intermodal_transfers`	1
`n_intramodal_transfers`	1
`n_total_transfers`	2
`mode_transfers`	[('Subway', 'Bus'), ('Bus', 'Bus')]
`total_transfer_penalty`	38
`total_intermodal_transfer_penalty`	17
`total_intramodal_transfer_penalty`	21
`intermodal_transfer_nodes`	[510]
`intramodal_transfer_nodes`	[145]
`traveled_distance`	1349

The 'path' refers to the sequence of nodes followed along the shortest route from the origin node to the destination node. For each OD pair, the following information is reported: the total GTC, total in-vehicle time, total waiting time and total transfer walking time. Additionally, detailed transfer information is provided, including the number of route (intramodal) transfers, the number of intermodal transfers, and the total number of transfers. The specific nodes at which transfers occur, the types of transfers made, and the associated penalties are also included. Finally, the total distance traveled along the shortest path is presented.

4.4. Extracting Accessibility Metrics

With the completion of the GTC function and the generation of a GTC-weighted OD matrix through sampled OD pairs, system-wide trip simulations have become feasible. This development enables not only the evaluation of structural accessibility through spatial network indicators, but also the assessment of dynamic accessibility via temporal performance metrics.

This section outlines the procedures used to extract both spatial and temporal metrics from the constructed L-space and P-space graphs, as well as the OD matrices derived from them. All computations are implemented in Python using the NetworkX library (Hagberg et al., 2008); full code listings are provided in Appendix E.

The physical integration of each public transport network is quantified by identifying all intermodal transfer edges in the L-space graph, including their frequency and spatial characteristics. Metrics related to infrastructural and multimodal integration, such as degree centrality, assortativity, intermodal degree, and characteristic path lengths, are also derived from the L-space and P-space graphs.

Temporal metrics are extracted using the attributes assigned to edges in the L-space graph (most notably 'n_vehicles') to compute service availability scores during different time intervals. To assess GTC-based network efficiency, the weighted average GTC and its component shares (in-vehicle time, waiting time, transfer penalties) are derived from the OD matrix.

Furthermore, temporal accessibility is analyzed through the extraction of GTC distribution percentiles and their normalization against maximum observed GTC values. Intermodal synchronization is measured by calculating the average waiting time for intermodal transfers across all valid GTC paths. Finally, the Off-peak/Peak Robustness of the system is evaluated by comparing key network efficiency metrics across two distinct time frames: 07:00–09:00 (peak) and 12:00–14:00 (off-peak), computing their relative performance ratios.

4.5. Simulated Network Outputs

In Chapter 3, the process of transforming GTFS databases into comprehensive graph representations of multimodal public transport networks was described in detail. This chapter has demonstrated how both spatial and temporal accessibility of these networks can be evaluated through various methods applied to the graphs, such as the introduction of intermodal transfer edges and the construction of a GTC-weighted sampled OD matrix to enable network operation simulation. Finally, it was discussed how the L-space and P-space network representations, along with the associated OD matrix, can be used to extract the metrics that form the theoretical framework introduced in Chapter 2.

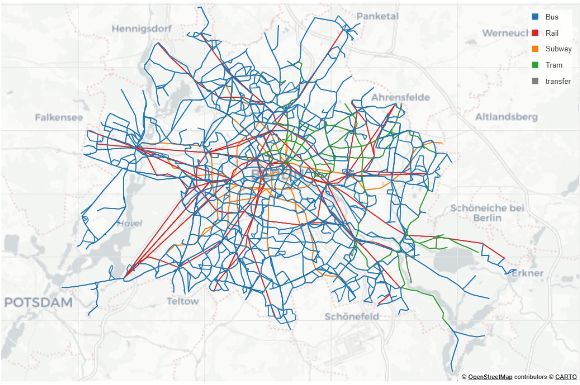
This entire process can now be applied to the GTFS datasets of all twelve cities, as introduced in Section 3.1.1. For each city, an L-space graph, a P-space graph, and a GTC-weighted OD matrix will be generated for the 07:00 to 09:00 (peak) time interval. These outputs will serve as the basis for both the spatial analysis and the initial temporal analysis used in the comparative assessment of network performance across cities.

To evaluate Off-peak/Peak Robustness, an additional set of L-space and P-space graphs, along with a corresponding OD matrix, will be created for the 12:00 to 14:00 (off-peak) interval. These outputs will be used exclusively for the robustness analysis. It is assumed that the network topology remains constant between peak and off-peak conditions, and that peak conditions are most representative of a system's operational performance. Therefore, the peak-period graphs and matrices are used for cross-city comparisons of network efficiency.

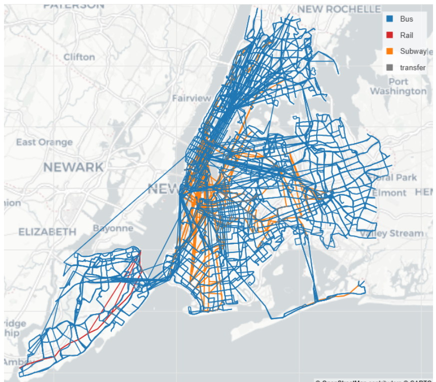
This results in the completion of all necessary graphs and tables for the twelve selected cities, which are now fully prepared for further analysis. To provide an overview of the outcomes and highlight differences in network characteristics, four of the final L-space graphs are presented in Figure 4.3. These examples were selected to illustrate the diversity in spatial structure and modal composition across the dataset.

Figure 4.3a shows Berlin, a network characterized by high modal diversity and a spacious, well-distributed layout. Figure 4.3b presents New York City, with a dense core network primarily dominated by two bus and metro. São Paulo's network, shown in Figure 4.3c, is an example of a highly bus-oriented system with evident urban sprawl and fewer structural redundancies. A similar pattern of sprawl can be seen in Figure 4.3d, though here the network exhibits greater modal diversity, including trams and commuter rail.

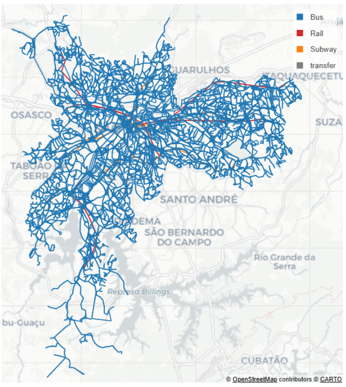
These examples demonstrate how visual inspection of the graphs can reveal meaningful differences in network form (e.g., density, mode dominance, and spatial reach) that align with broader system characteristics. As such, the graph visualizations provide a valuable first impression of each network's structural properties and complement the more formal metric-based analyses presented in the next chapter.



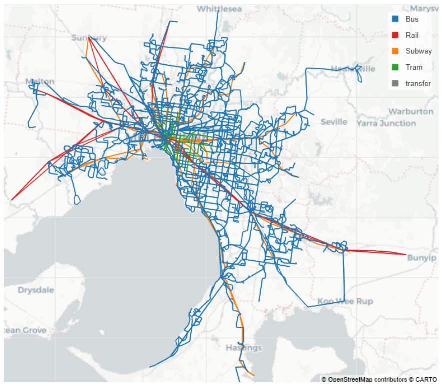
(a) Berlin



(b) New York City



(c) São Paulo



(d) Melbourne

Figure 4.3: Examples of public transport network topologies

4.5.1. Concluding Remarks

This chapter has outlined the procedures used to prepare the network graphs for metric extraction and explained how the accessibility framework is applied to each city's multimodal transport system. By simulating network operations for both peak and off-peak conditions, and by standardizing graph representations across cities, the foundation has been laid for consistent and comparable analysis. With this, the third sub-question — *"How can the appropriate metrics be applied to evaluate the performance of multimodal public transport networks in terms of accessibility and integration?"* —is now answered. The graphs are ready, the metrics are defined, and the next chapter will present the results of this analysis.

5

Results: Spatio-temporal Network Accessibility

Insights into structural and operational strategies across cities [0.2ex]

This chapter presents the results of a comparative analysis of twelve multimodal public transport networks. Building on the accessibility assessment framework introduced earlier, the analysis evaluates each network across key dimensions: spatial structure, operational efficiency and intermodal integration. The findings presented here are based on extensive data analysis across all extracted metrics for the twelve systems. Full datasets and details are provided in Appendix F. By grounding the assessment in metric-based indicators, the chapter aims to reveal how differences in network design and operational strategies shape everyday travel outcomes for public transport users.

5.1. Network Statistics

Table 5.1 presents the structural and operational characteristics of the twelve public transport networks included in this study. It reports the number of nodes and the number of edges in both L-space and P-space, derived from the created network graphs. Additionally, the table lists the number of transportation modes represented in each network, along with the total number of vehicle movements, offering a first impression of each system's spatial scale and temporal service availability.

Table 5.1: Multimodal network statistics

City	Nodes	L-space Edges	P-space Edges	No. of Modes	Vehicle Movements [/2h]
Bangkok	3,026	6,770	422,042	4	535,881
Berlin	2,967	7,890	62,067	4	223,662
Denver	825	1,678	15,855	3	21,366
Melbourne	5,842	12,631	116,356	4	762,033
Mexico City	4,001	7,927	68,224	3	363,342
New York City	10,606	19,566	122,519	3	792,348
Paris	1,347	4,462	25,550	4	227,400
Prague	1,620	4,313	36,480	4	157,253
São Paulo	7,484	16,734	238,016	3	501,457
Singapore	2,657	6,566	183,236	2	669,734
Toronto	3,660	8,679	96,610	4	304,908
Valencia	325	599	9,226	4	12,099

The table reveals significant variation in network size across the selected cities. New York City, São Paulo, and Melbourne operate particularly large systems, each consisting of thousands of nodes and hundreds of thousands of vehicle movements. These networks reflect extensive urban sprawl and cover broad metropolitan areas. In terms of size, they are followed by Mexico City, Toronto, Bangkok, and Berlin. These cities also exhibit elements of urban sprawl, albeit on a smaller scale.

By contrast, cities such as Singapore, Paris, and Prague feature more compact and dense networks. Although the total number of nodes is limited, these cities maintain a relatively high number of edges in both L-space and P-space, indicating a tightly connected system. On the other end of the spectrum, Denver and Valencia operate much smaller networks, both in terms of physical infrastructure and service intensity.

5.2. Spatial Reach and Network Density

Public transport users value ease of access and egress of public transport networks: they want to enter or exit the network near their homes, workplaces, shopping areas, or recreational destinations. To meet these expectations, a network must offer broad spatial coverage, with an emphasis on spatial equity and a high density of access and egress points. Furthermore, passengers seek direct, efficient journeys without unnecessary detours or excessive transfers. In other words, the network infrastructure should facilitate smooth operations and seamless spatial accessibility, minimizing the physical and cognitive effort required for travel.

Network analysis reveals that the scale of the public transport network, such as the number of nodes or the geographic extent of the city, does not automatically ensure strong spatial accessibility. Rather, it is the cohesion of the network, the connectivity between stops, and the availability of direct routing options (measurable through $C_D(i)$, CPL, and γ) that more accurately determine how easily and freely users can navigate the system. Crucially, this cohesion is rooted in the network's structural design and operational topology, so can be concluded from the network analysis.

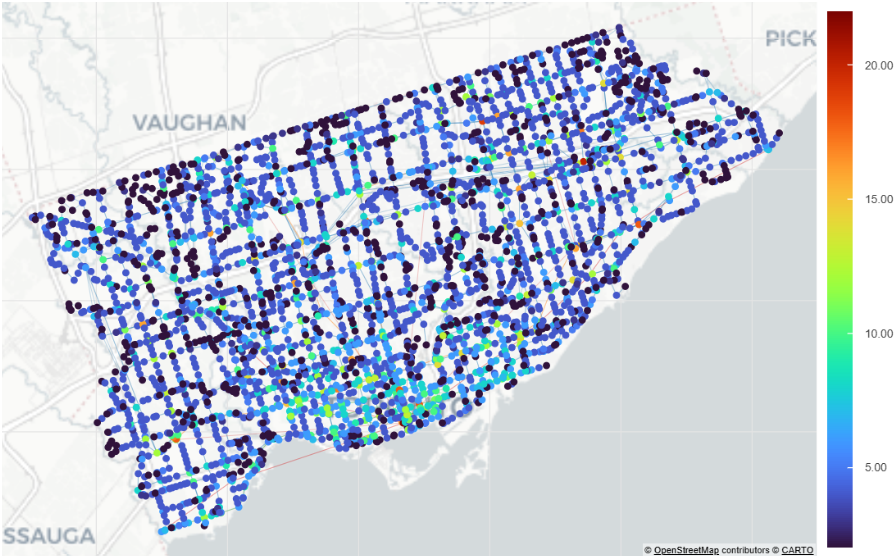
5.2.1. Spatial Design Strategies

Differences in spatial accessibility and network connectivity across cities provide valuable insights into the underlying structure and planning approaches of public transport networks. The analysis suggests that cities adopt distinct design strategies in their network topology, each of which has a significant impact on the user experience. From the data, two dominant structural strategies have emerged.

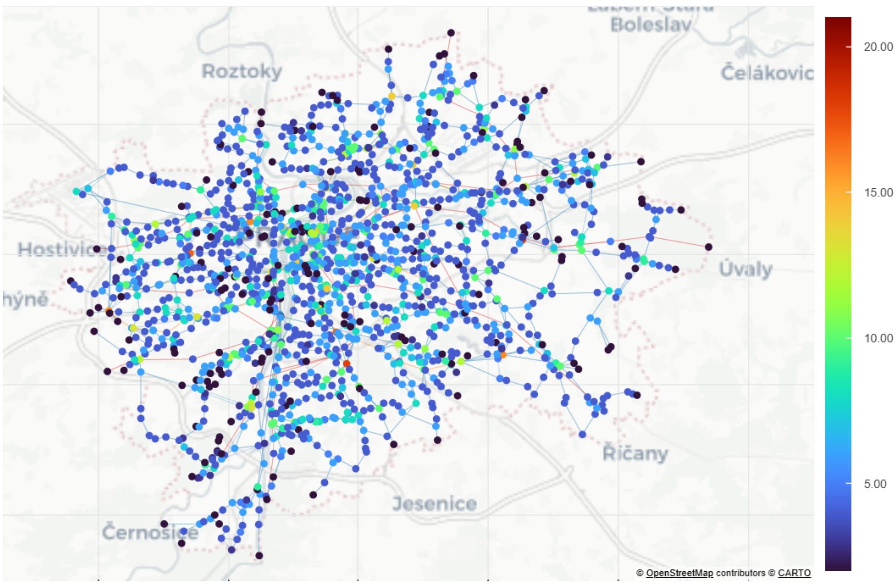
The first dominant strategy observed is characterized by distributed connectivity. Networks following this approach often exhibit a grid-like structure, with no clear hierarchy between nodes. Passengers often switch modes or lines to reach their destination, making transfers an intentional and embedded mechanism for navigating the system efficiently. This structure demands high infrastructural density, resulting in a high and evenly distributed average node degree, strong L-space and P-space connectivity, and short characteristic path lengths. Cities such as Paris, Berlin and Prague exemplify this strategy, with similar patterns also visible in Mexico City and Melbourne. Even Singapore, despite offering only two modes, emulates this logic through tight transfer synchronization and high-frequency operations, compensating for limited modal diversity.

The second dominant strategy is the centralized network model, which follows a more centroid-based structure with a hierarchical distribution of nodes, with a degree assortativity near zero. In these systems, multimodal hubs distributed across the city serve as primary gateways, connecting otherwise disconnected or peripheral routes. The design logic emphasizes long, uninterrupted single-mode trips, and often seeks to minimize transfers altogether. These networks typically exhibit lower degree centrality, weaker connectivity in both L-space and P-space, and longer characteristic path lengths. Cities such as New York City, São Paulo, Denver, and Bangkok follow this model, with Toronto's network also exhibiting similar patterns. While effective in serving major corridors, these systems may struggle to provide efficient operations for passengers traveling beyond high-demand zones, particularly in areas with less multimodal coverage.

Figure 5.1 shows the degree heatmap of two different cities. The color intensity reflects node degree, with higher values indicating greater connectivity at that location. In Figure 5.1a, it can be seen Toronto's high-degree nodes are clustered, typical of a centralized network structure. In contrast, Figure 5.1b shows that Prague displays a more uniform distribution of high-degree nodes, suggesting a decentralized, distributed connectivity model. These patterns help illustrate contrasting spatial planning philosophies reflected in network design.



(a) Toronto degree centrality heatmap: high-degree nodes (in green/yellow) are clustered in the central-southern part of the city



(b) Prague degree centrality heatmap: high-degree nodes (in green/yellow) are distributed more evenly across the network

Figure 5.1: Structural design differences between two cities

Although not every network aligns perfectly with a single structural model, the overall distinction is clear: network topology reflects a broader mobility philosophy. It either promotes short, modular, and adaptable journeys enabled by frequent, seamless transfers, or it emphasizes direct routing, often at the expense of routing flexibility and spatial equity.

This emerging distinction between distributed and centralized network design will remain relevant throughout the subsequent analysis, as these structural strategies are consistently reflected in patterns related to transfers, modal coordination, and service availability.

5.2.2. Network Coverage

A key requirement for public transport users is the ability to access the network close to both their origin and destination. This necessitates not only broad geographic coverage, but also spatial equity in the distribution of access points. As demonstrated in the previous section, the design of a network plays a critical role in shaping these characteristics.

Paris, Prague, and Berlin are limited in geographic area and total node count, yet demonstrate high node density relative to their size. As a result, users can access the network with ease, and thanks to the evenly distributed connectivity, most stops are only a few steps away from others. In such systems, even peripheral or minor stops offer meaningful access to the wider network, enhancing freedom of movement.

