Public Transport Timetable Synchronization using Optimization Techniques

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Abstract

This thesis aims to contribute to the improvement of Public Transport timetables using optimization techniques at the planning stage, with particular focus on their synchronization. Five main goals were addressed, all applied to the case study of Porto. The first goal, pursued in Chapter 2, focused on the literature review of the various stages of Public Transport planning and the systematization of the terminology used in the thesis. The second goal, pursued in Chapter 3, was to estimate OD matrices from entry-only AFC data. The main contributions attained include the estimation of alighting stops using the Trip Chaining Method (TCM), the identification of transfers, and the development and visualization of OD matrices. The third goal, addressed in Chapter 4, sought the development of a methodology to discover networks whose synchronization would most benefit the Public Transport system. The main contributions obtained include the identification of relevant transfer-connection, the identification of relevant transfer-nodes and subsequent identification and visualization of synchronization networks. The fourth goal, addressed in Chapter 5, refers to minimizing passengers' transfer waiting time using synchronization timetabling techniques. The main contribution was the proposal of a synchronization model which returns the timetables for a network under study by maximizing the number of synchronized transfer opportunities in the system. The last goal, pursued in Chapter 6, focused on mitigating negative impacts arising from uncertainty in Public Transport through optimization techniques at the planning stage and the assessment of timetables' robustness. The main contributions included an optimization model seeking to minimize deviations from the plan, both delays and earliness, and the proposal of eight measures to quantify the robustness of Public Transport timetables.

Resumo

Esta tese pretende contribuir para a melhoria dos horários dos Transportes Públicos, recorrendo a técnicas de optimização na fase de planeamento, com particular enfoque na sua sincronização. Foram abordados cinco objectivos principais, cuja aplicação prática foi realizada ao caso de estudo da cidade do Porto. O primeiro objetivo, prosseguido no Capítulo 2, centrou-se na revisão bibliográfica das várias fases do planeamento do Transporte Público e na sistematização da terminologia utilizada na tese. O segundo objetivo for prosseguido no Capítulo 3 e incidiu na estimação de matrizes OD a partir de dados Automatic Fare Collection (AFC) com informação apenas na entrada. As principais contribuições alcançadas incluem a estimação das paragens de desembarque usando o Trip Chaining Method (TCM), a identificação de transbordos e a construção e visualização de matrizes OD. O terceiro objetivo, abordado no Capítulo 4, visou o desenvolvimento de uma metodologia para a descoberta de redes cuja sincronização de horários traga um elevado benefício ao sistema de Transporte Público. As principais contribuições obtidas incluem a identificação de conexões de transbordo relevantes, a identificação de nós de transbordo relevantes e a subsequente identificação e visualização das redes de sincronização obtidas. O quarto objectivo, desenvolvido no Capítulo 5, refere-se à minimização do tempo de espera em transbordo dos passageiros usando técnicas de sincronização de horários. A principal contribuição foi a proposta de um modelo de sincronização que retorna os horários de uma rede em estudo maximizando o número de oportunidades de transbordo sincronizadas no sistema. O último objetivo, abordado no Capítulo 6, centrou-se na mitigação dos impactos negativos decorrentes da incerteza nos Transportes Públicos através de técnicas de otimização na fase de planeamento e na avaliação da robustez dos horários. As principais contribuições alcançadas incluíram um modelo de otimização visando minimizar os desvios ao planeado, tanto atrasos como antecipações, e a proposta de oito medidas para quantificar a robustez dos horários de Transportes Públicos.

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Declaration

The following publications are based on the work in Chapter 3 of this thesis.

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- Hora, Joana; Dias, Teresa Galvão; Ana Camanho. 2020. Estimating Aggregated Origin-Destination Matrices from Automatic Fare Collection. Paper presented in EWGT 2020 - 23rd EURO Working Group on Transportation, Paphos, Cyprus.
- Hora, Joana; Dias, Teresa Galvão; Ana Camanho. 2020. Estimating Alighting Stops and Transfers from Entry-Only Automatic Fare Collection: the Case-Study of Porto. Abstract presented in TRA 2020 - Transport Research Arena 2020 (Conference cancelled), Helsinki, Finland, 144-145.

The following publication is based on the work in Chapter 4 of this thesis.

- Hora, J., Galvão, T., & Camanho, A. (2020). Identifying relevant transfer-connections from entry-only automatic fare collection data: The case study of porto. In A. Martins, J. Ferreira, & A. Kocian (Eds.), *Intelligent transport systems. from research and development to the market uptake: Intsys 2019. lecture notes of the institute for computer sciences, social informatics and telecommunications engineering* (pp. 63–76)

The following publications are based on the work in Chapter 6 of this thesis.

- Hora, J., Galvão, T., & Camanho, A. (2015). Improving the robustness of bus schedules using an optimization model. In A. Póvoa & J. Miranda (Eds.), *Operations research and big data: Studies in big data* (pp. 79–87). Springer, Cham
- Hora, J., Galvão, T., & Camanho, A. (2016). Improving the service level of bus transportation systems: Evaluation and optimization of bus schedules' robustness. In T. Borangiu, M. Dragoicea, & H. Nóvoa (Eds.), *Exploring services science: Iess 2016. lecture notes in business information processing* (pp. 604–618). Springer, Cham

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Glossary

AFC (Automated Fare Collection) - an Intelligent Transportation System (ITS) system to admit passengers into Public Transport vehicles or stations automatically. It controls passengers' entrance to Public Transport upon fare payment through automated readers. Passengers can use these readers with smart cards, coins, tokens, or tickets.

AFC record - the set of data stored by the AFC system when a passenger taps a smart card. An AFC record includes elements such as a unique identifier of the smart card, location, time, route, direction, among others.

alighting-stop - the stop where a passenger alights from a trip-leg.

alighting-time - the time when a passenger alights from a trip-leg. Notation: Q_j^a is the passenger's alighting-time from trip-leg j. Units: point in time.

APC (Automatic Passenger Counter) - an electronic device installed in Public Transport vehicles, which records the number of boarding and alighting passengers at each stop. Automatic Passenger Counter (APC) records are often used for real-time operations control and for Public Transport planning tasks (such as determining peak-load points, analysis of dwell time, analysis of ridership use and patterns).

arrival-time - refers to the scheduled moment for the arrival of each run at each stop. With reference to the departure-time of each run from each stop, the arrival-time at the subsequent stop is calculated by cumulative inference, adding the expected running-time. Notation: $P_{u,s+1}^a$ is the arrival-time of run u at stop $s+1$, see Equation (2.2). Units: point in time.

AVL (Automated Vehicle Location) - an ITS system to track the location of each vehicle automatically. There are many benefits from using this technology, including real-time operations control and applying its datasets to improve Public Transport planning management. Automated Vehicle Location (AVL) can encompass one or more technologies, such as Global Positioning System (GPS), signposts, ground-based radio, or dead-reckoning COTA, 2019.

boarding-stop - the stop where a passenger boards to start a trip-leg.

boarding-time - the time when a passenger boards to start a trip-leg. Notation: Q_j^b is the passenger's boarding-time on trip-leg j. Units: point in time.

bunching refers to the phenomena where two or more vehicles running along different runs of the same directed-route, or running in a shared path under different routes, end up running in the same location at the same time. Bunching is usually caused by delay accumulation during operations (i.e., delays in running-time and dwell-time), such that the vehicle coming behind catches up the next run, or due to lack of bus schedules coordination. Bunching phenomena deteriorates service quality by increasing overall waiting-time, overcrowding in-vehicles and at-stops, and reducing service reliability. There may be situations in which strategic bunching can be induced for a period of time to manage overcrowding.

congestion-node refers to an area served by two or more routes and where vehicle congestion can happen. Congestion-nodes are usually targeted for minimization of bunching.

contact-period the time-window in which vehicles simultaneously meet at focal-points.

cycle-time - is the time spent by a vehicle to perform the round trip of a route, defined as the time between two successive departures of the same vehicle from the same terminus Notation: T is the cycle-time, see Equation (2.4). Units: minutes.

delay propagation - the transmission of delays resulting from dependencies of consecutive run-pieces whose slack times is not sufficient to absorb preceding delays.

departure-time - refers to the moment when a specific run is scheduled to depart from a specific stop. The departing-time from terminus marks the starting moment of the run, which can be used as a reference. The departing-time of each run from each stop can be calculated by cumulative inference, adding the expected running-time and dwell-time in the consecutive stops traveled by the vehicle. The departing-times of runs are defined at the Timetabling stage of Public Transport planning. Notation: $P_{u,s}^d$ is the departing-time of run u from stop s, see Equation (2.1). Units: point in time.

destination - the last alighting-stop of a full-trip.

direct-trip - a full-trip made by a single trip-leg, i.e., without any transfer.

directed-route - the transportation service performed by a route in one defined direction. A route operating in two directions can be analyzed through two distinct directed-routes.

directed-route length - the one-way distance a vehicle has to perform between the two termini of a directed-route. Notation: L is the directed-route length. Units: km.

directed-route path - the one-way geographic path performed by a Public Transport vehicle serving a route, crossing its ordered sequence of stops, and starting and ending at termini.

Driver Rostering Driver Rostering stage of Public Transport planning.

Driver Scheduling Driver Scheduling stage of Public Transport planning.

dwell-time - time spent by vehicle at a stop without moving, to allow boarding and alighting of passengers. Can be divided into five stages: door-unblocking, opening doors, passenger boarding and alighting, closing doors and vehicle dispatching. Dwell-time is frequently used as an efficiency measure of Public Transport, where shorter dwell-times are desirable. Passengers' in/out flows relate to passengers' alighting and boarding. The variability in dwell times is due to many factors, such as the size of vehicle doors, the number of passengers performing in/outflows, and the step height between platform and vehicle. Notation: $T^e_{u,s}$ is the dwell-time at stop s in run u. Units: minutes.

entry-exit AFC an AFC system requiring passengers to tap a smart card both at boarding and alighting.

entry-only AFC an AFC system requiring passengers to tap a smart card only when boarding.

even headway - refers to equally spaced headway. Timetables of even headway only require information on the first run departing-time and headway, for a specified Uniform Demand Period (UDP).

Feeding-Route - the directed-route taken by a passenger before transfer.

Feeding-Vehicle - the vehicle where the passenger traveled before transfer.

fleet size - the number of vehicles required in the operation of a route so to comply with the specified frequency or headway. Notation: N is the fleet size, see Equation (2.7). Units: vehicles.

focal-point a transfer-node of significant transferring demand, where Timed Transfers is desirable. A transfer-node where vehicles meet simultaneously to boost large amounts of transferring passengers.

frequency - the number of vehicle departures on a route during one hour. The inverse of headway. Notation: f is the frequency, see Equation (2.5). Units: hour^{-1}.

Frequency Setting Frequency Setting stage of Public Transport planning.

full-trip - a passenger performs a full-trip prompted to an activity such as work, school, shopping, or returning home. A full-trip may entail one or more trip-legs. Each pair

of consecutive trip-legs is linked by a transfer. Origin and destination refer to the boarding and alighting stops of the full-trip, respectively. A full-trip relates only to the passenger itinerary within the Public Transport network (i.e., the access to stops, also known as the last-mile, is not accounted for in this work).

headway - the time elapsing between consecutive departure-times of runs operated in the same directed-route path (i.e., the time it will take for the trailing vehicle to reach the position of the next vehicle). A shorter headway corresponds to more frequent service, since headway is the inverse of the frequency over a determined period. Its determination considers passenger demand, capacity of vehicles, and the desired Level of Service (LOS) (i.e., load factor and policy headway). Most systems have regulation for minimum and maximum headway thresholds, to ensure Public Transport service quality. Notation: h is the headway, see Equation (2.6). Units: minutes.

High-Frequency - when the frequency of the transportation service operates in short intervals (e.g., every five minutes).

intermodality - considers the provision of Public Transport service to passengers through the combined integration of different transportation means and transportation modes. For example the integration of the service provided by buses and metro (land transport) with the service provided by ferry (water transport). It can encompass using a common ticketing system.

ITS (Intelligent Transportation System) - ITS technologies include the devices, software and platform tools to support delivering ITS applications. ITS technologies include AVL, AFC, Mobile Data Terminals (MDT), APC, wireless communications, among others (for an exhaustive list see TWB, 2019).

last-mile the term last-mile gained popularity in commerce and logistics sectors, but it keeps the same meaning in the Public Transport field. It refers to the portion of passengers' commute between Public Transport stops and activities — for example, a cycling or walking path between a passenger's home and its origin stop.

lineup network a network setting composed by several aligned focal-points, interconnected by a main route, to which Timed Transfers is applied. Each focal-point has at least two routes scheduled to meet simultaneously (including the main route). All focal-points follow a linear arrangement. Uni-focal, Bi-focal, and Tri-focal are particular cases of a lineup network setting.