This spatial flexibility is further reflected in the high average node degree and low standard deviation found in these three systems, indicating a consistent level of connectivity across the network, which aligns well with the structural logic of distributed design. In contrast, São Paulo, Bangkok, and New York City, despite their much larger scale, exhibit lower average degree values and higher standard deviations, indicating a clear hierarchical structure. This suggests that access in these networks is concentrated around central hubs, resulting in reduced spatial equity and limited accessibility in outlying areas.

Table 5.2: Average node degree and standard deviation for selected cities

City	Average Degree	Standard Deviation
Paris	6.63	1.22
Berlin	5.32	1.36
Prague	4.89	1.48
São Paulo	3.31	2.03
Bangkok	3.24	1.84
New York City	3.12	1.91

In more centralized networks, accessing the system from a peripheral stop often requires traveling first to a central hub before broader movement becomes possible. The low average node degree in these systems indicates fewer direct connections per stop, which in turn limits travel flexibility and increases reliance on specific transfer points.

Consequently, the average degree emerges as a strong structural indicator of spatial equity. It reflects how evenly opportunities for movement are distributed across the network and how easily users can access a range of destinations from any given starting point.

5.2.3. Infrastructural Density

While spatial coverage describes how widely a public transport network reaches across the city, infrastructural density reflects how intensively the system is connected within that area. It captures the degree to which stops are interlinked, the number of routing options available, and the efficiency of infrastructure in supporting short and reliable trips.

Stops in grid-structured networks generally provide access to multiple surrounding nodes. This is reflected by the high average degree of these systems: passengers can traverse the network without reliance on a few central hubs. Additionally, this structure supports resilience and redundancy, with flexible routing options made possible across the city.

The centralized networks on the other hand have a more fragmented layout where connectivity is concentrated around a small number of major transfer hubs, leaving certain areas more isolated and limiting the flexibility of travel. These networks offer fewer direct connections to most nearby located stops, which reduces spatial equity and makes the system more sensitive to disruptions at central nodes.

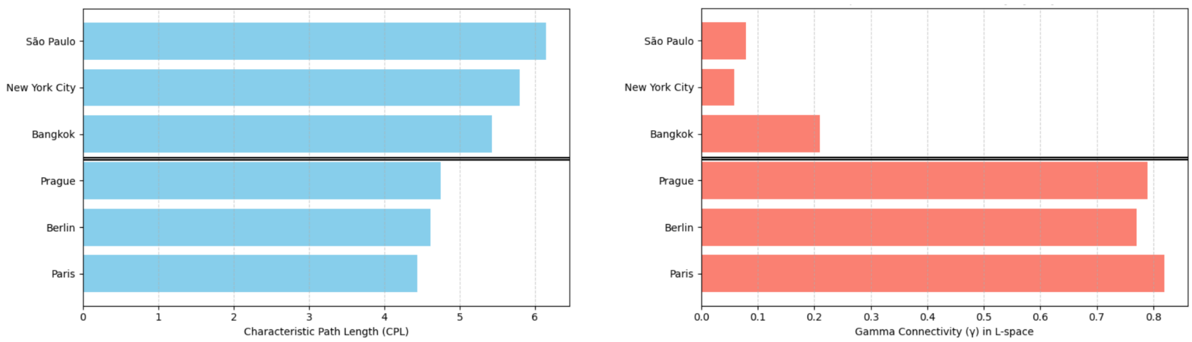
These structural patterns are confirmed by two additional indicators: the characteristic path length (CPL) and the connectivity ratio (γ). Cities with high node degrees also show shorter CPL values:

Paris (4.44), Berlin (4.61), and Prague (4.75). This reflects shorter average routes and better inter-stop accessibility. Similarly, Paris, Berlin and Prague score considerably better on the γ-index, indicating a high proportion of possible links are realized in the network, i.e. a high infrastructural density.

In contrast, São Paulo, New York City, and Bangkok illustrate how large-scale public transport systems can suffer from poor internal cohesion. Despite their vast size, these systems exhibit longer CPL and significantly lower γ-values, suggesting fragmented connectivity and fewer direct routing options.

To highlight these differences, Figure 5.2 compares only the top three and bottom three performing cities on these indicators. The CPL values in Figure 5.2a show that trips in São Paulo and New York City, on average, require considerably more hops than in Paris or Berlin. Likewise, Figure 5.2b shows that the γ-index in distributed networks is multiple times higher as in the most fragmented networks, clearly illustrating stronger spatial cohesion.

These gaps have important implications: networks with short path lengths and high connectivity offer more flexible, resilient, and equitable service, enabling users to traverse the system with fewer transfers and shorter detours. Conversely, centralized networks with poor cohesion are more vulnerable to disruption, less efficient for cross-city movement, and often reinforce spatial inequalities in accessibility.



(a) Characteristic Path Length (CPL)

(b) L-space Gamma Connectivity

Figure 5.2: Infrastructural density indicators for selected cities

5.2.4. Summary of Spatial Accessibility Indicators

Together, these findings suggest that both spatial coverage and infrastructural density are not merely functions of network size, but are primarily the result of deliberate design choices. Networks that follow a strategy of distributed connectivity, characterized by higher average node degrees, shorter characteristic path lengths, and stronger connectivity ratios, are generally better equipped to support efficient, resilient, and equitable urban mobility.

The analysis shows that Paris, Berlin, and Prague consistently score highest in terms of spatial reach and network density. These networks clearly embody the distributed connectivity model and perform well due to their cohesive, well-integrated structures. While not as dominant, Valencia and Mexico City also lean toward this strategy, although their scores reflect more modest outcomes.

In contrast, cities like New York City, São Paulo, and Bangkok, which follow a more centralized and corridor-based design across vast urban territories, struggle to achieve spatial equity and cohesive accessibility. Denver and Toronto demonstrate similar characteristics, with a low-density structure that limits its overall spatial efficiency.

Two noteworthy exceptions underscore the importance of structural logic over size or mode count. Melbourne balances spatial sprawl with strong internal connectivity, performing well despite its scale and design strategy. Meanwhile, Singapore achieves high spatial accessibility with just two modes, illustrating how thoughtful, synchronized design can effectively compensate for limited modal diversity.

Ultimately, the results indicate that network cohesion - not network scale - is the primary driver of spatial accessibility. Compact, well-connected systems often outperform larger, fragmented ones in delivering a seamless and user-friendly transport experience.

5.3. Temporal Network Efficiency

Spatial structure defines how easily passengers can access the network and how smooth operations are enabled by the networks topology. Operational efficiency determines how smoothly passengers can move through the network. From the user's perspective, this refers to how fast, direct, and seamless the journey of passengers is once they have entered the system. The quality of this experience depends not only on physical distances, but also on the time spent in transit, the need to transfer between modes, and time spent while waiting or navigating the system.

5.3.1. Transfers

Clear design strategies emerge from the network analysis, reflecting a broader design philosophy that mirrors the structural strategies outlined in Section 5.2.1, namely the distributed centrality and centralized approaches. This logic is particularly evident in how (intermodal) transfers are incorporated into the user experience: whether they are embraced as a strategic tool or avoided as an inconvenience.

Transfer Strategies

In networks following the distributed centrality model, often grid-structured systems, journeys are typically composed of a series of short, coordinated segments, with transfers functioning as the crucial links that enable seamless end-to-end travel. Rather than minimizing the number of transfers, these networks aim to minimize their burden through careful coordination, short walking distances, and frequent service intervals. Transfers are not merely tolerated; they are deliberately integrated into the network as a central mechanism to deliver flexibility, reach, and operational fluidity.

Conversely, centralized networks exhibit a different operational logic. Rooted in a centroid-based structure, they prioritize longer, more direct trips with fewer modal shifts. In these systems, transfers are often seen as barriers to be minimized or avoided. Transfers, when they occur, tend to be concentrated in a few major hubs rather than being distributed across the network, which can reduce routing options and increase system fragility under disruption.

The design strategy of public transport networks with regard to transfers is best illustrated by the frequency, distribution, and characteristics of intermodal transfer edges across the network. Network analysis reveals a clear contrast between systems: while distributed centrality networks embrace transfers as an integral component of efficient operations, centralized networks tend to avoid them wherever possible. This distinction is strongly supported by the data, which reveals consistent differences across three key dimensions: transfer intensity, transfer distribution, and transfer impedance.

Transfer Intensity

Figure 5.3 shows how many intermodal transfer edges are present per node in each network, using the same six example cities as in Section 5.2.1. The figure reveals a clear divide between cities that follow a distributed centrality logic (Paris, Berlin, and Prague) and those that do not.

In Paris, for example, more than 50% of all nodes are involved in transfer connections, resulting in an average of over 0.5 transfer edges per node. Berlin and Prague follow closely. In contrast, São Paulo, Bangkok, and New York City show significantly lower intensities, with transfer edges per node below 0.2. This stark difference highlights how distributed systems structurally embed transfers into the network to enable flexibility and routing efficiency. In centralized networks, by contrast, transfers are sparse and concentrated at a limited number of hubs.

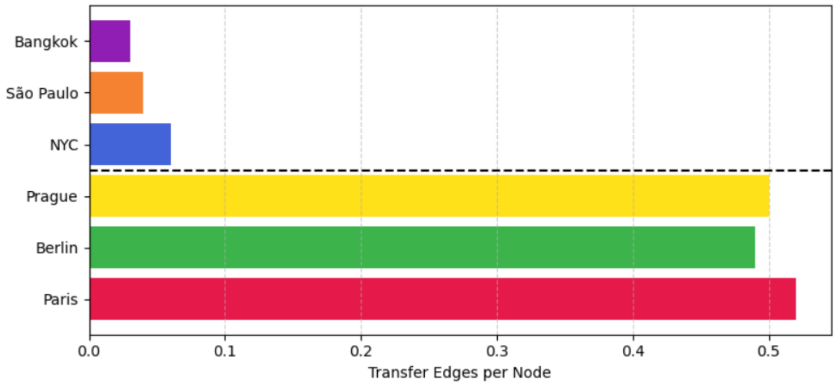


Figure 5.3: Number of transfer edges per node

Transfer Distribution

Figure 5.4 shows the share of all nodes involved in intermodal transfers. Again, the differences are substantial: in Paris, Berlin, and Prague, nearly half of the network nodes facilitate intermodal transfers with at least one intermodal transfer edge. Meanwhile, in Bangkok, São Paulo, and New York City, this share remains below 10%.

This means that in distributed systems, users are more likely to encounter transfer possibilities close to their origin or destination, enhancing both flexibility and spatial equity. In centralized systems, the low presence of transfer nodes reduces routing options and increases travel impedance, especially for trips that do not align with the main corridors.

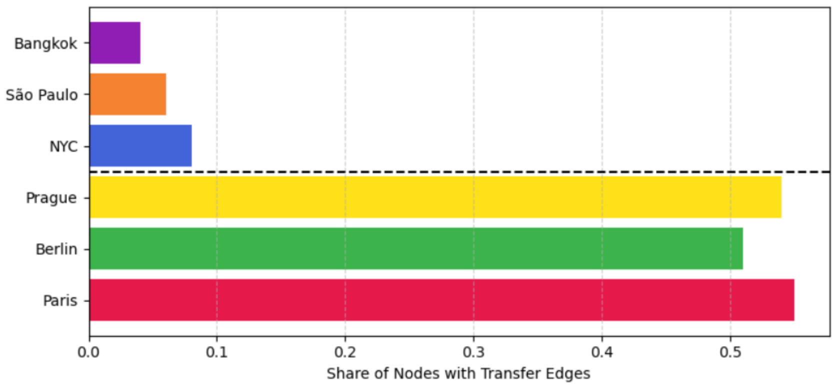
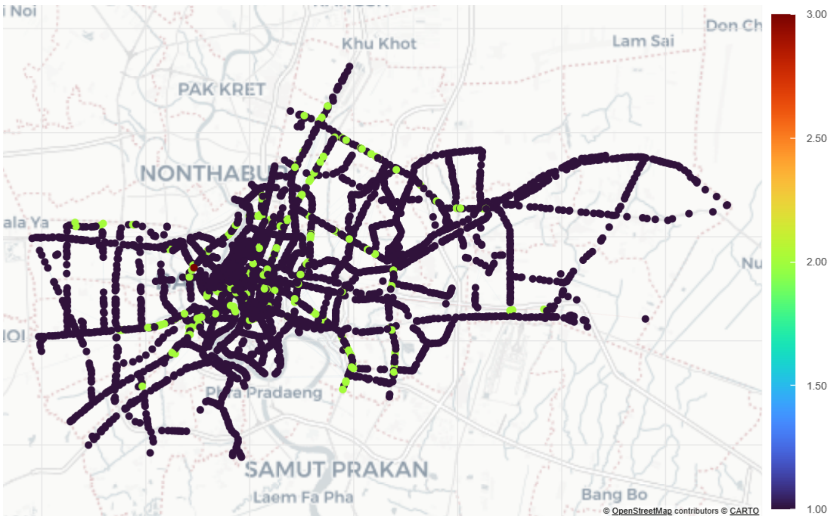


Figure 5.4: Share of nodes with transfer possibilities

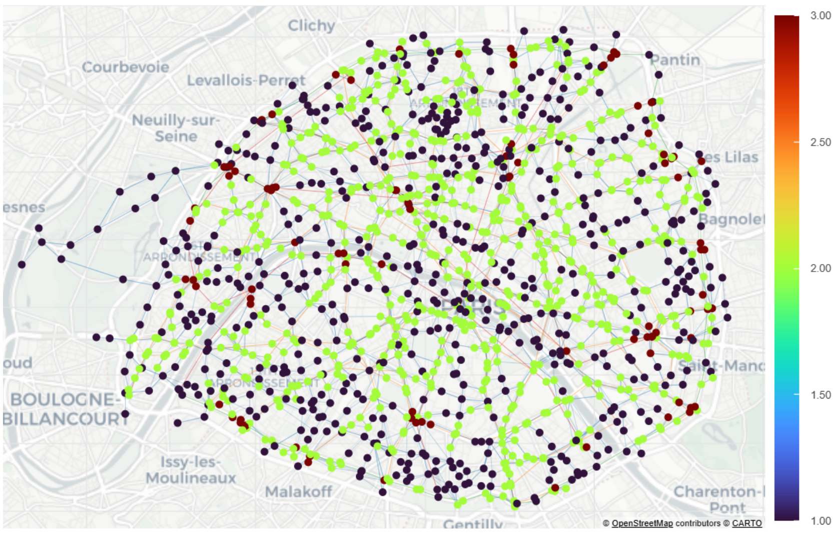
The contrast between cities becomes especially clear in Figure 5.5, which shows the intermodal degree heatmaps of Bangkok and Paris. Although both cities support four transit modes, their levels of intermodal integration differ significantly.

In Bangkok (Figure 5.5a), the vast majority of nodes are colored in dark blue tones, indicating very low intermodal degree values. Only a small number of nodes across the network is involved in intermodal transfers. These nodes represent the few multimodal hubs where mode changes are possible. As a result, transfer opportunities are limited in number, which constrains route flexibility and increases dependency on a small set of transfer points.

In stark contrast, the Paris network (Figure 5.5b) shows a much broader spatial distribution of high intermodal degree nodes. Here, green and red tones dominate the map, revealing that a large share of nodes facilitate connections between two or more modes. This not only makes intermodal transfers more prevalent throughout the city but also increases the redundancy and resilience of the network. Passengers in Paris are much more likely to find a nearby transfer point regardless of their location, supporting a seamless and equitable travel experience.



(a) Bangkok intermodal degree heatmap: most nodes are dark blue, indicating limited transfer opportunities



(b) Paris intermodal degree heatmap: green and red nodes reflect widespread modal integration

Figure 5.5: Differences in intermodal integration between cities

Transfer Impedance

Not only are transfer opportunities much more prevalent in the distributed systems, they also turn out to be much more user-friendly. This conclusion emerges when looking at the average length of transfer edges system-wide: the impedance travelers have to overcome in order to make an intermodal transfer. This metric is visualized in Figure 5.6. It becomes clear that in the three centralized networks examined, intermodal transfer edges are associated with significantly longer walking distances compared to the three distributed networks, where the average transfer impedance is notably lower.

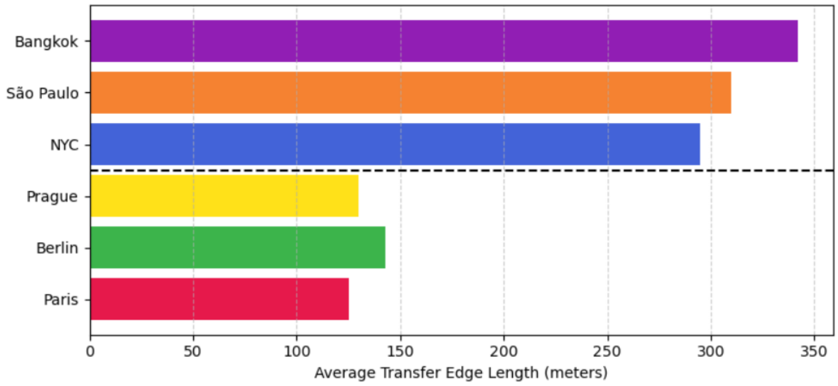


Figure 5.6: Average transfer edge length

Concluding Remarks

Together, these results show that distributed connectivity networks like Paris, Berlin, and Prague embed transfers deeply into their design, offering more intermodal transfer points, greater spatial distribution, and lower impedance. It turns out that these networks are not designed to avoid transfers: they are designed to minimize transfer impedance. Toronto and Melbourne, despite exhibiting some spatial characteristics of centralized networks, along with Mexico City, appear to lean toward the distributed connectivity model when it comes to transfers. These systems offer a relatively high share of transfer nodes and a reasonably balanced spatial distribution of intermodal connections. Although transfer distances may be somewhat longer and overall integration less seamless compared to leading distributed networks, these cities nonetheless show signs of embracing transfers as a fundamental element of their network design, aligning with the operational logic of distributed systems.