Low-Frequency - when the frequency of the transportation service operates in long intervals (e.g., every hour).

Medium-Frequency - when the frequency of the transportation service operates in medium intervals (e.g., every 15 minutes).

Network Design Network Design stage of Public Transport planning.

OD flow The number of passengers traveling from a specified origin to a specified destination over a period of time.

OD matrix is a matrix aggregating a set of OD flows consistently over time and space. Origin-Destination (OD) matrices can be built at different levels of geographical and time aggregation. Usually rows relate to origins and columns to destinations. The information of OD matrices is one of the most accurate sources to infer the distribution of Public Transport demand over time and space. For example, an OD matrix built at the stop level means that each row and column are a specific stop.

off-peak period a UDP of lower demand, i.e., when the Public Transport system carries the lowest number of passengers. Examples of commuting off-peak periods could be the night periods of weekdays.

operating-time - time spent by a vehicle to travel a directed-route path, starting and ending in its termini. Notation: T_o is the operating-time. Units: minutes.

operating-velocity - the average velocity a vehicle travels between termini (do not include terminus-time). Notation: V_o is the operating-velocity, see Equation (2.3). Units: km/h.

origin - the first boarding-stop of a full-trip.

origin waiting-time - the period between a passenger's readiness to board and his boarding-time at the origin of a full-trip. Notation: U_o^w is the passenger's waiting-time at the origin of a full-trip. Units: minutes.

passenger - a person traveling in a Public Transport system.

passenger itinerary - the sequence of geographic locations traveled by a passenger while using Public Transport on a full-trip.

peak period a UDP of increased demand, i.e., when the Public Transport system carries the highest number of passengers. Examples of commuting peak periods could be weekdays between 6 and 9 a.m. and between 3 and 6 p.m.

policy headway - the minimum headway that operators have to offer so to ensure a specified LOS (instead of defining the headway by a capacity requirement). Units: minutes.

primary delay - a delay in Public Transport operations that could not be prevented. Primary delays can propagate and induce secondary delays.

Public Transport - a broad term referring to the transportation service accessible to the general public. In this work, Public Transport refers mainly to the transportation

service provided by operators using established routes and schedules, usually subject to regulated fees, including buses, subways, railways, or trams. Public Transport can also refer to other transportation services such as taxis, transportation on demand, and others.

readiness to board - the time at which a passenger is ready to board at a stop. Notation: Q_j^r - is the time at which the passenger is ready to start trip-leg j. Units: point in time.

Receiving-Route the directed-route taken by a passenger after transfer.

Receiving-Vehicle - the vehicle where the passenger travels after transfer.

robustness - the ability of Public Transport timetables to absorb deviations from the plan and to prevent their propagation through the daily operations.

route - the Public Transport service provided through a sequence of stops, either in one or in two directions, typically grouped by the same color. For each direction, each route has specific starting and ending stops called termini, and a set of intermediate stops. In some cases, routes can include branched paths. Most authors consider the concepts of line and route indistinguishably. For a specified UDP, the service of a Public Transport route is fully defined in space and time by the following parameters: (1) the sequence of stops, and (2.a) if the service is non-periodic, the time of departure of each run from its terminus, or (2.b) if the service is periodic, the time of departure of the first run and the headway for the following runs.

run - the transportation service of each directed-route is delivered through several scheduled runs of its directed-route path in each UDP. Each run is unique since it is operated by a specific vehicle at a specific time. Each run covers all stops sequentially, starting and ending in termini. Each vehicle can perform several runs during the same UDP. Two consecutive runs of the same route are separated by a headway time.

run-piece - a segment or part of a run, starting and ending at specific stops (e.g., intermediate stops, TCPs, or other).

running-time - the time spent by a vehicle to travel between two consecutive stops. Notation: $T_{u,s}^r$ is the running-time between consecutive stops s and $s+1$ in run u. Units: minutes.

secondary delay - a delay in Public Transport operations that results from the propagation of delays in the system. When an already delayed run-piece leads to a delayed start of the next run-piece.

slack time - buffer or extra time built into Public Transport timetables to accommodate deviations to the plan during operations. The management of slack time can provide timetables with buffers able to absorb delay propagation.

smart card refers to the smart cards that passengers use to travel in Public Transport using AFC.

station - a Public Transport structure where city or intercity Public Transport vehicles stop to pick up and drop off passengers. It usually includes several stops. It may be intended as a terminus for some routes, or as a transfer station.

stop - a designated place where passengers board and alight from Public Transport vehicles, usually identified by a sign and including information for passengers. The size and facilities of Public Transport stops reflect their level of usage. Stops at busy locations may have shelters, seating and possibly electronic passenger information systems. Public Transport stops with lower demand may include a simple pole and flag to mark the location. Public Transport stops may be clustered together into transport hubs or stations, allowing transfer between routes.

TCP (Time Control Point) - stop integrating a directed-route where the Public Transport operator monitors the actual time of each run.

terminus - a Public Transport stop where vehicles start and end their directed-route path.

terminus-time - is the time spent by a vehicle at a terminus between the end of a run and the start of the next run. It includes time for vehicle checkup, turnaround time, and slack time. Slack time at termini is often planned to allow drivers to take rest breaks. Notation: T_u^t is the terminus-time of run u. Units: minutes.

Timetabling Timetabling stage of Public Transport planning.

transfer - when a passenger switches from one directed-route to another in order to complete a full-trip. The passenger transition between two consecutive trip-legs within the same full-trip. A transfer has four moments: alighting from a Feeding-Vehicle on the Feeding-Route, walking the path between the alighting-stop and the boarding-stop (when exists), waiting at the boarding-stop, and boarding into a Receiving-Vehicle on the Receiving-Route. Most Public Transport systems allow passengers to transfer paying only one fare, usually considering some constraints such as a maximum time to transfer.

transfer time - the sum of transfer walking-time and transfer waiting-time incurred by a passenger over a transfer. Notation: U_i^x is the passenger's transfer time at transfer i, see Equation (2.11). Units: minutes.

transfer wait-time on full-trip - the sum of transfer waiting-time made by a passenger at all transfers over a full-trip. Notation: U_l^y is the passenger's transfer wait-time on full-trip l, see Equation (2.12). Units: minutes.

transfer waiting-time - the time a passenger has to wait to transfer. The time elapsed between the passenger arrival at the boarding-stop and the arrival of the next Receiving-Vehicle. Notation: U_i^w is the passenger's transfer waiting-time at transfer i. Units: minutes.

transfer walking-distance - the distance a passenger has to walk to transfer. Distance between the alighting-stop of the Feeding-Route and the boarding-stop of the Receiving-Route. Units: meters.

transfer walking-time - the walking-time spent by a passenger to transfer. The time spent by a passenger on walking the distance between the Feeding-Route's alighting-stop and the Receiving-Route's boarding-stop. Notation: U_i^k is the passenger's transfer walking-time at transfer i. Units: minutes.

transfer-connection - the connection between two specific directed-routes (i.e., a Feeding-Route and a Receiving-Route) that is used by passengers to transfer.

transfer-flow - the number of passengers performing a transfer-connection over a specified UDP.

transfer-node - the geographic area where two or more directed-routes meet, cross, or merge, and where passengers can transfer between those directed-routes.

transportation mean - refer to the transport facilities used to carry people or goods. Examples of transportation means include walk, train, rail, bus, ferry, boat, airplane, bicycle, or car.

transportation mode - term used to distinguish between the different ways of transporting people or goods. Examples of transportation modes are air, water, and land transport.

travel-time - the period of time that a passenger spends in a trip-leg, defined as the difference between its alighting-time and boarding-time. Notation: U_j^t is the passenger's travel-time on the trip-leg j, see Equation (2.10). Units: minutes.

triangular network a network to which is applied the Timed Transfer scheduling approach, composed by three interconnected focal-points in a triangular arrangement. Each focal-point has at least two routes scheduled to meet simultaneously. The three focal-points are interconnected by one or two routes.

trip - refers to the general act of traveling by a passenger, can be associated either with a trip-leg or full-trip.

trip-leg - a portion of a full-trip performed by a passenger in Public Transport. It can relate to in-vehicle time or distance between the corresponding boarding-stop and alighting-stop.

UDP (Uniform Demand Period) - periods with expected low variability of the demand and running-times. UDP are used to build similar patterns throughout the operation, and often support the establishment of assumptions for deterministic parameters. Typically, a UDP relates to periods within the day, such as morning peak, normal hours (off-peak hours), afternoon peak, night hours. UDP can also relate to days of the week, such as weekend or holiday days.

uneven headway - refers to variably spaced headway. Timetables of uneven headway require information on the first run departure-time plus the sequence of headway to operate or equivalently the sequence of all run departure-times, for a specified UDP.

uni-focal network a network setting composed by a single focal-point to which Timed Transfers is applied, and where at least two routes are coordinated to meet simultaneously. Routes can cross or terminate at the focal-point.

Vehicle Scheduling Vehicle Scheduling stage of Public Transport planning.

wait-time on full-trip - the sum of the waiting-time at the origin and at all transfers incurred by a passenger over a full-trip. Notation: U_l^z is the passenger's wait-time on full-trip l, see Equation (2.13). Units: minutes.

waiting-time - the period between a passenger's readiness to board and his boarding-time. The time a passenger has to wait to board into a trip. Units: minutes.

Acronyms

AD Average Delay.

ADr Relative Average Delay.

AE Average Earliness.

AEr Relative Average Earliness.

AFC Automated Fare Collection.

APC Automatic Passenger Counter.

AVL Automated Vehicle Location.

DRT Demand Responsive Transport.

EU European Union.

FEUP Faculdade de Engenharia da Universidade do Porto.

GA Genetic Algorithm.

GDP Gross Domestic Product.

GHG Greenhouse Gas.

GPS Global Positioning System.

HTM Holding Time Models.

ICT Information and Communication Technologies.

INESC TEC Institute for Systems and Computer Engineering, Technology and Science.

ITS Intelligent Transportation System.

LCM Least Common Multiple.

LOS Level of Service.

MaaS Mobility as a Service.

MDT Mobile Data Terminals.

MDVS Multi Depot Vehicle Scheduling Problem.

MILP Mixed Integer Linear Programming.

MIP Mixed Integer Programming.

MIT Massachusetts Institute of Technology.

MP Metro do Porto.

NP-hard Non-deterministic Polynomial-time hard.

OD Origin-Destination.

OPT Optimização e Planeamento de Transportes, S.A..

PD Proportion of Delays.

PDr Relative Proportion of Delays.

PE Proportion of Earliness.

PEr Relative Proportion of Earliness.

PESP Periodic Event Scheduling Problem.

PMA Porto Metropolitan Area.

PoR Price of Robustness.

QAP Quadratic Assignment Problem.

RAM Random Access Memory.

SDVS Single Depot Vehicle Scheduling problem.

STCP Sociedade de Transportes Colectivos do Porto, S.A..

TCM Trip Chaining Method.

TCP Time Control Point.

TIP Transportes Intermodais do Porto.

UDP Uniform Demand Period.

UID Unique IDentifier.

USA United States of America.

1 Introduction

1.1 Context

The mobility and transport landscape of urban areas has been changing over the past few decades as mobility needs followed the growth of urban centers worldwide. The mobility and transport sectors represent the second-largest area of expenditure for European Union (EU) households, contributing for 5% of Gross Domestic Product (GDP) and employing roughly 10 million workers. The benefits from mobility and transport include the mobility of citizens for the most diverse activities, from daily commuting to work and education, health services, commerce, leisure activities, tourism, or visiting family and friends, and also the supply chains for general goods required in daily life and industrial production. The negative impacts include air, noise, and water pollution, Greenhouse Gas (GHG) emissions, accidents and road crashes, traffic congestion, and biodiversity loss (COM, 2020).

Many international organizations point out attaining sustainable development as the main challenge of transports, particularly in urban areas (COM, 2019, 2020; OECD/ITF, 2020). Pursuing the sustainability of our society as whole, and more closely in transportation, encompasses aspects crossing the three bottom line of sustainability, i.e., social, economic and environmental dimensions. The EU is taking actions to enhance sustainability in transportation, in particular the target of reducing -55% in GHG emissions by 2030, and reaching climate neutrality by 2050 (COM, 2019, 2020).