In contrast, centralized systems like New York City, São Paulo, and Bangkok provide fewer, less accessible transfer options. This highlights a key distinction in network philosophy: some systems embrace transfers as a core feature, while others treat them as a necessary inconvenience. Singapore, Denver, and Valencia align more closely with the centralized model, albeit for different reasons. Singapore achieves operational efficiency through high-frequency coordination rather than spatially widespread transfers. Denver and Valencia, on the other hand, show limited transfer integration due to their smaller size and modal structure, relying more on direct single-mode trips than interconnected multimodal flows.

5.3.2. GTC Composition

The composition of the GTC across different networks reflects the role and importance of transfer connections within each system. As expected, networks following a distributed connectivity strategy tend to exhibit a higher share of transfer burden in their average weighted GTC: an observation consistently supported by the data.

Network analysis reveals that cities with greater transfer shares, such as Paris, Prague, and Berlin, align with the distributed model. In these cities, the transfer component exceeds 40% of the average GTC, while the in-vehicle time remains the lowest among all twelve networks. This indicates a system designed around shorter trip segments, where transfers serve as the structural mechanism for enabling flexibility and spatial reach within a grid-like network.

In contrast, more centralized networks, such as São Paulo, New York City, and Bangkok, rely less on intermodal transfers. These systems favor longer, single-mode trips with fewer intermodal transfers. This is reflected in the in-vehicle time share, which exceeds 45% of the GTC in each of these networks, representing the highest values across all cases. Correspondingly, the transfer burden in these cities is notably lower, highlighting their operational strategy of minimizing transfers rather than integrating them.

These contrasts are visualized in Figure 5.7, where the distributed networks of Paris, Prague, and Berlin show a significantly lower in-vehicle time share and a higher transfer burden, while São Paulo, New York, and Bangkok follow the opposite trend. Interestingly, the shares of transfer walking time and waiting time appear relatively stable across networks, suggesting that the primary differences lie in the structure and frequency of modal switching, rather than the time costs associated with each individual transfer.

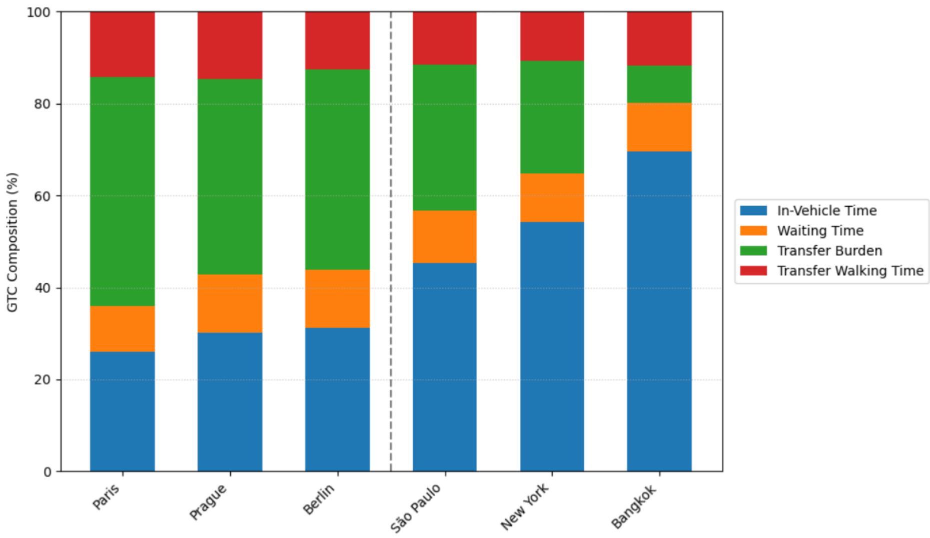


Figure 5.7: GTC composition of various networks

It can be concluded that the GTC composition of different networks clearly reveals distinct design strategies. Distributed networks like Paris, Berlin, and Prague allocate a larger share of travel effort to transfers, suggesting that these systems embrace transfers as a central part of their operation. While this leads to more frequent modal switches, it allows for shorter in-vehicle segments and improves network flexibility and spatial reach. However, it also implies that these systems are highly dependent on well-integrated transfer infrastructure and timetable synchronization. If coordination is lacking, users may face high cumulative transfer burdens.

In contrast, centralized systems such as São Paulo, New York City, and Bangkok show higher shares of in-vehicle time, indicating a preference for direct, longer trips with minimal transfers. While this reduces the need for synchronization and intermodal coordination, it can limit routing flexibility, especially in peripheral areas, and lead to longer average trip durations. These systems may offer simpler user experiences but are more vulnerable to bottlenecks and reduced equity in accessibility.

From a planning perspective, these findings highlight two key implications:

- **Distributed systems** must prioritize the quality of transfers. This includes reducing physical impedance, improving schedule coordination, and enhancing passenger information systems to support seamless modal switching.
- **Centralized systems**, meanwhile, may benefit more from expanding multimodal connectivity and developing secondary hubs, to relieve pressure on core corridors and improve accessibility in underserved areas.

Therefore, the GTC composition is not just an efficiency indicator; it also exposes the underlying operational philosophy of the network and informs where targeted improvements could yield the greatest accessibility gains.

5.3.3. Operational strategies and Service Balance

While the composition of GTC reflects the structural and strategic emphasis of each network, favoring either direct connections or intermodal transfers, it does not fully capture how consistently and reliably temporal accessibility is experienced by passengers in practice. From the user's perspective, what matters most is not only how fast a trip can be made under ideal conditions, but also how predictably and smoothly it can be completed across different trip types and different times of day. Travelers expect a system that is not only efficient, but also resilient, coordinated, and equitable.

To evaluate these qualities, the twelve networks are assessed for temporal network accessibility using three key metrics drawn from the accessibility assessment framework:

- **Peak and off-peak service availability** — indicating whether service levels are maintained consistently throughout the day;
- **Intermodal synchronization** — assessing how well connections between different modes are coordinated.
- **GTC threshold ratios** — capturing how evenly travel times are distributed across users;

Together, these indicators help identify temporal performance profiles across the twelve networks. From the analysis, three major operational strategies emerge: frequency-based, coordination-based and hybrid temporal strategies.

Frequency-Focused Networks

Frequency-focused systems aim to ensure temporal accessibility primarily by maintaining high vehicle frequencies, especially in the core of the network. Rather than relying on intermodal coordination, these systems operate under the implicit assumption that if vehicles arrive often enough, the need for tightly scheduled transfers is reduced. This approach simplifies operations but places more responsibility on the user to time their transfers, especially during off-peak hours or in peripheral areas.

Networks in this category are typically characterized by: high peak-hour service availability (sometimes with steep off-peak declines), low intermodal synchronization scores and high GTC threshold ratios, that indicate greater disparity in accessibility between short and long trips. Despite high average performance in central areas, the lack of systemic coordination leads to more variable travel times and user experience across the network.

Stable and Well-Coordinated Networks

By contrast, coordination-based networks prioritize synchronization over frequency. These systems demonstrate a high degree of integration across time, space, and modes. Their temporal performance is built on synchronized timetables, carefully designed transfer hubs, and spatial redundancy, allowing for consistent accessibility, even with moderate service frequencies.

Common traits among these networks include high intermodal synchronization scores, small differences between peak and off-peak availability (suggesting temporal resilience) and low GTC threshold dispersion, indicating consistent trip quality regardless of trip length or time. In these systems, accessibility is not dependent on service volume alone, but is achieved through careful planning and coordination, reducing uncertainty and improving the overall passenger experience.

Hybrid/Segmented Networks

Hybrid or segmented systems combine elements of both strategies, typically coordinating services in certain areas or modes, while relying on frequency in others. Coordination may be effective along major corridors or during peak periods but breaks down in less prioritized parts of the network (geographically, temporally, or modally).

These networks generally exhibit moderate synchronization scores, with partial intermodal integration, intermediate GTC threshold values, reflecting variability across the network and notable off-peak drops in service availability, though less extreme than in frequency-focused systems. This category reflects systems where integration is evolving, incomplete, or constrained by institutional complexity. From the user's standpoint, experiences may vary significantly based on location and time of travel.

Network Classification

Table 5.3 presents three key indicators of temporal accessibility: the spread of GTC threshold values, the Off-Peak/Peak ratio of service availability, and the Weighted Intermodal Transfer Wait Time Score. These metrics are shown for three representative cities, Paris, Mexico City, and Prague, to illustrate contrasting temporal accessibility profiles across different networks.

Table 5.3: Temporal performance metrics for three networks

City	GTC Spread ($\bar{t}_{75} - \bar{t}_{25}$)	Availability Ratio (Off-Peak/Peak)	Synchronization (min)
Paris	20.35	0.71	29.54
Mexico City	11.79	0.69	22.36
Prague	13.06	0.78	18.91

These standardized findings are visualized in the radar chart presented in Figure 5.8. From this figure, several insights can be drawn regarding the temporal operational profiles of the selected cities. In Paris, the relatively high GTC spread, combined with lower intermodal synchronization and notable fluctuations in service availability, suggest a system that is primarily frequency-driven. In contrast, the Prague network displays strong synchronization and stable service availability, indicative of a well-coordinated system that emphasizes consistent intermodal integration. Mexico City appears to follow a hybrid model, falling between the two extremes. It exhibits moderate synchronization, service availability patterns similar to Paris, and a GTC spread more aligned with Prague. These differences reflect distinct strategic approaches to managing temporal accessibility across multimodal networks.

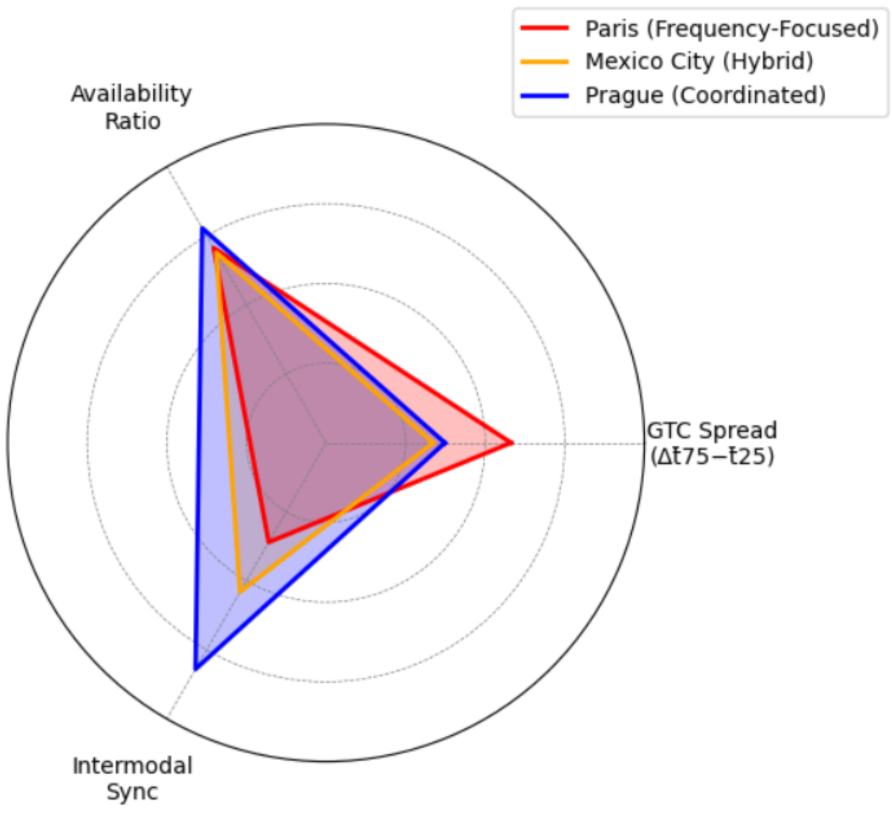


Figure 5.8: Radar chart of temporal accessibility scores

Comparative analysis of all twelve networks reveals that Paris, New York City, São Paulo, and Valencia follow a predominantly frequency-focused model, relying on high peak service intensity to compensate for limited intermodal synchronization. Both Paris and New York stand out with particularly high GTC spread values and weaker coordination performance, suggesting a reliance on service volume rather than timing alignment across modes. However, New York City demonstrates relatively strong temporal performance in terms of service intensity and intermodal transfer wait times, reflecting a system optimized for direct, high-capacity operations rather than flexible trip chaining. The network of São Paulo on the other hand maintains a stable availability profile throughout the day, though it continues to show limited transfer integration and high transfer impedance.

Prague, Berlin, and Singapore exemplify coordinated and stable networks, achieving low GTC threshold dispersion and high synchronization with minimal drop in off-peak service, especially Singapore, which combines both frequency and timing efficiency. The remaining cities, Mexico City, Toronto, Melbourne, Bangkok, and Denver, display characteristics of hybrid or segmented systems, with partial synchronization and moderate availability drops. Notably, Prague has the lowest transfer wait time score, while Paris records the highest, emphasizing the operational contrast between these models.

From a policy perspective, networks with a coordination, based and stable operational strategy, tend to offer more consistent performance in terms of temporal accessibility. Their success is not solely built on high-frequency service, but on the system-wide alignment of schedules, spatial redundancy, and the presence of well-integrated intermodal hubs. Frequency-focused systems can be highly effective during peak periods, especially when service intensity is sufficient to reduce waiting times and support user flexibility. However, they are more vulnerable to inconsistencies during off-peak periods, longer trip segments, and weaker intermodal integration.

While each approach has its own operational strengths, data suggests that coordinated (especially well-synchronized) networks are often more robust and efficient from a policy standpoint, particularly because they require fewer interventions to maintain consistent service quality across different temporal and spatial contexts.

These classifications reinforce a key finding: temporal accessibility, just like spatial accessibility, is not solely a product of volume, but of system design. Coordinated networks, even when operating with fewer vehicles, deliver smoother, more reliable public transport experiences. For cities seeking to improve accessibility, especially with constrained resources, investment in intermodal synchronization, transfer infrastructure, and schedule integration may yield greater benefits than simply increasing frequency alone.

5.4. Conclusion: Typology of Multimodal Network Performance

Two distinct spatial strategies were identified in earlier sections: distributed connectivity and centralized connectivity. Each approach shapes how public transport networks are structured across urban space and how transfers are embedded into the system. In parallel, three operational strategies emerged as dominant approaches to maintaining accessibility over time: coordination-based, frequency-focused, and hybrid. By combining these two dimensions, it is now possible to classify each of the twelve cities into coherent network profiles that reflect how their systems function both spatially and temporally in practice.

5.4.1. Network Classifications

This integrated classification provides a comprehensive understanding of how different public transport systems deliver accessibility to users. It highlights not only their network structure but also the strategic and operational choices that influence user experience throughout the day. As such, it forms a valuable foundation for developing policy recommendations tailored to each system's specific strengths and challenges. Four distinct categories of public transport networks have been identified:

- Well-Integrated Networks
- Strong Network Structure, Temporally Weak
- Efficient Network, Spatially Sparse
- Underdeveloped, Transitional Systems

The following sections assign each city to one of these categories and provide a detailed explanation of the defining characteristics of each typology, illustrating how the networks of these cities exemplify these traits.

Well-Integrated Networks
Berlin, Prague, and Singapore perform consistently well across both spatial and temporal dimensions of accessibility and are thus classified as well-integrated networks.

Objective indicators reinforce this classification: all three cities exhibit short characteristic path lengths (around 2.0 stops on average in L-space), strong synchronization ratios close to 1.0, and low generalized travel cost spreads (below 55 minutes). Additionally, their networks show robust connectivity (γ values above 2.3) and maintain stable service availability during off-peak hours. This combination of spatial compactness and operational robustness places them among the most efficiently structured multimodal networks analyzed.

Strong Network Structure, Temporally Weak
This cluster includes Paris, Toronto, and Melbourne. These cities feature dense, well-integrated networks with strong spatial equity and established intermodal hubs, reflected by high connectivity indicators (γ values above 2.4), relatively short characteristic path lengths (around 2.2 to 2.3 stops in L-space), and high average degree centrality (typically above 4.5 connections per node). However, their temporal performance is less robust. Synchronization ratios remain below 1.0, and off-peak service availability lags behind more efficient systems, resulting in longer waiting times and reduced operational consistency. Generalized travel cost variability also remains moderate to high (spreads of 47 to 57 minutes), suggesting uneven travel reliability. Enhancements in timetable coordination and off-peak service frequency could significantly improve overall network performance and user experience.

Efficient Network, Spatially Sparse
New York City and Bangkok fall into this category. These networks offer efficient, high-frequency operations with relatively low transfer burdens and strong timetable coordination, as evidenced by high synchronization ratios (1.33 for New York City and 1.46 for Bangkok) and elevated vehicle movement ratios (both exceeding 0.85). However, they exhibit weak spatial integration due to limited transfer points and sparse intermodal connectivity. Both show low connectivity indicators (γ indices among the lowest), relatively long characteristic path lengths (around 2.6 to 2.7 stops in L-space), and low average degree centralities (around 3.7 to 4.5), indicating less compact network structures. Consequently, their operational efficiency is not always matched by spatial accessibility or routing flexibility, which limits network resilience and passenger options.