Public Transport play a central role for the sustainable development of urban areas. Public Transport is the transportation backbone of cities due to its efficiency regarding space usage to move people (i.e., it allows moving large numbers of passengers within minimal space on streets), especially in densely populated urban areas. Public Transport typically provides trips from established routes and schedules, and charges a regulated fee. These include buses, subways, railways, or trams.

Public Transport services enable our economy to thrive and promote social equity, while contributing to environmental sustainability by reducing traffic congestion and air pollution when compared to the use of private cars. Despite Public Transport demand in-

creasing along with cities' growth (Ibarra-Rojas, Delgado, et al., 2015), the increasing ownership of private vehicles has led to a decrease in the share of Public Transport in daily commuting. Several efforts have been made to boost the usage of Public Transport. These include improving Public Transport service quality regarding capacity, frequency, coverage, reliability and comfort (Kepaptsoglou & Karlaftis, 2009), while ensuring its safety, environmental sustainability and energy efficiency (UNECE, 2015).

At the same time, urban areas are witnessing mobility changes with the increase of Mobility as a Service (MaaS) and demand personalized solutions. These include the emergence of vehicle sharing services, many times fostered by online apps (e.g., car-sharing, bike-sharing, or ride-sharing), Demand Responsive Transport (DRT) systems, taxis and ride-sourcing. These solutions are flexible and reactive to the demand, and they do not depend on fixed routes or fleets.

More recently, since the beginning of 2020, the Covid-19 pandemic brought the need for dramatic changes in mobility worldwide. New rules and constraints were implemented in each region depending on the pandemic development, including restrictions on travel between countries or specific geographic areas or the compulsory population confinement. Besides, to reduce the spread of Covid-19, citizens had to comply with new habits when moving in public spaces, such as to ensure social distancing within 2 meters, the use of personal protective equipment such as face masks, or the disinfection of hands (UNWTO, 2021).

1.1.1 Public Transport Stakeholders

The Public Transport main stakeholders are passengers, operators, regulating authorities, and local and national governance institutions. This section provides a brief overview of the most relevant aspects underlying the perception of each Public Transport stakeholder regarding the quality of the service provided.

Passengers expect Public Transport services to satisfy their travel needs. Even though needs and expectations differ from person to person, in general the following complementary aspects can be identified as relevant for passengers to choose Public Transport: a) travel price (i.e., if trips are affordable); b) overall time spent on the system, including travel and waiting times; c) availability and regularity of the service (i.e., adequate level of service particularly regarding frequencies); d) proximity and convenience of stops and stations (i.e., adequate geographic coverage and connectivity of the network, considering the trade-off between direct connections and resources available); e) reliability of the service (whether the service operates as expected and without delays or disruptions, if the system is trustworthy); f) travel comfort (i.e., whether vehicles and infrastructure are clean and enjoyable to use, alongside with other aspects of travel comfort such as crowd density, available travel seats and space, vehicle acceleration and jerk, temperature, airflow, or

noise); g) travel safety and security (i.e., low risk of suffering accidents or being a victim of crimes); h) accessibility (i.e., passengers of reduced mobility can access and use the system infrastructure including vehicles, stops and stations, and other spaces); i) travel information (i.e., travel information is accurate, intuitive and easy to find).

Public Transport operators provide transportation services to passengers and can be public or private. Even knowing that each operator is in itself a system with several specificities, whether due to the geographical area where it operates or due to resource constraints, the following interconnected aspects describe the main challenges and goals faced by Public Transport operators: a) comply with law and regulation; b) ensuring financial viability, usually from balancing revenue from ticketing and governmental support with operation costs; c) boost the attractiveness of the transportation service, in order to retain current passengers and attracting new passengers; d) to provide the best possible quality of service and promote its continuous improvement toward satisfying passengers' needs and expectations; e) enhance operational efficiency; f) provide a sustainable service respecting the environment, mitigating negative impacts such as pollution; g) improve transportation flexibility and intermodality.

Given the importance of Public Transport to the sustainable development of societies, EU policy makers and local governments seek the establishment of an adequate policy framework encompassing the coordination of competences from different stakeholders at different levels. At the same time, Public Transport authorities are established for each region, either centralized or decentralized (depending on the needs and choices taken by each government) to ensure compliance with policies and fair and affordable access to Public Transport in each region.

Policies emerge from the awareness of the negative impacts arising from population growth and dependency on private cars, including pollution, traffic congestion, road safety, economic and health issues, among others, while acknowledging the specific aspects of each area. The following goals are highlighted: a) promote Public Transport use by the population while reducing car dependency (positive impacts from this goal are felt subsequently in traffic congestion, parking management, and pollution); b) ensure Public Transport service coverage in time and space, including the imposition of specific routes and their frequencies to which operators have to adjust their resources (i.e., provide a minimum transportation service to the population that depends on it at low fares, even when it is unprofitable); c) when necessary, subsidize the Public Transport service to ensure it is affordable for all; d) integration of different transportation means and transportation modes (i.e., intermodality); e) adjust guidelines to comply with international sustainability goals, including accessibility and equitable access to mobility and the reduction of gas emissions.

1.1.2 New Technologies in Public Transport

Intelligent Transportation System (ITS) technologies include the devices, software and platform tools to support delivering ITS applications. ITS technologies include Automated Vehicle Location (AVL), Automated Fare Collection (AFC), Mobile Data Terminals (MDT), Automatic Passenger Counter (APC), wireless communications, among others (for an exhaustive list see TWB, 2019). The large availability of data obtained from ITS on several key features such as the geographic position of vehicles, running-times, dwell-times or passenger counts, coupled with the considerable development in computing processing capacity of the last years, allowed: (a) the improvement of real-time operations control, including the dynamic handling of unexpected events; (b) the enhancement of Public Transport planning, with the development of solutions more aligned with the specific reality of each system and with the ability to respond to larger and more complex problems (such as integrated approaches to Public Transport planning). These new data sources bring the considerable potential for developing innovative optimization techniques, the continuous improvement of Public Transport systems, and supporting the enhanced understanding of impacts in the decision-making processes. However, in most cases, the full potential from such large data sets remains unexploited.