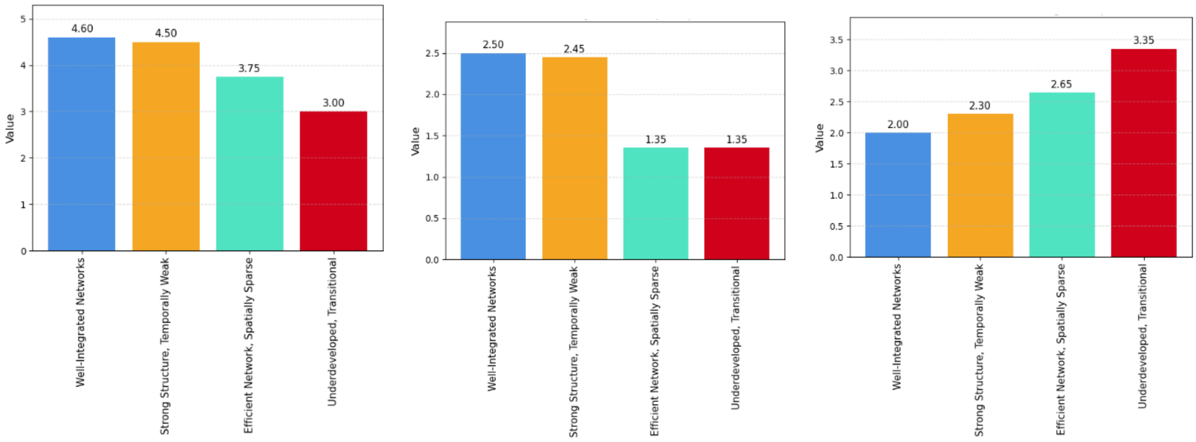
Underdeveloped, Transitional Systems
The networks of São Paulo, Mexico City, Denver, and Valencia can be considered evolving systems often lacking clear spatial or temporal strategies, which negatively impact overall performance. Spatially, average connectivity levels remain low—São Paulo and Mexico City exhibit very limited intermodal connections (γ values below 1.5), while Denver and Valencia, despite somewhat higher connectivity, suffer from long characteristic path lengths (above 3.2 stops in L-space). Average degree centrality is low across this group, indicating few direct transfer opportunities per stop.

Temporally, synchronization ratios are modest (around 0.9 to 1.0), and vehicle movement frequencies vary inconsistently across modes and periods. Off-peak robustness is unreliable, particularly in São Paulo and Valencia, where service availability declines significantly outside peak hours. Generalized travel cost spreads are high, ranging from 50 to 67 minutes, indicating uneven travel experiences across time and locations. These systems provide limited transfer opportunities, especially São Paulo and Mexico City, leading to high transfer impedance and uneven accessibility. Major improvements are needed to enhance intermodal coordination, densify transfer hubs, and create more equitable and efficient public transport networks.

5.4.2. Synthesizing Metrics
As discussed in Section 2.5.1, classifying cities into distinct categories does not rely solely on exact values from the accessibility assessment framework. Instead, it emerges from a holistic interpretation of overall patterns in the data, including spatial and temporal strategies and insights from network visualizations. No city fits perfectly within a single category; rather, the framework offers a general indication of each network's key challenges. To further support these classifications, empirical evidence is presented to illustrate how accessibility metrics and network characteristics align with and reinforce each city's assigned category.

Spatial Indicators

Figure 5.9 presents three plots showing average values of key spatial accessibility indicators for cities within each network category. Figure 5.9a highlights that well-integrated networks and those with a strong spatial structure tend to have higher average degree centrality compared to high-efficiency and underdeveloped networks. Similarly, Figure 5.9b shows that these networks exhibit greater connectivity in L-space. Finally, Figure 5.9c demonstrates that networks classified as having strong spatial structure generally have lower characteristic path lengths in L-space, indicating more direct and accessible routing.

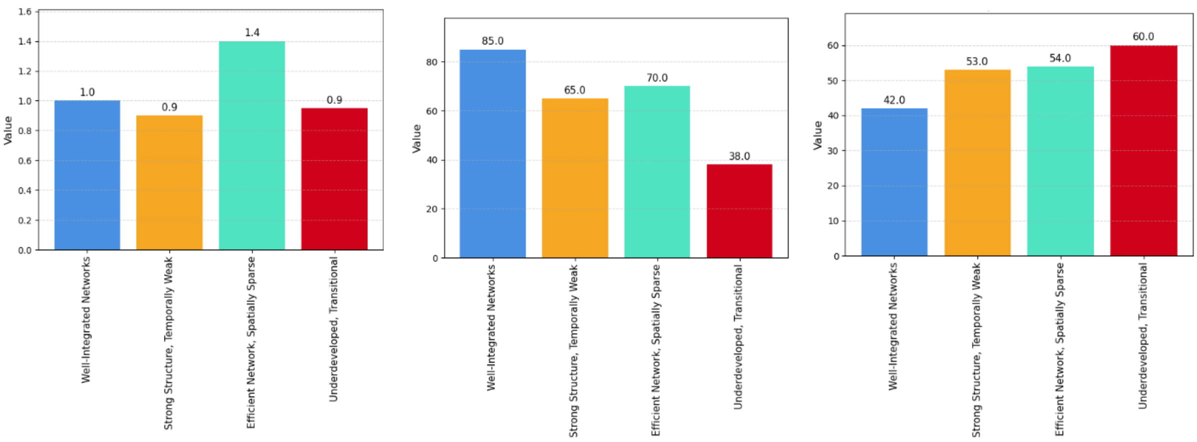


(a) Average Degree Centrality **(b)** Connectivity □□ γ L-space **(c)** Characteristic Path Length L-space

Figure 5.9: Comparison of key spatial accessibility indicators across four network categories

Temporal Indicators

Similarly, Figure 5.10 illustrates that well-integrated networks and those classified as efficient but structurally sparse consistently achieve moderate to high scores across three key temporal indicators from the accessibility assessment framework. As shown in Figure 5.10a, these two categories outperform others on average in terms of synchronization. This trend is further supported by Figure 5.10b, which shows that they also maintain the highest levels of service availability during off-peak periods. Additionally, Figure 5.10c reveals that these categories experience relatively moderate to low variability in generalized travel cost across predefined percentiles compared to other networks. Overall, these findings highlight that networks classified as efficient tend to perform better on temporal accessibility indicators.



(a) Synchronization Ratio **(b)** Service Availability (Off-Peak) **(c)** Generalized Travel Cost Spread (minutes)

Figure 5.10: Comparison of key temporal accessibility indicators across four network categories

With the twelve public transport systems now classified from a user perspective, the next step is to translate these findings into targeted policy recommendations. The following chapter will present these recommendations in detail, offering strategies to help each city improve its network operations and user outcomes.

6 Strategic Insights for Network Improvement

Policy recommendations based on multimodal performance typologies

The previous chapter combined the spatial and temporal analyses presented to provide a comprehensive classification of the twelve public transport networks studied. By combining insights on network structure, service availability, intermodal coordination, and generalized travel cost, a typology was developed that reflects how each system performs from the perspective of the user.

The classification highlights key differences in how cities organize and operate their multimodal networks. The resulting categories allow for a deeper understanding of system-level strategies and challenges, laying the foundation for targeted recommendations that will be presented in this chapter.

6.1. Well-Integrated Networks

The cities of Berlin, Prague, and Singapore demonstrate cohesive network structures combined with strong temporal coordination. Their systems are already well-optimized for both spatial and temporal accessibility, and all three can be characterized as compact public transport networks. In each case, the existing modes of transport extend across the entire urban territory, with a relatively high stop density that ensures accessibility throughout the city. Operational efficiency is maintained through a combination of high vehicle frequencies and intermodal timetable coordination, resulting in seamless integration between sub-systems.

6.1.1. Case Study: Singapore

An especially notable example is Singapore, which, despite operating with only two public transport modes (bus and subway) achieves a level of performance and integration that places it firmly in this top-performing category. This case exemplifies how coordination and design efficiency, rather than modal complexity, can produce a highly accessible and resilient system.

A defining feature of Singapore's network is the exceptionally high number of edges in the P-space graph: over 183,000, a figure that reflects the tight synchronization between services and the high prevalence of functional direct connections across the network. This suggests that passengers benefit from well-coordinated multimodal options, even with limited modal diversity.

Moreover, service consistency is maintained across different time periods: the network exhibits minimal variation between peak and off-peak conditions, highlighting its operational robustness. As shown in Figure 6.1, the L-space representation illustrates the extensive reach and coverage of the system.

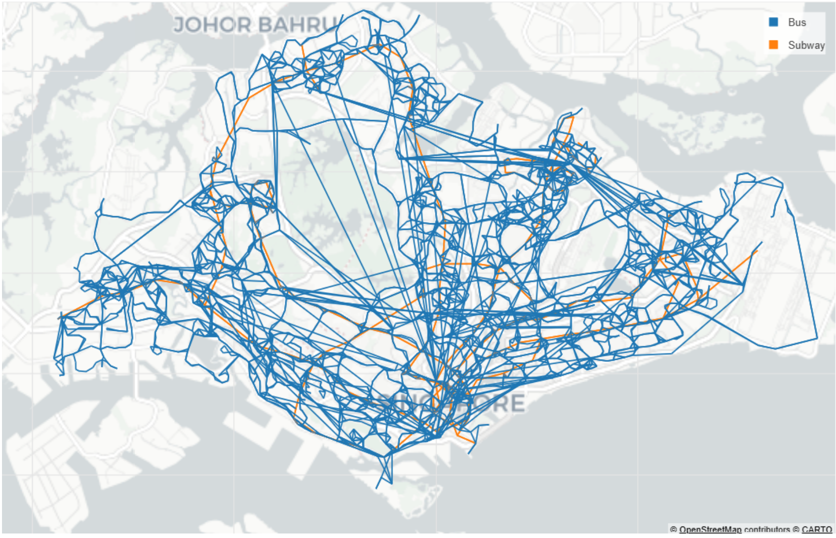


Figure 6.1: Singapore network representation (L-Space)

The dense and frequent bus schedule compensates for spatial gaps in the rail system, allowing for short, rapid connections throughout the city. This is further supported by a low characteristic path length and a high connectivity index in the P-space representation. Singapore effectively demonstrates how strategic design and synchronization can substitute for extensive modal variety, resulting in a well-integrated, highly efficient, and resilient public transport system.

6.1.2. Future Developments

While Singapore, Prague, and Berlin currently rank among the highest in terms of spatio-temporal network accessibility, maintaining such high performance levels may become increasingly challenging. Pressures from urban growth, climate change, and evolving mobility demands will require proactive strategies to ensure continued resilience and efficiency.

To sustain and strengthen their leading positions, policy efforts in these cities should gradually shift from expansion to consolidation. Rather than building new capacity, the focus should lie on optimizing existing infrastructure and operations. The following strategic domains offer a framework for maintaining high accessibility and preparing for future challenges.

Infrastructure and Vehicle Maintenance

This research has shown that high accessibility is not solely determined by network scale or modal diversity, but by the structural and operational strategies of the system. This includes how well transfer points function and how reliably services are offered throughout the day. Preventing service disruptions is essential to maintain the offered level of operational efficiency. Regular maintenance of infrastructure and rolling stock is therefore not just a technical concern, but a direct enabler of reliable timetable adherence and low generalized travel cost.

Cities with long public transport histories like Berlin must prioritize modernization programs without compromising daily operations. Singapore and Prague, while smaller in scale than Berlin, can benefit from preventive maintenance cycles and investment in new-generation vehicle fleets that improve energy efficiency and accessibility. The implementation of Artificial Intelligence technologies in infrastructure and vehicle maintenance, as outlined by the American Public Transportation Association (2025), offers promising developments for these three cities to enhance operational efficiency and predictive asset management. Maintenance is not only a technical requirement: it has to be considered a user-facing policy that directly affects perceived service quality.

Climate Adaptation and Urban Growth Strategies

One of the central findings of this thesis is that accessibility outcomes are shaped by how well spatial design and operational strategies align with urban structure. Climate resilience and urban growth planning must therefore be integrated with the ongoing evolution of the transport network.

Even the most efficient networks must adapt to changing environmental and urban conditions. Climate resilience should be built into all future infrastructure plans, including strategies for changing weather patterns. Berlin and Prague may face challenges related to aging physical structures, while Singapore's tropical climate demands systems that can handle high rainfall and heat stress. Additionally, as all three cities continue to grow, public transport networks must align with land use changes. Strategic densification around multimodal hubs, expansion of first and last mile infrastructure, and integration with cycling and walking networks can help preserve accessibility as urban form evolves.

To further evolve toward more sustainable and low-emission public transport networks, Berlin, Singapore, and Prague could implement noise-reduction strategies, as suggested by Keolis Group (2025), and accelerate the transition to cleaner fleets. This may involve expanding the adoption of electric vehicles or exploring emerging technologies such as hydrogen-powered buses, as proposed by Transport for London and Air Products and Chemicals, Inc. (2017).

Passenger Comfort and User-Centric Design

Perceived accessibility of a network is influenced not only by structural design and operational metrics, but also by the user's experience of traversing the network. High synchronization scores and low transfer impedance do not automatically translate into high satisfaction if passengers face overcrowded or confusing environments.

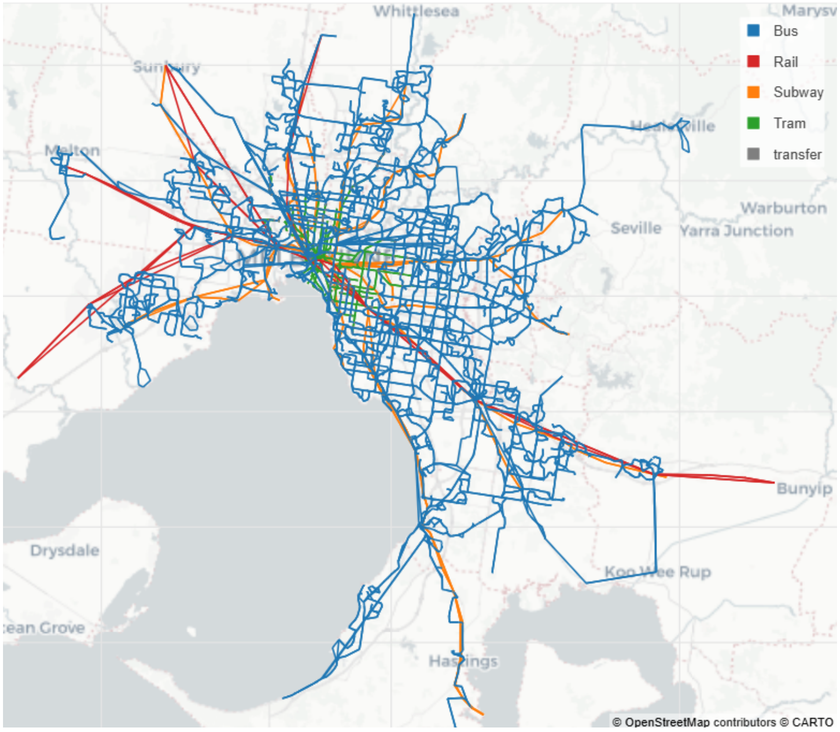
While operational performance is strong, maintaining high public satisfaction will increasingly depend on enhancing the qualitative aspects of the user experience. Priorities include reducing overcrowding, improving way-finding, upgrading station environments, and ensuring universal design for accessibility. Even in high-performing systems, passenger perception can be undermined by bad traveling comfort. Enhancing seating, ventilation, cleanliness, and digital services (such as real-time information, journey planners) can reinforce the sense of reliability. It is recommended that a user-centered strategy should guide future interventions.

6.2. Structurally Strong, Operationally Inconsistent

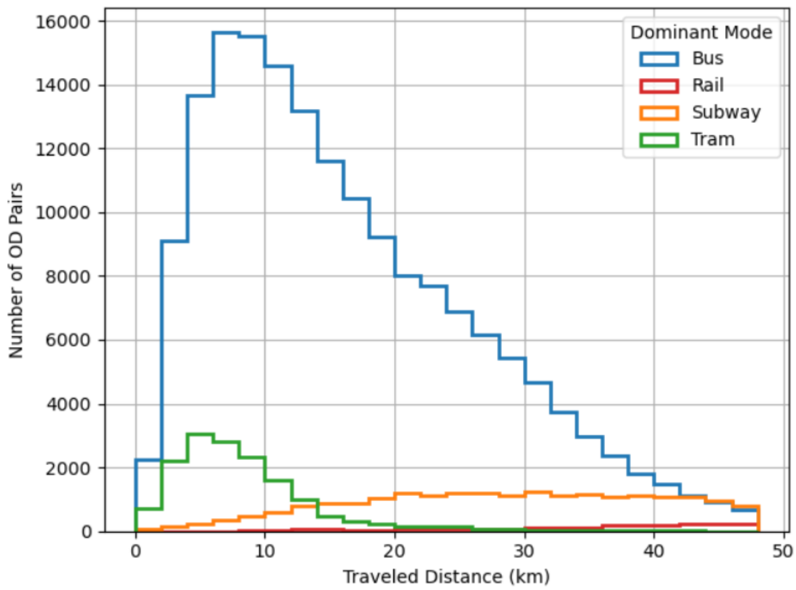
The cities of Paris, Toronto, and Melbourne exhibit dense and spatially well-integrated public transport networks. They perform strongly on measures of spatial equity and intermodal transfer availability, indicating well-developed physical and modal structures. However, when examining temporal efficiency, there remains room for improvement. Targeted policy interventions, particularly in the areas of vehicle deployment, timetable synchronization, and service coordination, could further enhance network performance and help these cities achieve a higher level of overall accessibility.

6.2.1. Case Study: Melbourne

Melbourne offers an example of how spatial integration can be achieved even within a highly dispersed urban sprawl. Unlike several other cities where modal roles interfere and compete, Melbourne's public transport system exhibits a strikingly segmented modal structure, as shown in Figure 6.2. Figure 6.2a shows the network in L-space representation, and 6.2b show the distribution of the trips over the traveled distance, split by mode of transportation. It can be seen how every mode operates within a relatively well-defined distance band, minimizing redundancy.



(a) Melbourne network representation (L-Space)



(b) Dominant public transport mode by traveled distance for Melbourne

Figure 6.2: Melbourne spatial structure

Buses are dominant for short- to mid-distance OD pairs, with the sub-network reaching out to all suburban areas. Trams, which also appear in the short-range spectrum, cover high-demand corridors closer to the city center. In contrast, subways and rail modes become increasingly dominant for medium- to long-distance trips, beginning around the 20 km mark and extending toward the city's outer areas.

This clear separation of modal roles reflects good planning logic, enabling each mode to perform optimally within its designated spatial niche. Importantly, it also reduces network friction: travelers can rely on buses and trams for local trips, while transferring to higher-capacity rail or metro for regional connectivity. In combination with timetable synchronization strategies, this network structure has the potential of reaching a high level of multimodal integration.

6.2.2. Opportunities for Improving Temporal Performance

Challenges for the cities of Melbourne, Toronto, and Paris lie in their temporal performance. Even though the spatial cohesion of these networks supports equity and connectivity, there is a risk of deteriorated user experiences when temporal coordination is not sufficiently prioritized. Policy efforts in these cities should therefore shift focus from coverage to consistency. The following interventions may help these systems achieve stronger temporal performance.

Invest in Off-Peak Vehicle Volumes

Temporal accessibility metrics, particularly during off-peak periods, show significant drops in service frequency and longer average waiting times for the cities of Paris, Toronto and Melbourne. These temporal inconsistencies can undermine overall network performance and disproportionately affect users who travel outside of traditional commuting hours.

To address this, targeted increases in off-peak vehicle volumes are recommended. Increasing vehicle volumes during off-peak periods is thus essential in these three cities. This will not only improve availability, but also reduce waiting times in areas with lower frequencies. In doing so, equitable access can be ensured for populations traveling outside dominant time windows. These targeted investments are expected to strengthen overall network robustness. Full peak-level services are not required; instead, the focus should be on strategically enhancing frequencies during midday, evenings, and weekends to prevent the system from becoming functionally inaccessible. TransitCenter (2023) suggest the support of reliable transit access for travelers outside standard hours by flexible off-peak services, guaranteed ride-home programs and subsidized employer programs.

Implement Cross-Modal Synchronization

Despite well-developed physical infrastructure and dense multimodal networks, Paris, Toronto, and Melbourne face persistent challenges related to intermodal coordination. The metric-based analysis shows that long intermodal transfer waiting times and poor timetable alignment continue to limit temporal accessibility in these cities. These coordination gaps increase generalized travel cost and reduce the efficiency of multimodal journeys.

To improve transfer efficiency, policy efforts should prioritize the synchronization of services at major interchanges, especially those with multiple modal operators. Data shows that coordination failures are often concentrated in such multi-operator environments. A further recommendation is to invest in dynamic coordination tools that use real-time data to adjust vehicle dispatch and improve the reliability of transfers. An interesting operational measure for these cities may be Mobility-on-Demand measures, as proposed by Ward and Oakley (2022): these policies target underserved suburban populations, offering cross-boundary service integration.

6.3. Efficient Operations, Spatially Sparse

New York City and Bangkok represent systems with strong operational performance in their central corridors but limited spatial cohesion across the wider urban areas they serve. These networks are characterized by high vehicle frequencies, direct single-mode trips, and low reliance on intermodal transfers. However, they often fail to distribute accessibility evenly, with peripheral areas experiencing poor modal coverage, limited transfer options, and high travel impedance.

Decentralized, equity-driven planning can strengthen spatial cohesion in Bangkok and New York City, where strong central transit corridors contrast with underserved urban areas. Kittelson & Associates

(2024) recommend developing secondary hubs and feeder services to improve access beyond core areas, while expanding intermodal infrastructure, such as bike-to-transit connections and seamless transfers, can reduce travel impedance and promote more inclusive, resilient networks.

The absence of spatial redundancy and intermodal integration can lead to the exclusion of users in underserved areas and longer first/last mile journeys. To address this, two policy interventions are recommended in this section.

Creation of Secondary Hubs

The spatial network analysis shows that both New York City and Bangkok rely heavily on a limited number of central multimodal hubs, resulting in a highly centralized connectivity strategy. While this is efficient in terms of operational throughput in core areas, it leaves outer districts with limited access to transfers and modal options, thereby increasing generalized travel costs for users in those regions.

To mitigate this, policy should prioritize the development of secondary hubs in peripheral zones, supported by reliable feeder services that connect to main lines. This approach can help distribute connectivity more evenly. Ultimately, this may result in higher modal assortativity, improving cooperation between transport modes and enhancing the overall travel experience.

Expand Intermodality

This study has demonstrated that spatial cohesion is not only a matter of network density, but also of how well different modes are integrated. Both Bangkok and New York exhibit gaps in modal integration, particularly in outlying neighborhoods, which limits access and increases user impedance. Investment in infrastructure is necessary, such as extending (light-)rail lines to urban peripheries or enhancing bike-to-transit infrastructure, including bike lanes and secure parking near major stops.

Infrastructure improvements may also focus on reducing transfer impedance through walkable interchanges, clear signage, and user-friendly wayfinding. These upgrades can help foster equitable access for all users - not just those in central zones - and contribute to a more cohesive and inclusive network. Policies should be evaluated for equity impact and ensure that spatial cohesion is prioritized.

6.4. Transitional or Evolving Networks

São Paulo, Mexico City, Denver, and Valencia represent transitional or underdeveloped networks with limited cohesion, weak intermodal integration, and significant variation in accessibility across time and space. Despite certain strengths, such as high-capacity corridors (São Paulo and Denver) or dense modal coverage (Mexico City and Valencia), these networks currently lack coordinated planning, operational alignment, and the infrastructure needed to support consistent performance.

The following areas are essential for policy focus: expanding spatial coverage, implementing intermodal synchronization, reducing transfer impedance, and increasing off-peak frequencies. Policy efforts should aim to build a strong institutional, infrastructural, and operational foundation for long-term system integration.

Creation of Intermodal Hubs with Universal Design Goals

This research has shown that fragmented and inaccessible transfer points are a key contributor to high generalized travel costs in these cities. Many transfer locations lack adequate physical and operational integration, imposing a disproportionate burden on passengers and limiting spatial cohesion.

To address this, authorities should prioritize the creation of strategically located intermodal hubs that follow principles of standardized design, universal accessibility, and fare integration. To support equitable and inclusive multimodal hub development in these four cities, policy makers may learn from the design principles outlined by both the American Public Transportation Association (2020) and the EMEL - Empresa Municipal de Mobilidade e Estacionamento de Lisboa (2023). The first report emphasizes universally accessible design and operational consistency across all transport modes, while the second guide offers a comprehensive, people-centered framework grounded in seven design principles that prioritize seamless integration, safety, inclusivity, and long-term adaptability. Together, these reports provide a strong foundation for cities to create hubs that are not only physically accessible but also socially inclusive, environmentally sustainable, and responsive to the diverse needs of passengers, staff, and local communities.

Launch Synchronization Pilots

Temporal analysis in this study revealed that service availability and coordination are inconsistent across modes and time periods. Even modest synchronization improvements can substantially enhance perceived accessibility and reduce travel impedance.

Governments should encourage agency collaboration, while piloting real-time coordination platforms, especially in off-peak periods. These platforms can help align different services and minimize travel effort.

To further support coordination, cities may consider creating a centralized public transport authority. This body could oversee multimodal planning, encourage data sharing, and unify transit under a cohesive mobility framework. Reports by Vuchic (2005) and Urban Transport Group and International Association of Public Transport (UITP) (2022) conclude that centralized authorities not only enhance network efficiency and network integration, but also increase transparency, accountability, and long-term resilience of urban transport networks by unifying vision, budgets, and operational standards under a cohesive framework.

Strengthen Suburban Connectivity

The spatial analysis identified significant accessibility gaps in suburban and peripheral areas. While central corridors may offer frequent service, outer zones are often underserved, leading to fragmented travel chains and inequitable access. Developing feeder networks (bus or light rail) can enhance connectivity between peripheral areas and major hubs (Vasiutina et al., 2025). Additionally, supporting neighborhood connectivity, such as cycling and carpool infrastructure, as suggested by Pradeep and Gowande (2025), can strengthen first/last mile accessibility and ensure a more equitable and complete network.

6.5. Conclusion

This chapter has analyzed the spatial and temporal performance of twelve multimodal public transport systems, applying the full accessibility framework to classify their structure, operations, and overall user experience. By comparing networks across consistent indicators, each city has been placed into a typology reflecting how accessibility is delivered in practice.

This typology provides more than a descriptive overview: it reveals how spatial structure, service availability, and transfer coordination each contribute to accessibility outcomes, and where targeted policy intervention may help address the identified shortcomings of the networks. The classification revealed that high accessibility comes not only from physical coverage, but from coherent operations, coordinated transfers, and resilience across time. Well-performing systems combine strong spatial design with effective temporal strategies, while underperforming networks tend to suffer from fragmentation, off-peak weakness, or lack of intermodal planning.

With this, the fourth and final sub-question – "How can the analysis of multimodal public transport systems' performance provide insights on network planning and recommendations for improving accessibility?" – has been addressed through the development and application of the accessibility typology, alongside the identification of suitable policy intervention options grounded in existing literature. The accessibility framework enables a diagnosis of each system's strengths and weaknesses, forming the foundation for the final chapter, which will translate these findings into practical recommendations for future policy and network planning.

7
Conclusion

The main purpose of this research is to evaluate the network accessibility of multimodal public transport systems, with focus on both spatial structure and temporal coordination of transit services. Through the development of a set of standardized metrics and applying these to structured network representations of public transport systems in twelve cities around the globe, the study has provided a comparative analysis of network performance. This analysis has revealed how differences in network design, transfer impedance, operational strategy and timetable coordination shape the accessibility outcomes in different urban environments. These findings support detailed understanding of multimodal accessibility. Moreover, they form a basis for drawing conclusions on network planning and transforming these into targeted strategies for improving the effectiveness and integration of public transport systems.

With these outcomes, the main research question of this thesis — *What insights into network accessibility can be gained from a comparative, metric-based analysis of multimodal public transport networks, considering both spatial and temporal dimensions?* — has been addressed by developing and applying a standardized methodological framework for accessibility assessment. This framework enables structured, cross-city comparisons of how multimodal transport systems perform in terms of integration, coverage, and operational coordination.

The application of this methodology to twelve global case studies has demonstrated that it can reveal meaningful insights into the spatial and temporal strategies of public transport systems. In particular, it highlights how design and scheduling decisions shape accessibility outcomes, and where performance gaps occur across modes and time periods. These insights form the basis for targeted policy recommendations that respond to the specific structural and operational weaknesses identified in different network typologies.

This research clearly shows that improving accessibility is not a matter of simply expanding network size or adding more modes. Instead, accessibility depends primarily on two interdependent dimensions:

- The structural design configuration of the network, determining how well different modes are physically and spatially integrated.
- The operational strategy of the network, responsible for the scheduling, synchronization and maintenance of services throughout the day.

These findings directly address the two central research objectives of this study. First, they demonstrate that network scale and modal diversity alone are insufficient to guarantee high accessibility: what matters more is how effectively the network is structured and operated. Second, they show that specific spatial design choices (such as distribution of transfer points) and operational strategies (such as timetable synchronization and service availability) fundamentally shape the actual travel experience of users. These insights enable a more nuanced understanding of multimodal network accessibility.

Answers to the Sub-questions

1. A set of metrics has been identified and organized into an accessibility assessment framework, including the spatial integration of networks, availability of services, transfer impedance and the generalized travel costs.
2. A cohesive framework for network visualization was constructed, making usage of GTFS data, producing L-space and P-space graph representations that enable the extraction of standardized accessibility indicators
3. The extracted metrics from the theoretical framework enables an extensive and comparative evaluation of public transport network performances across different cities, revealing the key structural and temporal approaches and strategies of networks.
4. The network assessment enabled concrete, actionable planning insights. Networks have been classified into typologies based on their spatio-temporal strategies, with clear policy implications on how network accessibility can be strengthened by infrastructural investments and operational alignment.

Final Remarks

The primary contribution of this thesis lies in the development of a robust and transferable methodology for evaluating the accessibility of multimodal public transport systems. This contribution unfolds across four key dimensions:

- This research introduces a comprehensive metric-based framework that captures both spatial and temporal components of accessibility. By integrating indicators such as network structure, transfer impedance, service availability, and generalized travel cost, the framework enables multidimensional assessment of multimodal transit performance.
- The study offers systematic guidance for the processing of GTFS data into structured, graph-based network representations. This includes the generation of L-space and P-space models that allow consistent comparison of transit networks across different cities and modes.
- A standardized procedure for metric extraction and comparative analysis is proposed. This approach allows accessibility to be quantitatively evaluated in terms of user-relevant indicators, while preserving network heterogeneity across urban environments.
- The research demonstrates how insights derived from this analytical process can inform the classification of network types and support strategic planning. Although the results for twelve global cities illustrate the framework's application, the primary value lies in the underlying method, which is scalable, reproducible, and adaptable to different contexts.

Together, these contributions provide planners, researchers, and policymakers with a set of tools for diagnosing network performance and guiding interventions. By offering a clear and structured methodology, this thesis helps close the gap between academic analysis and practical decision-making in public transport planning.

8
Discussion and Recommendations

This chapter will reflect on the methodology and the findings presented in this report, adding critical notes to the strengths, limitations and implications of the analytical process. It will be addressed how the development of the accessibility framework can contribute to the understanding of multimodal public transport systems and how it identifies key areas for improvement for further research. The chapter concludes by outlining recommendations for further research on the development of integrated and equitable public transport networks.

8.1. Discussion

The framework developed in this report has allowed for a structured and comparative analysis of public transport systems across different aspects. By integrating spatial and temporal dimensions, the methodology has demonstrated how accessibility is shaped by the interaction of topology and operations.

The classification of network types has helped overcome theory and practice, translating technical metrics into user-based profiles. This method has not only enabled clarification of strengths and weaknesses of the different systems, but has also provided a basis for planning strategies and policy making.

A major strength of this study lies in the use of GTFS-based, graph-theoretic analysis to extract spatial and temporal accessibility indicators in a standardized way across cities. The application of both L-space and P-space allowed a nuanced look at both physical connectivity and operational coordination.

However, several limitations should be acknowledged. At first, the analysis is based on GTFS Schedule data, and therefore only reflects scheduled services in ideal circumstances. The actual performance of networks may therefore be overestimated. Working with real-time data and implementation of delays and disruptions would not only create a more realistic image of the system's performance, it would also allow for better assessment of the network's true robustness and resistance to disparities.

Another limit of GTFS datasets is that both land use and demand can not be explicitly modeled. As a result, accessibility is only looked at from a supply perspective. Taking into account real-life travel patterns and passenger volumes is not possible in this methodology.

This also holds for the time- and comfort-based modeling of travel impedance. One important aspect that is not taken into account in this research is the cost of traveling in monetary terms, which also adds impedance to public transport networks. Fare structures and zone-based pricing can significantly influence the accessibility of transit systems, as well is people's perception towards public transport. Integrating monetary cost into the model would allow a more comprehensive understanding of total accessibility, especially from the equity perspective.

Graph construction relies on administrative boundaries and node-merging rules that may simplify complex urban environments. Besides, sampling strategies and transfer limits, though computationally necessary, may slightly distort final simulation results. These limitations should be considered when interpreting the results of the comparative network analysis.

At last, this report offers general policy recommendations based on the network classifications. Translating these strategies into practice would require more attention to the local context of each city. This could include travel patterns, socioeconomic conditions and institutional context. These may vary across urban areas and strongly influence the feasibility and effectiveness of the policies that were proposed. Incorporating empirical data regarding travel patterns, financial constraints and institutional and legislative arrangements would allow future recommendations to be more accurate and feasible. This way, the planning strategies are not solely based on the performance of the system, but also align with the entire urban context.

8.2. Recommendations for Further Research

This thesis has developed a standardized methodology for assessing network accessibility of multimodal public transport systems based on GTFS data and graph-theoretical network representations. While this approach provides valuable insights into the spatial and temporal dimensions of accessibility, several limitations of this research point to opportunities for future research. This section therefore suggests five directions to improve the scope, realism, and policy relevance of the framework.

Integrate real-time data to assess operational robustness
The current analysis is based on scheduled service timetables, which do not account for delays, disruptions, or irregular operations. As a result, network performance may be overestimated. Future research should incorporate real-time transit data (e.g. GTFS Realtime) to evaluate how accessibility varies under non-ideal conditions. This would support a more accurate assessment of operational reliability and resilience, particularly in systems with frequent service variability.

Combine accessibility analysis with land use and demand patterns
The accessibility framework presented focuses on the supply side of public transport. However, it does not explicitly account for land use patterns or travel demand. Future studies could incorporate data on population density, employment locations, or actual origin-destination flows to identify where accessibility mismatches occur between transport supply and demand. This would help evaluate how well public transport networks serve different urban areas and user groups.