AFC is a ticketing system increasingly used in Public Transport to automatically admit passengers into vehicles or stations. It controls passengers' entrance to Public Transport upon fare payment through automated readers. Passengers can use these readers with smart cards, coins, tokens, or tickets. AVL allows tracking the location of each vehicle automatically. There are many benefits from using AVL, including real-time operations control and applying its datasets to improve Public Transport planning and management. APCs are electronic devices installed in each vehicle to gather boarding and alighting data at each stop systematically. APC records are used for real-time operations control and for Public Transport planning tasks (such as determining peak-load points, analysis of dwell-times, analysis of ridership use and patterns).

1.1.3 Public Transport Planning

The two primary goals of Public Transport are to satisfy the demand using resources efficiently (e.g., infrastructure, capital, and operational inputs) and to increase Public Transport attractiveness (i.e., capturing and maintaining passengers by satisfying their demand and meeting their expectations in terms of service quality). The planning of Public Transport has a crucial role in pursuing these goals. It encompasses the main decisions of providing transport service while dealing with uncertainty, climate risks, and incorporating continuous technological advances.

Public Transport planning is normally carried out through the following sequence of inter-

dependent stages: Network Design, Frequency Setting, Timetabling, Vehicle Scheduling, Driver Scheduling and Driver Rostering. Figure 1.1 schematizes this sequence of stages, including information regarding their main inputs and outputs.

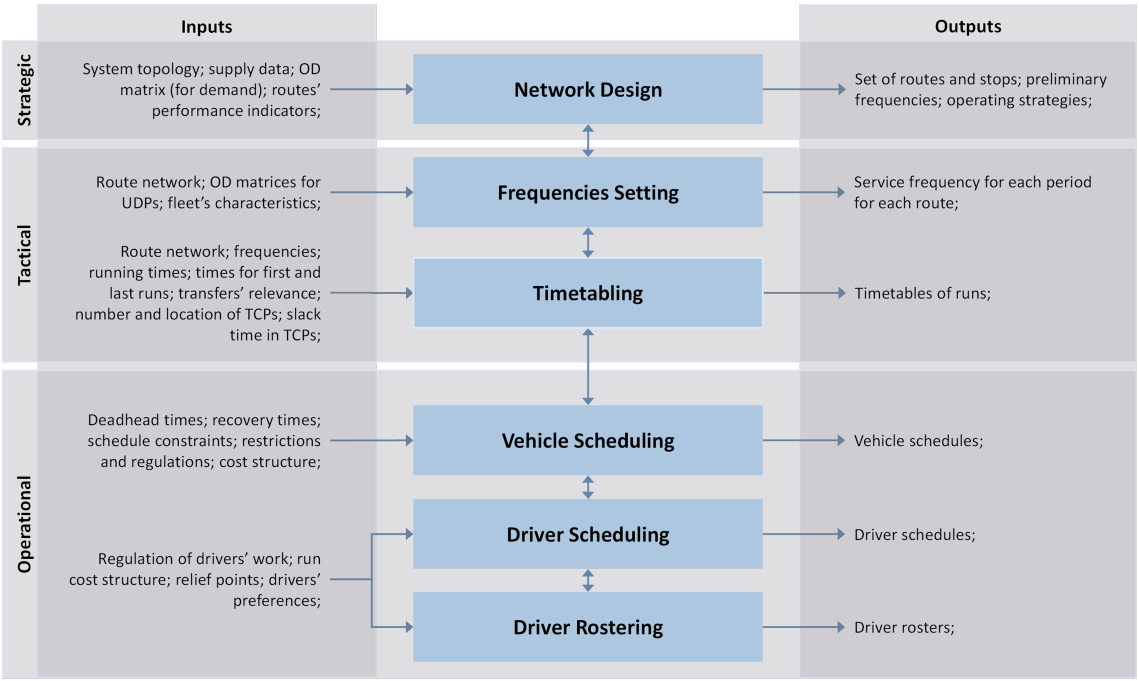


Figure 1.1: Sequence of Public Transport planning main stages and their inputs and outputs.

Each Public Transport planning stage is usually solved separately, and its output serves as input information for the next stage. In the event of the impossibility of solving a particular stage (e.g., due to scarcity of resources), it is possible to revisit the previous step with additional restrictions to find a viable solution. Some studies propose the joint solving of two or more planning stages depending on each system's specific needs alongside the ability to address its inherent complexity.

As highlighted in Figure 1.1, decisions made at the Network Design stage impact the system at the strategic level, meaning they endure for the long term. Decisions made at the Frequency Setting and Timetabling stages impact the system at the tactical level, meaning they stand for a medium-term time horizon. The decisions made at the last three stages, Vehicle Scheduling, Driver Scheduling, and Driver Rostering, impact the system at the operational level, meaning these are decisions made in the short term (Farahani et al., 2013; Ibarra-Rojas et al., 2014; Mesquita et al., 2011).

The Network Design encompasses decisions such as the establishment and modification of Public Transport networks, routes, and stops, as well as evaluating possible changes to an existing network. At the tactical level, Frequency Setting and Timetabling stages support decisions for the best usage of Public Transport infrastructure and resources to comply with the demand and boost passengers' Level of Service (LOS). At the operational level, Vehicle Scheduling, Driver Scheduling, and Driver Rostering support scheduling decisions

of vehicles and crew and drivers' rostering.

The frequencies obtained in the Frequency Setting planning stage are used as input to Timetabling techniques, in particular Synchronization Timetabling techniques. They represent the best compromise between the available resources and the LOS to provide to passengers. Synchronization Timetabling techniques, as well as any Timetabling technique, must comply with the given frequencies, in the most coordinated way possible, and keeping unchanged the fleet size of each route. The frequency of each route may vary over the day, usually divided into Uniform Demand Period (UDP). It is usual to increase a route's frequency during peak periods and to adopt lower frequency for the rest of the day.

Over a specified UDP, frequencies can be defined evenly or unevenly. The adoption of each case depends on several interrelated aspects. Advantages of adopting even headway include: i) when passenger demand is reasonably stable, it allows approximately constant loading in each vehicle; ii) schedule stability which is attractive for passengers (easy to understand); iii) the coordination of transfers can be made by repetition of a transfer pattern; iv) even headway reduce the complexity of timetables, as they are defined only by two pieces of data: a single headway value and the departure-time of the first run.