Include fare structures and travel costs in accessibility modeling
Monetary cost is an important factor in perceived and experienced accessibility, but is not included in the current model. As a result, all transit modes are treated as interchangeable, regardless of differences in fare levels, pricing structures, or ticketing systems. However, users may face significant financial barriers when switching between modes, especially in systems without integrated fare policies.

Incorporating fare structures, zone-based pricing, and affordability thresholds would allow for a more realistic estimation of travel impedance. It would also provide greater insight into the equity implications of public transport networks, by identifying areas and user groups for whom cost limits access to multimodal travel options. Future models should consider integrating monetary cost alongside temporal and spatial dimensions to produce a more comprehensive and user-sensitive measure of accessibility.

Implement individual behavior in travel cost and transfer modeling
The current approach applies generalized travel cost using fixed weightings for in-vehicle time, waiting time, and transfers. While this enables cross-city comparability, it does not reflect user-specific preferences or behaviors. Future research could explore ways to calibrate these weightings based on observed travel patterns or user surveys, allowing for more realistic modeling of travel choices and experiences.

Consider institutional and contextual factors in policy applications
Although this thesis provides general policy recommendations based on the spatio-temporal classification of network types, the practical implementation of these strategies depends on the local context. Factors as governance structures, agency coordination, funding models, and political priorities can strongly influence whether proposed improvements are feasible in a given city.

Further research should explore how these institutional conditions shape public transport performance and integration. The presence of a centralized transit authority may potentially facilitate cross-modal synchronization and fare integration, while fragmented agency responsibilities can hinder coordinated planning. Similarly, differences in financial autonomy, public investment capacity, or legal mandates may constrain the ability of cities to implement certain strategies, even when technical evidence supports them.

Understanding these contextual variables is essential to bridge the gap between theoretical performance analysis and real-world planning outcomes. By combining accessibility assessments with institutional analysis, future studies can offer more grounded and actionable recommendations that are tailored to the administrative and political realities of specific urban environments.

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A

GTFS Datasets

Table A.1: GTFS dataset overview

City	GTFS Feed Publisher	Publication Date	Source	Selected Date
Bangkok	Office of Transport and Traffic Policy and Planning	17-03-2025	MobilityData (2024)	10-12-2024
Berlin	Verkehrsverbind Berlin Brandenburg	28-10-2024	MobilityData (2024)	29-10-2024
Denver	Regional Transportation District (RTD)	31-03-2025	Interline Technologies LLC (2024)	20-02-2025
Melbourne	Metro V/Line Yarra Trams SkyBus Journey Beyond PTV Regional Bus PTV Metropolitan Bus PTV Regional Coach	14-03-2025 14-03-2025 14-03-2025 14-03-2025 14-03-2025 17-03-2025 17-03-2025 17-03-2025	Interline Technologies LLC (2024)	14-03-2025
Mexico City	Cablebus	23-12-2024	MobilityData (2024)	03-12-2024
New York City	MTA Subway MTA Bus Queens MTA BC MTA Bus Staten Island MTA Bus Brooklyn MTA Bus Manhattan MTA New York City Transit PATH MTA - Long Island Railroad MTA - Metro-North Rail NJ Transit Bus NJ Transit Train	07-02-2025 07-02-2025 15-02-2025 15-02-2025 15-02-2025 15-02-2025 16-02-2025 22-02-2025 24-02-2025 20-02-2025 20-01-2025 13-02-2025	Interline Technologies LLC (2024)	20-02-2025
Paris	Ile-de-France Mobilité	30-09-2024	MobilityData (2024)	22-10-2024
Prague	PID	02-10-2024	MobilityData (2024)	28-10-2024
Sao Paulo	SPTRANS	17-03-2025	MobilityData (2024)	05-12-2023
Singapore	Go Ahead Singapore	08-02-2024	MobilityData (2024)	01-06-2022
Toronto	Toronto Transit Commission GO Transit	30-09-2024 10-10-2024	MobilityData (2024)	14-10-2024
Valencia	EMT Valencia Metro Valencia Renfe Operadora	29-03-2025 16-03-2025 31-03-2025	Interline Technologies LLC (2024)	18-4-2025

B

Python Code: Generating Graphs

The functions presented in this appendix are modified and extended versions of a script originally obtained from a private GitLab repository maintained by TU Delft. The original codes served as a foundation and were substantially expanded to support multimodal public transport networks, spatial-temporal filtering, and enhanced node and edge annotations. Full source code of the base script, including standard, third-party and customized library imports, are not published here due to copyright and usage restrictions. For detailed information, see De Ruijter (2023).

B.1. Generate Multimodal Graph (L-space)

```python
def generate_multimodal_graph(gtfs_feed, modes, city_center, max_distance_km,
    start_hour=6, end_hour=24, date=None):

    if not (0 <= start_hour < end_hour <= 24):
        raise ValueError("Start hour must be >= 0 and end hour <= 24, with
            start_hour < end_hour")
    if not all(isinstance(mode, str) for mode in modes):
        raise TypeError("Modes should be a list of strings")
    if not isinstance(start_hour, int) or not isinstance(end_hour, int):
        raise TypeError("Start and end hours should be integers")
    if not date:
        raise ValueError("A date must be provided in 'YYYY-MM-DD' format")

    cursor = gtfs_feed.conn.cursor()
    cursor.execute("SELECT name FROM sqlite_master WHERE type='table' AND name='
        calendar_dates';")
    calendar_dates_count = 0
    if cursor.fetchone():
        cursor.execute("SELECT COUNT(*) FROM calendar_dates;")
        calendar_dates_count = cursor.fetchone()[0]

    print(f"Using date: {date}")
    day_start_unix = gtfs_feed.get_day_start_ut(date)
    range_start = start_hour * 3600
    range_end = end_hour * 3600 - 1

    total_trips = 0
    for mode in modes:
        if mode not in mode_code or mode_from_string(mode) not in gtfs_feed.
            get_modes():
            print(f"Skipping mode {mode}: Not available in dataset")
            continue
```

```

        valid_code = str(mode_from_string(mode))
        date_num = date.replace("-", "")

        if calendar_dates_count > 0:
            query = f"""
                SELECT COUNT(*)
                FROM stop_times st
                JOIN trips t ON st.trip_id = t.trip_id
                JOIN routes r ON t.route_id = r.route_id
                LEFT JOIN calendar_dates cd ON t.service_id = cd.service_id
                LEFT JOIN calendar c ON t.service_id = c.service_id
                WHERE (cd.date = '{date_num}' OR c.start_date = '{date_num}')
                  AND r.route_type = {valid_code}
                  AND (
                      (CAST(SUBSTR(st.departure_time, 1, 2) AS INTEGER) * 3600) +
                      (CAST(SUBSTR(st.departure_time, 4, 2) AS INTEGER) * 60) +
                      (CAST(SUBSTR(st.departure_time, 7, 2) AS INTEGER))
                  ) BETWEEN {range_start} AND {range_end}
            """
        else:
            query = f"""
                SELECT COUNT(*)
                FROM stop_times st
                JOIN trips t ON st.trip_id = t.trip_id
                JOIN routes r ON t.route_id = r.route_id
                JOIN calendar c ON t.service_id = c.service_id
                WHERE '{date_num}' BETWEEN c.start_date AND c.end_date
                  AND r.route_type = {valid_code}
                  AND (
                      (CAST(SUBSTR(st.departure_time, 1, 2) AS INTEGER) * 3600) +
                      (CAST(SUBSTR(st.departure_time, 4, 2) AS INTEGER) * 60) +
                      (CAST(SUBSTR(st.departure_time, 7, 2) AS INTEGER))
                  ) BETWEEN {range_start} AND {range_end}
            """

        count = pd.read_sql_query(query, gtfs_feed.conn).iloc[0, 0]
        print(f"Trips for mode {mode}: {count}")
        total_trips += count

    print(f"Total trips across modes: {total_trips}")
    multimodal_graph = nx.DiGraph()

    for mode in modes:
        if mode not in mode_code or mode_from_string(mode) not in gtfs_feed.
            get_modes():
            continue

        G_mode = networks.stop_to_stop_network_for_route_type(
            gtfs_feed,
            mode_from_string(mode),
            link_attributes=["shape_id", "headsign", "duration_avg", "n_vehicles",
                 "d", "route_I_counts", "direction_id"],
            start_time_ut=day_start_unix + range_start,
            end_time_ut=day_start_unix + range_end,
            date=date
        )

        for node, data in G_mode.nodes(data=True):
            data["mode"] = mode
            data["original_ids"] = [node]
```

```python
        for u, v, data in G_mode.edges(data=True):
            data["mode"] = mode

        multimodal_graph = nx.compose(multimodal_graph, G_mode)

    for node, data in multimodal_graph.nodes(data=True):
        data.setdefault("mode", "unknown")

    filtered_graph = filter_nodes_by_distance(multimodal_graph, city_center,
        max_distance_km)

    final_nodes_per_mode = {}
    for _, data in filtered_graph.nodes(data=True):
        m = data.get("mode", "unknown")
        final_nodes_per_mode[m] = final_nodes_per_mode.get(m, 0) + 1

    return filtered_graph, final_nodes_per_mode
```

Listing B.1: Function to generate Multimodal Graph

B.2. Spatial Filtering

```python
def filter_graph_by_city_boundaries(graph, polygon):
    nodes_to_keep = [
        node for node, data in graph.nodes(data=True)
        if "lat" in data and "lon" in data and polygon.contains(Point(data["lon"],
            data["lat"]))
    ]
    return graph.subgraph(nodes_to_keep).copy()

def merge_stops(graph, name_similarity_threshold=75, max_distance=500):
    print("Starting stop merging by mode...")

    merged_total = 0
    merged_ids = set()

    # Group nodes by mode
    mode_groups = {}
    for node, data in graph.nodes(data=True):
        mode = data.get("mode")
        if mode:
            mode_groups.setdefault(mode, []).append((node, data))

    for mode, node_data_list in mode_groups.items():
        print(f"\nProcessing mode: {mode} ({len(node_data_list)} stops)")

        df_stops = pd.DataFrame([data for _, data in node_data_list])
        df_stops["stop_id"] = [node for node, _ in node_data_list]
        df_stops["lat"] = df_stops["lat"].astype(float)
        df_stops["lon"] = df_stops["lon"].astype(float)
        coords_radians = np.radians(df_stops[["lat", "lon"]].values)

        earth_radius = 6371000  # meters
        tree = BallTree(coords_radians, metric='haversine')
        stop_ids = df_stops["stop_id"].tolist()
        merged = set()

        for i, row in df_stops.iterrows():
            stop_i = row["stop_id"]
            if stop_i not in graph.nodes or stop_i in merged or stop_i in
                merged_ids:
```

```
                continue

            latlon_rad = coords_radians[i].reshape(1, -1)
            indices = tree.query_radius(latlon_rad, r=max_distance / earth_radius)
                [0]

            for j in indices:
                stop_j = stop_ids[j]
                if stop_j == stop_i or stop_j in merged or stop_j in merged_ids:
                    continue

                name_i = str(graph.nodes[stop_i].get("name", "")).lower()
                name_j = str(graph.nodes[stop_j].get("name", "")).lower()

                if fuzz.ratio(name_i, name_j) >= name_similarity_threshold:
                    try:
                        merge_nodes(graph, stop_i, stop_j)
                        merged.add(stop_j)
                        merged_ids.add(stop_j)
                    except Exception as e:
                        print(f"Error merging {stop_i} and {stop_j}: {e}")

        print(f"Merged {len(merged)} stops in mode {mode}.")
        merged_total += len(merged)

    print(f"\nMerging complete across all modes. Total merged: {merged_total}")
```

Listing B.2: Function to perform spatial filtering of the graph

B.3. Sanity Check

```
def perform_sanity_check(graph):

    # Remove disconnected nodes (islands)
    islands = list(nx.isolates(graph))
    if islands:
        graph.remove_nodes_from(islands)
        print(f"Removed {len(islands)} disconnected nodes (islands).")
    else:
        print("No disconnected nodes found.")

    # Remove self-loops
    self_loops = [(u, v) for u, v in graph.edges if u == v]
    if self_loops:
        graph.remove_edges_from(self_loops)
        print(f"Removed {len(self_loops)} self-loop edges.")
    else:
        print("No self-loops found.")

    # Remove edges with invalid or zero duration
    invalid_duration_edges = [
        (u, v) for u, v, d in graph.edges(data=True)
        if d.get("duration_avg", 1) <= 0
    ]
    if invalid_duration_edges:
        graph.remove_edges_from(invalid_duration_edges)
        print(f"Removed {len(invalid_duration_edges)} edges with invalid durations
            .")
    else:
        print("No edges with invalid durations found.")
```

Listing B.3: Function to perform sanity check

B.4. Generate P-space Graph

```
def generate_pspace_graph(
    gtfs_feed,
    l_graph,
    modes,
    start_hour=5,
    end_hour=24,
    direction_field=None,
    max_transfer_distance=500
):

    if not (0 <= start_hour < end_hour <= 24):
        raise AssertionError("Start hour must be >= 0 and end hour <= 24, with start_hour < end_hour")
    if not all(isinstance(mode, str) for mode in modes):
        raise AssertionError("Modes should be a list of strings")

    analysis_duration = end_hour - start_hour
    p_graph = nx.DiGraph()
    p_graph.add_nodes_from(l_graph.nodes(data=True))

    for mode in modes:
        print(f"Processing mode: {mode}")
        routes = get_routes_for_mode(gtfs_feed, mode)

        # Automatically detect direction field if not provided
        if not direction_field:
            direction_field = 'direction_id'
            for _, _, edge_data in l_graph.edges(data=True):
                if 'headsign' in edge_data:
                    direction_field = 'headsign'
                elif 'shape_id' in edge_data:
                    direction_field = 'shape_id'
                break
        print(f"Using '{direction_field}' as direction indicator.")

        for route in routes:
            directions = set()
            for _, _, edge_data in l_graph.edges(data=True):
                if route in edge_data.get('route_I_counts', {}):
                    for val in edge_data.get(direction_field, {}):
                        directions.add(val)

            for direction in directions:
                route_subgraph = nx.DiGraph()

                for u, v, edge_data in l_graph.edges(data=True):
                    if (
                        route in edge_data.get('route_I_counts', {}) and
                        direction in edge_data.get(direction_field, {})
                    ):
                        route_subgraph.add_edge(u, v, **edge_data)

                for source_node in route_subgraph:
                    for target_node in route_subgraph:
                        if source_node != target_node and nx.has_path(route_subgraph, source_node, target_node):
                            path = nx.shortest_path(route_subgraph, source_node, target_node)

                            out_edge = next((
```

```
                                (a, b, d) for a, b, d in route_subgraph.out_edges(source_node, data=True)
                                if a in path and b in path
                            ), None)
                            in_edge = next((
                                (a, b, d) for a, b, d in route_subgraph.in_edges(target_node, data=True)
                                if a in path and b in path
                            ), None)

                            if out_edge and in_edge:
                                vehicles_out = out_edge[2]['route_I_counts'][route]
                                vehicles_in = in_edge[2]['route_I_counts'][route]
                                vehicles = min(vehicles_out, vehicles_in)

                                veh_per_hour = vehicles / analysis_duration
                                max_wait = 60 / veh_per_hour
                                avg_wait = max_wait / 2

                                if p_graph.has_edge(source_node, target_node):
                                    p_graph[source_node][target_node]['veh'].setdefault(route, {})[direction] = veh_per_hour
                                    total_veh = sum(
                                        sum(d.values()) for d in p_graph[source_node][target_node]['veh'].values()
                                    )
                                    p_graph[source_node][target_node]['avg_wait'] = (60 / total_veh) / 2
                                    p_graph[source_node][target_node]['mode'] = mode
                                else:
                                    p_graph.add_edge(
                                        source_node,
                                        target_node,
                                        veh={route: {direction: veh_per_hour}},
                                        avg_wait=avg_wait,
                                        mode=mode
                                    )

    print(f"Final P-space graph: {len(p_graph.nodes())} nodes, {len(p_graph.edges())} edges.")
    return p_graph
```

Listing B.4: Function to generate P-space graph

C

Python Code: Multimodal Systems

C.1. Intermodal Transfer Edges

```
def add_intermodal_transfer_edges(
    graph,
    gtfs_feed,
    max_geodesic_distance=500,
    max_walking_distance=400
):

    stop_query = "SELECT stop_id, stop_lat, stop_lon FROM stops"
    stops_df = pd.read_sql_query(stop_query, gtfs_feed.conn)
    stop_locations = {
        row["stop_id"]: (row["stop_lat"], row["stop_lon"])
        for _, row in stops_df.iterrows()
    }

    candidate_edges = []
    nodes = list(graph.nodes(data=True))

    for i, (stop1, data1) in enumerate(nodes):
        for j, (stop2, data2) in enumerate(nodes):
            if i >= j:
                continue
            if data1["mode"] == data2["mode"]:
                continue

            coord1 = stop_locations.get(stop1)
            coord2 = stop_locations.get(stop2)

            if coord1 and coord2:
                geod_dist = geodesic(coord1, coord2).meters
                if geod_dist <= max_geodesic_distance:
                    candidate_edges.append((stop1, stop2, coord1, coord2))

    for index, (stop1, stop2, coord1, coord2) in enumerate(candidate_edges, start=1):
        travel_time, walk_dist = calculate_walking_time(coord1, coord2)

        if travel_time is not None and walk_dist <= max_walking_distance:
            graph.add_edge(
                stop1, stop2,
                type="transfer",
                travel_time=travel_time,
```

```
                length=walk_dist,
                weight=walk_dist
            )
            graph.add_edge(
                stop2, stop1,
                type="transfer",
                travel_time=travel_time,
                length=walk_dist,
                weight=walk_dist
            )

    return graph
```

Listing C.1: Function to add intermodal transfer edges to the graph

C.2. GTC-based OD-matrix

```
def assign_gtc_weights(
    graph_l,
    graph_p,
    wait_penalty,
    transfer_penalty,
    transfer_penalties_by_mode
):

    for u, v, data in graph_l.edges(data=True):
        in_vehicle_time = data.get('duration_avg', 300) / 60
        transfer_travel_time = data.get('travel_time', 0) / 60
        wait_time = graph_p[u][v].get('avg_wait', 5) if graph_p.has_edge(u, v)
            else 5

        wait_component = wait_time * wait_penalty

        mode_u = graph_l.nodes[u].get("mode")
        mode_v = graph_l.nodes[v].get("mode")
        transfer_cost = 0
        if mode_u and mode_v:
            pair = (mode_u, mode_v)
            if mode_u != mode_v or data.get("type") == "transfer":
                transfer_cost = transfer_penalties_by_mode.get(pair, 0)

        gtc = in_vehicle_time + wait_component + transfer_cost +
            transfer_travel_time
        graph_l[u][v]['gtc_weight'] = gtc

    return graph_l


def sample_od_pairs(
    graph_l,
    graph_p,
    nodes,
    k_paths,
    wait_penalty,
    transfer_penalty,
    max_intermodal,
    max_total,
    transfer_penalties_by_mode,
    runtime_limit,
    max_trials
):
```

```python

    start = time.time()
    results = {}
    od_pairs = []
    seen = set()
    trials = 0
    sample_target = 10000
    duration_limit = runtime_limit * 60

    while trials < max_trials:
        if time.time() - start > duration_limit:
            break

        o, d = random.sample(nodes, 2)
        if o == d or (o, d) in seen:
            continue

        if o not in results:
            results[o] = {}

        try:
            paths = k_shortest_paths(graph_l, o, d, k_paths, 'gtc_weight')
        except:
            trials += 1
            continue

        for path in paths:
            try:
                dist, tt, wait, transfer_tt = 0, 0, 0, 0
                mode_transfers = []
                intermodal, intramodal = [], []
                current_mode = graph_l.nodes[path[0]].get('mode')
                routes = None
                transfers = [o]

                for u, v in zip(path, path[1:]):
                    data = graph_l[u][v]
                    tt += data.get('duration_avg', 300)
                    dist += data.get('d', 0)
                    next_mode = graph_l.nodes[v].get('mode')
                    rset = get_routes_dirs_multimodal(graph_p, u, v)

                    t_flag = False
                    if rset == {"transfer"} or (routes and not rset.intersection(
                        routes)) or (current_mode != next_mode):
                        t_flag = True

                    if t_flag:
                        transfers.append(u)
                        transfer_tt += data.get('travel_time', 0) / 60
                        mode_transfers.append((current_mode, next_mode))
                        (intermodal if current_mode != next_mode else intramodal).
                            append(u)

                    current_mode = next_mode
                    routes = rset if rset != {"transfer"} else set()

                transfers.append(d)
                tt_min = round(tt / 60)

                for u, v in zip(transfers, transfers[1:]):
```

```
                    wait += graph_p[u][v].get('avg_wait', 5) if graph_p.has_edge(u, v) else 5

                wait = round(wait)
                transfer_tt = math.ceil(transfer_tt)

                penalties = [
                    transfer_penalties_by_mode.get(pair, 0) + (transfer_penalty if i > 0 else 0)
                    for i, pair in enumerate(mode_transfers)
                ]

                total_pen = sum(penalties)
                total_inter = sum(p for i, p in enumerate(penalties) if mode_transfers[i][0] != mode_transfers[i][1])
                total_intra = sum(p for i, p in enumerate(penalties) if mode_transfers[i][0] == mode_transfers[i][1])

                n_inter, n_intra = len(intermodal), len(intramodal)
                n_total = n_inter + n_intra

                if n_inter > max_intermodal or n_total > max_total:
                    continue

                total_gtc = tt_min + wait * wait_penalty + total_pen + transfer_tt
                result = {
                    'path': path,
                    'GTC': total_gtc,
                    'in_vehicle': tt_min,
                    'waiting_time': wait,
                    'transfer_travel_time': transfer_tt,
                    'n_intermodal_transfers': n_inter,
                    'n_intramodal_transfers': n_intra,
                    'n_total_transfers': n_total,
                    'traveled_distance': dist,
                    'mode_transfers': mode_transfers,
                    'transfer_stations': transfers,
                    'total_transfer_penalty': total_pen,
                    'total_intermodal_transfer_penalty': total_inter,
                    'total_intramodal_transfer_penalty': total_intra,
                    'intermodal_transfer_nodes': intermodal,
                    'intramodal_transfer_nodes': intramodal
                }

                results[o][d] = [result]
                seen.add((o, d))
                od_pairs.append((o, d))

                if len(od_pairs) >= sample_target:
                    return results, od_pairs

                break

            except:
                continue

        trials += 1

    return results, od_pairs
```

Listing C.2: Function to calculate GTC-based OD-matrix

D

OD-matrix Details

In case no value is filled in for 'Actual Matrix Size', the matrix size equals the number of desired valid OD-pairs.

Table D.1: Overview of OD pair sampling efficiency and coverage

City name	Attempts for 10,000 Valid OD-pairs	% Valid Pairs	Final %	Desired Valid OD-pairs	Actual Matrix Size
Bangkok	10,007	0.999	0.0500	457,682	-
Berlin	35,584	0.281	0.0141	123,201	-
Denver	19,763	0.506	0.0253	17,198	-
Melbourne	57,420	0.174	0.00870	296,871	226,813
Mexico City	59,410	0.168	0.00842	134,753	-
New York City	14,297	0.699	0.0350	3,936,682	792,548
Paris	24,646	0.4057	0.0203	36,805	-
Prague	28,046	0.357	0.0173	45,374	-
Sao Paulo	29,263	0.342	0.0171	957,647	209,117
Singapore	14,602	0.685	0.0342	352,849	-
Toronto	28,500	0.351	0.0175	234,358	-
Valencia	20,539	0.487	0.0243	2,558	-

E

Python Code: Metric Extraction

```
# --- Node Statistics ---

Nodes_L = L_graph.number_of_nodes()

modes = ['Bus', 'Tram', 'Rail', 'Subway']
modal_counts = {mode: 0 for mode in modes}
for _, data in L_graph.nodes(data=True):
    mode = data.get('mode', 'unknown')
    if mode in modal_counts:
        modal_counts[mode] += 1

# --- Link Statistics ---

Links_L = L_graph.number_of_edges()
Links_P = P_graph.number_of_edges()

# --- Vehicle Movements (Peak) ---

total_vehicle_movements = sum(data.get("n_vehicles", 0) for _, _, data in L_graph.
    edges(data=True))
movements_by_mode = {}
for _, _, data in L_graph.edges(data=True):
    mode = data.get("mode", "unknown")
    if mode != "unknown":
        movements_by_mode[mode] = movements_by_mode.get(mode, 0) + data.get("
            n_vehicles", 0)

# --- Transfer Edge Analysis ---

transfer_edges = [(u, v) for u, v, attr in L_graph.edges(data=True) if attr.get("
    type") == "transfer"]
num_unique_transfers = len(transfer_edges) // 2
num_nodes = L_graph.number_of_nodes()
transfers_per_node = num_unique_transfers / num_nodes

nodes_with_transfers = {n for edge in transfer_edges for n in edge}
num_nodes_with_transfers = len(nodes_with_transfers)
percentage_nodes_with_transfers = (num_nodes_with_transfers / num_nodes) * 100

from collections import defaultdict
transfer_edge_counts = defaultdict(int)
for u, v, data in L_graph.edges(data=True):
    if data.get("type") == "transfer":
```

```
        mode_u = L_graph.nodes[u].get("mode", "unknown")
        mode_v = L_graph.nodes[v].get("mode", "unknown")
        if mode_u != mode_v:
            pair = tuple(sorted([mode_u, mode_v]))
            transfer_edge_counts[pair] += 1

# --- Transfer Lengths ---

def collect_all_transfer_lengths(graph, min_duration=5):
    lengths = []
    for u, v, data in graph.edges(data=True):
        if data.get("type") == "transfer":
            if graph.nodes[u].get("mode") != graph.nodes[v].get("mode"):
                try:
                    length = float(data.get("length", 0))
                    if length >= min_duration:
                        lengths.append(length)
                except:
                    pass
    return lengths

all_durations = collect_all_transfer_lengths(L_graph)

# --- Intermodal Degree ---

def compute_intermodal_degree(graph):
    return {
        node: len({graph.nodes[neighbor].get('mode') for neighbor in graph.
            neighbors(node) if graph.nodes[neighbor].get('mode')})
        for node in graph.nodes
    }

# --- Degree Centrality ---

deg_L = nx.degree_centrality(L_graph)
deg_P = nx.degree_centrality(P_graph)
nx.set_node_attributes(L_graph, deg_L, "Degree")
nx.set_node_attributes(P_graph, deg_P, "Degree")

# --- Characteristic Path Length and Connectivity ---

CPL_L = nx.average_shortest_path_length(L_graph)
CPL_P = nx.average_shortest_path_length(P_graph)
Gamma_L = Links_L / (3 * Nodes_L - 6)
Gamma_P = Links_P / (3 * Nodes_L - 6)

# --- Assortativity Coefficients ---

assort_L = nx.degree_assortativity_coefficient(L_graph)
assort_P = nx.degree_assortativity_coefficient(P_graph)
mode_assort_L = nx.attribute_assortativity_coefficient(L_graph, "mode")
mode_assort_P = nx.attribute_assortativity_coefficient(P_graph, "mode")

# --- Temporal Parameters ---
interval_hours = 2

# --- Peak: Vehicle Movements ---
movements_by_mode = {}
for _, _, data in L_graph.edges(data=True):
    mode = data.get("mode", "unknown")
    if mode != "unknown":
```

```python
        movements_by_mode[mode] = movements_by_mode.get(mode, 0) + data.get("
            n_vehicles", 0)

total_vehicle_movements = sum(movements_by_mode.values())

modal_node_counts = {
    mode: sum(1 for _, d in L_graph.nodes(data=True) if d.get("mode") == mode)
    for mode in movements_by_mode
}

mode_weights = {
    mode: count / total_vehicle_movements
    for mode, count in movements_by_mode.items()
}

weighted_scores = {
    mode: (movements_by_mode[mode] / (modal_node_counts.get(mode, 1) *
        interval_hours)) * mode_weights[mode]
    for mode in movements_by_mode
}

composite_score = sum(weighted_scores.values())

# --- Off-Peak: Vehicle Movements ---
movements_by_mode_offpeak = {}
for _, _, data in L_graph_offpeak.edges(data=True):
    mode = data.get("mode", "unknown")
    if mode != "unknown":
        movements_by_mode_offpeak[mode] = movements_by_mode_offpeak.get(mode, 0) +
             data.get("n_vehicles", 0)

total_vehicle_movements_offpeak = sum(movements_by_mode_offpeak.values())

modal_node_counts_offpeak = {
    mode: sum(1 for _, d in L_graph_offpeak.nodes(data=True) if d.get("mode") ==
        mode)
    for mode in movements_by_mode_offpeak
}

mode_weights_offpeak = {
    mode: count / total_vehicle_movements_offpeak
    for mode, count in movements_by_mode_offpeak.items()
}

weighted_scores_offpeak = {
    mode: (movements_by_mode_offpeak[mode] / (modal_node_counts_offpeak.get(mode,
        1) * interval_hours)) * mode_weights_offpeak[mode]
    for mode in movements_by_mode_offpeak
}

composite_score_offpeak = sum(weighted_scores_offpeak.values())
```

Listing E.1: Function to extract metrics

F

Full Results

F.1. Bangkok

Table F.1: Accessibility assessment framework results for Bangkok

Network Statistics	
Number of Nodes	3026
Edges in L-space	6770
Edges in P-space	422042
Total Vehicle Movements	535881
Spatial Indicators	
Unique Transfer Edges	160
Transfer Edges per Node	0.0529
Nodes with Transfer Edges	255 (8.43%)
Intermodal Transfer Edge Length (m)	Mean: 225.32, SD: 120.66, Min: 5.20, Max: 400.00
Degree Centrality (Mean)	L-space: 0.001479, P-space: 0.040443
Degree Assortativity Coefficient	L-space: 0.2633, P-space: 0.1539
CPL	L-Space: 2.7457, P-Space: 0.4220
Connectivity γ	L-Space: 0.2466, P-Space: 15.3739
Intermodal Degree (Mean)	L-space: 1.0806, P-space: 1.1381
Mode Assortativity Coefficient	L-space: 0.6309, P-space: 0.8194
Temporal Indicators (Peak)	
Weighted Service Availability Score	90.50
Weighted Vehicle Movements per Node per Hour	Bus: 89.48, Subway: 0.64, Tram: 0.39, Rail: 0.00
Average Generalized Travel Cost (GTC)	59.42 min
GTC Composition	IVT: 69.6%, Wait: 10.5% (6.27 min), Transfer: 8.2%
GTC Thresholds	Max: 264.00 min, $\bar{t}_{25}$: 38.00, $\bar{t}_{50}$: 50.00, $\bar{t}_{75}$: 71.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 14.39%, $\bar{t}_{50}$: 18.94%, $\bar{t}_{75}$: 26.89%
Avg. Intermodal Transfer Wait Score	25.42 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	80.53
Weighted Avg. Waiting Time	9.59 min
Avg. Intermodal Transfer Wait	37.01 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	0.890
Average Wait Time Ratio	1.531
Wait Contribution to GTC Ratio	0.993
Intermodal Synchronization Ratio	1.456

F.2. Berlin

Table F.2: Accessibility assessment framework results for Berlin

Network Statistics	
Number of Nodes	2967
Edges in L-space	7890
Edges in P-space	62067
Total Vehicle Movements	223662
Spatial Indicators	
Unique Transfer Edges	526
Transfer Edges per Node	0.1773
Nodes with Transfer Edges	765 (25.78%)
Intermodal Transfer Edge Length (m)	Mean: 231.16, SD: 118.26, Min: 5.20, Max: 399.00
Degree Centrality (Mean)	L-space: 0.001793, P-space: 0.014106
Degree Assortativity Coefficient	L-space: 0.1641, P-space: 0.2029
CPL	L-Space: 1.9819, P-Space: 0.6360
Connectivity γ	L-Space: 0.2990, P-Space: 2.3518
Intermodal Degree (Mean)	L-space: 1.2922, P-space: 1.3411
Mode Assortativity Coefficient	L-space: 0.6400, P-space: 0.8976
Temporal Indicators (Peak)	
Weighted Service Availability Score	41.01
Weighted Vehicle Movements per Node per Hour	Bus: 21.86, Subway: 3.28, Tram: 10.19, Rail: 5.68
Average Generalized Travel Cost (GTC)	97.34 min
GTC Composition	IVT: 31.1%, Wait: 12.7% (12.40 min), Transfer: 43.7%
GTC Thresholds	Max: 333.00 min, $\bar{t}_{25}$: 75.00, $\bar{t}_{50}$: 100.00, $\bar{t}_{75}$: 121.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 22.52%, $\bar{t}_{50}$: 30.03%, $\bar{t}_{75}$: 36.34%
Avg. Intermodal Transfer Wait Score	27.47 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	46.17
Weighted Avg. Waiting Time	11.56 min
Avg. Intermodal Transfer Wait	27.05 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	1.126
Average Wait Time Ratio	0.932
Wait Contribution to GTC Ratio	0.942
Intermodal Synchronization Ratio	0.984

F.3. Denver

Table F.3: Accessibility assessment framework results for Denver

Network Statistics	
Number of Nodes	825
Edges in L-space	1678
Edges in P-space	15855
Total Vehicle Movements	21366
Spatial Indicators	
Unique Transfer Edges	31
Transfer Edges per Node	0.0376
Nodes with Transfer Edges	45 (5.45%)
Intermodal Transfer Edge Length (m)	Mean: 251.53, SD: 117.66, Min: 29.30, Max: 392.00
Degree Centrality (Mean)	L-space: 0.004937, P-space: 0.046646
Degree Assortativity Coefficient	L-space: 0.2721, P-space: 0.0783
CPL	L-Space: 3.2272, P-Space: 0.6066
Connectivity γ	L-Space: 0.8238, P-Space: 7.7838
Intermodal Degree (Mean)	L-space: 1.0545, P-space: 1.0545
Mode Assortativity Coefficient	L-space: 0.5962, P-space: 0.8663
Temporal Indicators (Peak)	
Weighted Service Availability Score	14.54
Weighted Vehicle Movements per Node per Hour	Bus: 11.06, Tram: 3.27, Rail: 0.21
Average Generalized Travel Cost (GTC)	101.90 min
GTC Composition	IVT: 23.3%, Wait: 18.5% (18.86 min), Transfer: 39.0%
GTC Thresholds	Max: 261.00 min, $\bar{t}_{25}$: 75.00, $\bar{t}_{50}$: 105.00, $\bar{t}_{75}$: 130.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 28.74%, $\bar{t}_{50}$: 40.23%, $\bar{t}_{75}$: 49.81%
Avg. Intermodal Transfer Wait Score	24.67 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	16.61
Weighted Avg. Waiting Time	16.40 min
Avg. Intermodal Transfer Wait	22.53 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	1.142
Average Wait Time Ratio	0.869
Wait Contribution to GTC Ratio	0.900
Intermodal Synchronization Ratio	0.913