Uneven frequencies are designed to compensate for demand changes over time, to balance both vehicles' capacity and crowding levels of passengers at stops. Advantages of uneven headway include: i) the optimization of even headway (i.e., when timetables repeat itself) can always be established as a particular case of the optimization of uneven headway; ii) can reduce unnecessary transfer waiting-time; iii) can reduce unnecessary operating costs; iv) an uneven headway implies the specification of the departure-time of the first run and the sequence of headway values for all consecutive runs, which is equivalent to specify the departure-times of all runs. Overall requires more information than even frequencies to fully define a timetable.

1.1.4 Uncertainty in Public Transport

Public Transport daily operations are highly exposed to uncertainty arising from unforeseen events, such as traffic, weather conditions, mechanical failures, roadblock, strikes, or unexpected peaks of demand (Farahani et al., 2013; Naumann et al., 2011). Unforeseen events lead to the occurrence and propagation of deviations from the schedule (i.e., delays and earliness) and service disruptions and cancellations (Amberg et al., 2011; Naumann et al., 2011; Veelenturf et al., 2012).

Uncertainty negatively impacts passengers in different and interrelated aspects such as: a) dissatisfaction from loss in the LOS; b) increased waiting time; c) transfers become more difficult, mainly due to the possibility of missing connections and the consequent increase

in transfer waiting time; d) for some passengers, waiting-time unpredictability is worse than the waiting-time magnitude, causing frustration and preventing travel planning; e) the different disutility that waiting-time have for different passengers is ignored when applying models that assess waiting costs identically for all passengers (note that the consequences of reaching a destination early or late differ from passenger to passenger).

The impacts of uncertainty on operators include: a) need for additional costs from corrective actions; b) deterioration of service and operating efficiency; c) intensification of deviations from the plan with their propagation (i.e. if a vehicle runs behind (or ahead) of schedule, it typically will pick up more (or less) passengers and get even further behind (or ahead) of schedule. d) deviations from the plan occurring on one route will impact the Public Transport system, both along the same route and over other network routes.

Delays can be classified into two categories: primary delays and secondary delays. A primary delay cannot be prevented and induces the late arrival of a run-piece that has departed on time (Naumann et al., 2011). A secondary delay occurs when an already delayed run-piece leads to the delayed start of the next run-piece. This transmission of delays is called delay propagation (Amberg et al., 2011; Naumann et al., 2011). Delay propagation results from dependencies of consecutive run-pieces whose slack time is not sufficient to absorb preceding delays (Amberg et al., 2011; Naumann et al., 2011). Only secondary delays can be minimized by adjusting the timetables (Carey, 1999; Kramkowski et al., 2009).

The management of uncertainty in Public Transport systems can be strengthened with optimization techniques at their planning process. The Timetabling stage is best suited for pursuing this goal within the Public Transport planning process, as it allows incorporating slack time specifically designed to absorb delay propagation at strategic locations of the Public Transport network. These strategic locations are stops or stations that have adequate infrastructure to hold vehicles in case they are early, and where deviations from schedule are systematically recorded for service quality assessment. They are called Time Control Point (TCP)s.

1.2 Public Transport in Porto

Porto Metropolitan Area (PMA) is located on the northwest coast of Portugal and is the second biggest metropolitan area of Portugal. PMA has a Mediterranean climate, with warm humid summers and mild rainy winters. PMA encompasses an area of 2,040 km2 and had 1,762,524 inhabitants in 2011 (INE).

The PMA transportation network includes 126 bus lines from 7 urban and regional operators. Sociedade de Transportes Colectivos do Porto, S.A. (STCP) is the largest bus

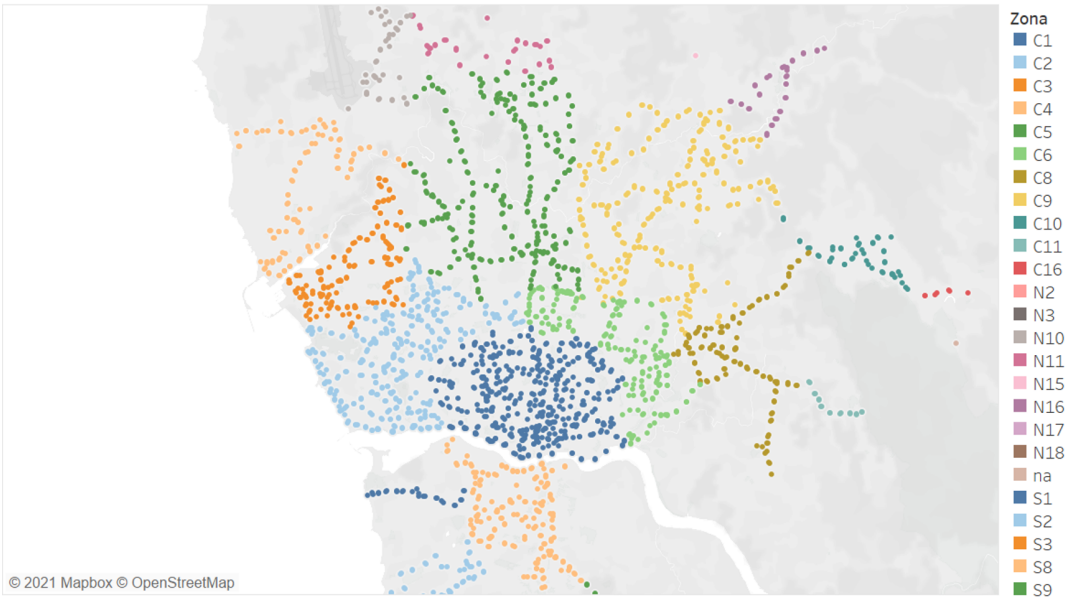


Figure 1.2: Map of all stops in PMA with different colors for each zone.

operator, serving 6 municipalities. Its network has approximately 522 km, with 2,651 bus stops and 81 bus lines (of which 11 lines operate at night). The fleet of STCP has around 470 buses (Gomes et al., 2015). During 2011, STCP served around 108 million passengers, with an occupancy rate of only 15% (Gomes et al., 2015).

The PMA network also includes the metro operator Metro do Porto (MP), with 6 lines crossing 7 municipalities, with a total of 82 metro stops along 70 km (includes duplicate paths), most at the surface (9.5km of underground).