F.4. Melbourne

Table F.4: Accessibility assessment framework results for Melbourne

Network Statistics	
Number of Nodes	5842
Edges in L-space	12631
Edges in P-space	116356
Total Vehicle Movements	762033
Spatial Indicators	
Unique Transfer Edges	408
Transfer Edges per Node	0.0698
Nodes with Transfer Edges	596 (10.2%)
Intermodal Transfer Edge Length (m)	Mean: 182.57, SD: 106.91, Min: 5.70, Max: 395.70
Degree Centrality (Mean)	L-space: 0.00074, P-space: 0.00682
Degree Assortativity Coefficient	L-space: 0.1313, P-space: 0.2509
CPL	L-Space: 3.3148, P-Space: 0.7781
Connectivity γ	L-Space: 0.1234, P-Space: 1.1368
Intermodal Degree (Mean)	L-space: 1.1034, P-space: 1.1838
Mode Assortativity Coefficient	L-space: 0.7701, P-space: 0.9402
Temporal Indicators (Peak)	
Weighted Service Availability Score	85.02
Weighted Vehicle Movements per Node per Hour	Bus: 36.05, Subway: 8.44, Tram: 40.34, Rail: 0.19
Average Generalized Travel Cost (GTC)	112.47 min
GTC Composition	IVT: 36.7%, Wait: 10.7% (12.07 min), Transfer: 38.4%
GTC Thresholds	Max: 349.00 min, $\bar{t}_{25}$: 84.00, $\bar{t}_{50}$: 113.00, $\bar{t}_{75}$: 141.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 24.07%, $\bar{t}_{50}$: 32.38%, $\bar{t}_{75}$: 40.40%
Avg. Intermodal Transfer Wait Score	29.54 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	96.02
Weighted Avg. Waiting Time	11.20 min
Avg. Intermodal Transfer Wait	27.93 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	1.129
Average Wait Time Ratio	0.928
Wait Contribution to GTC Ratio	0.962
Intermodal Synchronization Ratio	0.945

F.5. Mexico City

Table F.5: Accessibility assessment framework results for Mexico City

Network Statistics	
Number of Nodes	4001
Edges in L-space	7927
Edges in P-space	68224
Total Vehicle Movements	363342
Spatial Indicators	
Unique Transfer Edges	155
Transfer Edges per Node	0.0387
Nodes with Transfer Edges	253 (6.32%)
Intermodal Transfer Edge Length (m)	Mean: 228.27, SD: 106.16, Min: 6.60, Max: 396.30
Degree Centrality (Mean)	L-space: 0.000991, P-space: 0.008526
Degree Assortativity Coefficient	L-space: 0.0730, P-space: 0.4570
CPL	L-Space: 3.2349, P-Space: 0.7079
Connectivity γ	L-Space: 0.1651, P-Space: 1.4213
Intermodal Degree (Mean)	L-space: 1.0610, P-space: 1.0610
Mode Assortativity Coefficient	L-space: 0.6913, P-space: 0.9518
Temporal Indicators (Peak)	
Weighted Service Availability Score	50.46
Weighted Vehicle Movements per Node per Hour	Bus: 37.67, Subway: 12.33, Tram: 0.46
Average Generalized Travel Cost (GTC)	101.21 min
GTC Composition	IVT: 35.8%, Wait: 10.0% (10.15 min), Transfer: 43.4%
GTC Thresholds	Max: 424.00 min, $\bar{t}_{25}$: 75.00, $\bar{t}_{50}$: 100.00, $\bar{t}_{75}$: 125.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 17.69%, $\bar{t}_{50}$: 23.58%, $\bar{t}_{75}$: 29.48%
Avg. Intermodal Transfer Wait Score	18.91 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	51.07
Weighted Avg. Waiting Time	10.00 min
Avg. Intermodal Transfer Wait	18.38 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	1.012
Average Wait Time Ratio	0.985
Wait Contribution to GTC Ratio	0.992
Intermodal Synchronization Ratio	0.972

F.6. New York City

Table F.6: Accessibility assessment framework results for New York City

Network Statistics	
Number of Nodes	10606
Edges in L-space	19566
Edges in P-space	122519
Total Vehicle Movements	792348
Spatial Indicators	
Unique Transfer Edges	1200
Transfer Edges per Node	0.1131
Nodes with Transfer Edges	1306 (12.31%)
Intermodal Transfer Edge Length (m)	Mean: 242.81, SD: 108.63, Min: 5.70, Max: 399.70
Degree Centrality (Mean)	L-space: 0.000348, P-space: 0.009331
Degree Assortativity Coefficient	L-space: 0.2144, P-space: 0.1251
CPL	L-Space: 2.6360, P-Space: 0.5362
Connectivity γ	L-Space: 0.0580, P-Space: 0.3631
Intermodal Degree (Mean)	L-space: 1.1255, P-space: 1.1678
Mode Assortativity Coefficient	L-space: 0.2000, P-space: 0.9252
Temporal Indicators (Peak)	
Weighted Service Availability Score	38.01
Weighted Vehicle Movements per Node per Hour	Bus: 35.16, Subway: 2.42, Rail: 0.43
Average Generalized Travel Cost (GTC)	120.09 min
GTC Composition	IVT: 54.2%, Wait: 10.6% (12.77 min), Transfer: 24.5%
GTC Thresholds	Max: 319.00 min, $\bar{t}_{25}$: 96.00, $\bar{t}_{50}$: 123.00, $\bar{t}_{75}$: 147.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 30.09%, $\bar{t}_{50}$: 38.56%, $\bar{t}_{75}$: 46.08%
Avg. Intermodal Transfer Wait Score	15.72 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	47.76
Weighted Avg. Waiting Time	9.32 min
Avg. Intermodal Transfer Wait	20.87 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	1.257
Average Wait Time Ratio	0.730
Wait Contribution to GTC Ratio	0.947
Intermodal Synchronization Ratio	1.328

F.7. Paris

Table F.7: Accessibility assessment framework results for Paris

Network Statistics	
Number of Nodes	1347
Edges in L-space	4462
Edges in P-space	25550
Total Vehicle Movements	227400
Spatial Indicators	
Unique Transfer Edges	689
Transfer Edges per Node	0.5115
Nodes with Transfer Edges	779 (57.83%)
Intermodal Transfer Edge Length (m)	Mean: 251.31, SD: 109.31, Min: 13.00, Max: 399.80
Degree Centrality (Mean)	L-space: 0.004922, P-space: 0.028184
Degree Assortativity Coefficient	L-space: 0.0771, P-space: 0.1334
CPL	L-Space: 1.6131, P-Space: 0.5082
Connectivity γ	L-Space: 0.8210, P-Space: 4.7009
Intermodal Degree (Mean)	L-space: 1.6459, P-space: 1.6459
Mode Assortativity Coefficient	L-space: 0.3579, P-space: 0.8861
Temporal Indicators (Peak)	
Weighted Service Availability Score	123.51
Weighted Vehicle Movements per Node per Hour	Bus: 26.51, Subway: 83.66, Tram: 2.50, Rail: 10.85
Average Generalized Travel Cost (GTC)	70.29 min
GTC Composition	IVT: 26.1%, Wait: 9.8% (6.88 min), Transfer: 49.9%
GTC Thresholds	Max: 167.00 min, $\bar{t}_{25}$: 54.00, $\bar{t}_{50}$: 70.00, $\bar{t}_{75}$: 88.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 32.34%, $\bar{t}_{50}$: 41.92%, $\bar{t}_{75}$: 52.69%
Avg. Intermodal Transfer Wait Score	22.36 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	98.15
Weighted Avg. Waiting Time	12.94 min
Avg. Intermodal Transfer Wait	21.72 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	0.795
Average Wait Time Ratio	1.881
Wait Contribution to GTC Ratio	1.532
Intermodal Synchronization Ratio	0.971

F.8. Prague

Table F.8: Accessibility assessment framework results for Prague

Network Statistics	
Number of Nodes	1620
Edges in L-space	4313
Edges in P-space	36480
Total Vehicle Movements	157253
Spatial Indicators	
Unique Transfer Edges	270
Transfer Edges per Node	0.1667
Nodes with Transfer Edges	379 (23.4%)
Intermodal Transfer Edge Length (m)	Mean: 236.76, SD: 114.94, Min: 5.00, Max: 399.50
Degree Centrality (Mean)	L-space: 0.003289, P-space: 0.027818
Degree Assortativity Coefficient	L-space: 0.0790, P-space: 0.4397
CPL	L-Space: 2.0582, P-Space: 0.6119
Connectivity γ	L-Space: 0.5485, P-Space: 4.6392
Intermodal Degree (Mean)	L-space: 1.2981, P-space: 1.3667
Mode Assortativity Coefficient	L-space: 0.6108, P-space: 0.7867
Temporal Indicators (Peak)	
Weighted Service Availability Score	59.67
Weighted Vehicle Movements per Node per Hour	Bus: 24.69, Tram: 29.03, Subway: 5.81, Rail: 0.15
Average Generalized Travel Cost (GTC)	94.13 min
GTC Composition	IVT: 30.1%, Wait: 12.8% (12.09 min), Transfer: 42.5%
GTC Thresholds	Max: 360.00 min, $\bar{t}_{25}$: 70.00, $\bar{t}_{50}$: 95.00, $\bar{t}_{75}$: 117.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 19.44%, $\bar{t}_{50}$: 26.39%, $\bar{t}_{75}$: 32.50%
Avg. Intermodal Transfer Wait Score	28.52 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	49.58
Weighted Avg. Waiting Time	12.96 min
Avg. Intermodal Transfer Wait	29.20 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	0.831
Average Wait Time Ratio	1.072
Wait Contribution to GTC Ratio	1.046
Intermodal Synchronization Ratio	1.024

F.9. São Paulo

Table F.9: Accessibility assessment framework results for São Paulo

Network Statistics	
Number of Nodes	7484
Edges in L-space	16734
Edges in P-space	238016
Total Vehicle Movements	501457
Spatial Indicators	
Unique Transfer Edges	146
Transfer Edges per Node	0.0195
Nodes with Transfer Edges	216 (2.89%)
Intermodal Transfer Edge Length (m)	Mean: 245.11, SD: 118.29, Min: 7.90, Max: 399.00
Degree Centrality (Mean)	L-space: 0.000598, P-space: 0.008500
Degree Assortativity Coefficient	L-space: 0.1277, P-space: 0.1788
CPL	L-Space: 3.4089, P-Space: 0.6020
Connectivity γ	L-Space: 0.0996, P-Space: 1.4169
Intermodal Degree (Mean)	L-space: 1.0295, P-space: 1.0295
Mode Assortativity Coefficient	L-space: 0.6097, P-space: 0.8675
Temporal Indicators (Peak)	
Weighted Service Availability Score	33.74
Weighted Vehicle Movements per Node per Hour	Bus: 32.48, Subway: 1.19, Rail: 0.07
Average Generalized Travel Cost (GTC)	130.00 min
GTC Composition	IVT: 45.3%, Wait: 11.5% (14.91 min), Transfer: 31.7%
GTC Thresholds	Max: 402.00 min, $\bar{t}_{25}$: 96.00, $\bar{t}_{50}$: 130.00, $\bar{t}_{75}$: 163.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 23.88%, $\bar{t}_{50}$: 32.34%, $\bar{t}_{75}$: 40.55%
Avg. Intermodal Transfer Wait Score	28.23 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	23.88
Weighted Avg. Waiting Time	16.85 min
Avg. Intermodal Transfer Wait	28.92 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	0.708
Average Wait Time Ratio	1.130
Wait Contribution to GTC Ratio	1.105
Intermodal Synchronization Ratio	1.024

F.10. Singapore

Table F.10: Accessibility assessment framework results for Singapore

Network Statistics	
Number of Nodes	2657
Edges in L-space	6566
Edges in P-space	183236
Total Vehicle Movements	669734
Spatial Indicators	
Unique Transfer Edges	151
Transfer Edges per Node	0.0568
Nodes with Transfer Edges	246 (9.26%)
Intermodal Transfer Edge Length (m)	Mean: 251.33, SD: 115.26, Min: 7.60, Max: 398.30
Degree Centrality (Mean)	L-space: 0.001861, P-space: 0.051930
Degree Assortativity Coefficient	L-space: 0.1873, P-space: 0.2591
CPL	L-Space: 1.9868, P-Space: 0.4065
Connectivity γ	L-Space: 0.3103, P-Space: 8.6583
Intermodal Degree (Mean)	L-space: 1.0926, P-space: 1.0926
Mode Assortativity Coefficient	L-space: 0.6688, P-space: 0.9585
Temporal Indicators (Peak)	
Weighted Service Availability Score	127.96
Weighted Vehicle Movements per Node per Hour	Bus: 126.10, Subway: 1.86
Average Generalized Travel Cost (GTC)	88.28 min
GTC Composition	IVT: 46.2%, Wait: 8.3% (7.36 min), Transfer: 37.4%
GTC Thresholds	Max: 265.00 min, $\bar{t}_{25}$: 60.00, $\bar{t}_{50}$: 87.00, $\bar{t}_{75}$: 115.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 22.64%, $\bar{t}_{50}$: 32.83%, $\bar{t}_{75}$: 43.40%
Avg. Intermodal Transfer Wait Score	9.20 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	110.78
Weighted Avg. Waiting Time	7.39 min
Avg. Intermodal Transfer Wait	9.17 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	0.866
Average Wait Time Ratio	1.004
Wait Contribution to GTC Ratio	1.010
Intermodal Synchronization Ratio	0.996

F.11. Toronto

Table F.11: Accessibility assessment framework results for Toronto

Network Statistics	
Number of Nodes	3660
Edges in L-space	8679
Edges in P-space	96610
Total Vehicle Movements	304908
Spatial Indicators	
Unique Transfer Edges	458
Transfer Edges per Node	0.1251
Nodes with Transfer Edges	509 (13.91%)
Intermodal Transfer Edge Length (m)	Mean: 250.37, SD: 113.88, Min: 5.30, Max: 399.80
Degree Centrality (Mean)	L-space: 0.001296, P-space: 0.014428
Degree Assortativity Coefficient	L-space: 0.2205, P-space: 0.1589
CPL	L-Space: 2.2226, P-Space: 0.5427
Connectivity γ	L-Space: 0.2161, P-Space: 2.4053
Intermodal Degree (Mean)	L-space: 1.1571, P-space: 1.1691
Mode Assortativity Coefficient	L-space: 0.4557, P-space: 0.8298
Temporal Indicators (Peak)	
Weighted Service Availability Score	44.62
Weighted Vehicle Movements per Node per Hour	Bus: 34.09, Subway: 3.08, Tram: 4.99, Rail: 2.46
Average Generalized Travel Cost (GTC)	102.85 min
GTC Composition	IVT: 33.9%, Wait: 11.3% (11.65 min), Transfer: 43.5%
GTC Thresholds	Max: 319.00 min, $\bar{t}_{25}$: 80.00, $\bar{t}_{50}$: 105.00, $\bar{t}_{75}$: 127.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 25.08%, $\bar{t}_{50}$: 32.92%, $\bar{t}_{75}$: 39.81%
Avg. Intermodal Transfer Wait Score	23.90 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	48.75
Weighted Avg. Waiting Time	10.48 min
Avg. Intermodal Transfer Wait	21.84 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	1.093
Average Wait Time Ratio	0.900
Wait Contribution to GTC Ratio	0.988
Intermodal Synchronization Ratio	0.914

F.12. Valencia

Table F.12: Accessibility assessment framework results for Valencia

Network Statistics	
Number of Nodes	325
Edges in L-space	599
Edges in P-space	9226
Total Vehicle Movements	12099
Spatial Indicators	
Unique Transfer Edges	42
Transfer Edges per Node	0.1292
Nodes with Transfer Edges	62 (19.08%)
Intermodal Transfer Edge Length (m)	Mean: 253.27, SD: 95.62, Min: 55.80, Max: 398.90
Degree Centrality (Mean)	L-space: 0.011377, P-space: 0.236201
Degree Assortativity Coefficient	L-space: 0.1842, P-space: 0.1087
CPL	L-Space: 2.9564, P-Space: 0.7774
Connectivity γ	L-Space: 1.9020, P-Space: 29.2959
Intermodal Degree (Mean)	L-space: 1.2554, P-space: 1.1321
Mode Assortativity Coefficient	L-space: 0.3373, P-space: 0.1297
Temporal Indicators (Peak)	
Weighted Service Availability Score	194.16
Weighted Vehicle Movements per Node per Hour	Bus: 2.70, Tram: 20.29, Subway: 171.17, Rail: 0.00
Average Generalized Travel Cost (GTC)	90.60 min
GTC Composition	IVT: 27.4%, Wait: 17.7% (16.01 min), Transfer: 35.0%
GTC Thresholds	Max: 202.00 min, $\bar{t}_{25}$: 60.00, $\bar{t}_{50}$: 91.00, $\bar{t}_{75}$: 119.00
Threshold Ratios to Max GTC	$\bar{t}_{25}$: 29.70%, $\bar{t}_{50}$: 45.05%, $\bar{t}_{75}$: 58.91%
Avg. Intermodal Transfer Wait Score	19.41 min
Temporal Indicators (Off-peak)	
Weighted Service Availability Score	146.34
Weighted Avg. Waiting Time	14.69 min
Avg. Intermodal Transfer Wait	16.37 min
Off-peak/Peak Ratio	
Vehicle Movements Ratio	0.754
Average Wait Time Ratio	0.918
Wait Contribution to GTC Ratio	0.945
Intermodal Synchronization Ratio	0.843