The PMA network also includes three rail lines, 1 cable line and 3 tram lines (Costa et al., 2015). The rush hour occurs between 7h30 a.m. and 9h30 a.m. with severe traffic congestion on the main highways (similarly to other metropolitan areas).

All Public Transport services operating in the PMA are focused at its center, which is the city of Porto. The city of Porto has an area of $41 km^2$ and had a population of 237,591 in 2011 (INE). In addition to the Public Transport services already described, the city of Porto has 63 taxi stops and 2 car sharing operators (Citizenn and Mob Carsharing).

The mobility of Porto was seriously negatively affected by new commuting patterns resulting from urban sprawl (i.e., during the last decade people moved from the center to the suburbs), leading to longer commuting trips. This change in behavior resulted in increased congestion. In the past few years, Porto was typically congested at the city center. Nowadays, congestion occurs at the main entrances/exits of the city. Currently, the most popular transportation mean in Porto is the car, with an increase in commuting trips made by a car between 2001 and 2011 from 46% to 62% (INE). A shift in transport policy has also occurred in Porto, from a focus on increasing road capacity (past) to the perspective of improving the Public Transport system (present).

The Public Transport system operating in Porto uses an inter-modal entry-only AFC system for ticketing, based on smart cards. Other ITS applications at metro stations include: a) electronic signs with real-time information; b) the mobile app SMSBUS (by STCP), which provides information on the waiting-time for each route; c) the mobile app MOVE-ME (by Optimização e Planeamento de Transportes, S.A. (OPT)), which allows passengers to plan their best travel path in real-time, considering inter-modal services of different operators; d) the mobile app ANDA (by Transportes Intermodais do Porto (TIP)), which allows passengers to travel using smartphones instead of smart cards and charges the minimum possible value for all trips in the month.

1.3 Thesis's Structure and Contribution

The research carried out in this thesis sought to improve the synchronization of Public Transport timetables using optimization techniques. Figure 1.3 overviews the goals and contributions of each Chapter in the Thesis.

Chapter	Goals	Main Contributions
Chapter 2 - Review of Public Transport Planning Problems and Terminology	• Literature review; • Terminology Standardization;	• Literature review of Public Transport planning stages; • Synthesis of terminology used in the thesis;
Chapter 3 - Estimating Origin-Destination Matrices from Automated Fare Collection Data	• To estimation OD matrices from entry-only AFC data;	• Estimation of alighting-stops of entry-only AFC records using the Trip Chaining Method (TCM); • Identification of transfers; • Development and visualization of OD matrices;
Chapter 4 - Identifying Synchronization Networks	• To develop a methodology suitable for identifying networks whose synchronization would most benefit the Public Transport system;	• Identification of relevant transfer-connection; • Identification of relevant transfer-nodes; • Identification of synchronization networks;
Chapter 5 – Synchronizing Public Transportation Networks	• To minimize transfer waiting-time of passengers; • To synchronize Public Transport timetables;	• Development of a synchronization timetabling model using Mixed Integer Linear Programming; • Maximization of synchronized transfer opportunities;
Chapter 6 - Robustness in Public Transport Timetables	• To mitigate negative impacts arising from uncertainty in Public Transport through optimization techniques at the planning stage; • To assess the robustness of Public Transport timetables;	• Development of an optimization model seeking the minimization of deviations from the plan, both delays and anticipations; • Proposal of eight measures to quantify the robustness of Public Transport timetables;

Figure 1.3: Goals and main contributions of each Chapter in the Thesis.

The starting point of this research work was the literature review on Public Transport planning, which is presented in Chapter 2. This literature review allowed an under-

standing the interconnections of the different Public Transport planning stages and their associated problems. Public Transport systems can benefit from the application of optimization methods focused on its different stages (i.e., Network Design, Frequency Setting, Timetabling, Vehicle Scheduling, Driver Scheduling, and Driver Rostering), as well as the problems connected to them, such as the estimation of OD matrices which is required as an input to some planning stages.

The literature review also made it possible to understand that the terminology used in this research area is not standardized. This work includes a listing of the terms used and their meaning, detailed in the second part of Chapter 2 and the Glossary.

The work presented in this thesis applied data from ITS, namely AFC systems and Global Positioning System (GPS). In light of the increasing availability and quality of these technologies and the data extracted from them, exploring optimization methods capable of taking advantage of these new data sources is an important contribution of this thesis.

Chapter 3 focuses on the inference of OD matrices using entry-only AFC data. The inference of OD matrices reported in this study encompasses the estimation of alighting-stops for each trip-leg, and the subsequent identification of transfers. The Trip Chaining Method (TCM) was chosen to estimate alighting-stops, being the most recognized method for this task in the literature. Furthermore, a set of criteria was established for the identification of transfers, considered as adequate for this particular case study, as well as aligned with the state-of-the-art in the topic. The adequacy of the methodology adopted was demonstrated with its implementation to the case study of Porto, resulting in the estimation and visualization of OD matrices considering their segmentation on different features. Chapter 3 also provides a literature review on the topics explored, both TCM and identification of transfers, targeted at the assumptions adopted in each study, which is an important contribution of this work.

Chapter 4 proposes a methodology to identify Public Transport networks which could benefit most from synchronization given data on transfers performed by passengers. The methodology starts by identifying transfer-connections offering potential for synchronized according to a set of criteria. The transfer-connections identified are then used to identify and aggregate transfer-nodes. Finally, transfer-nodes sharing common routes are allocated to the same synchronization network. The methodology was applied to the case study of Porto, using a data set of transfers estimated with the methodology described in Chapter 3. The results include the identification and visualization of a set of synchronization networks for the case study of Porto.

Chapter 5 pursues the goal of minimizing passengers' transfer waiting-time through the synchronization of Public Transport networks. To pursue this goal a Mixed Integer Linear Programming (MILP) model was developed. The model returns the optimized timetables of a Public Transport network. Timetables are defined with the departure-times of all

runs. The objective function maximizes a binary variable stating whether two run-pieces are synchronized or not (i.e., it maximizes the number of synchronized run-pieces). The decision variables are the binary variable on synchronized run-pieces and the departure-times of all run-pieces. Different constraints were included to ensure the adequacy of the timetables obtained, including the minimum and maximum headway, and geographic and temporal feasibility of transfers and runs.

The research presented in Chapter 6 aims to assess the robustness of Public Transport timetables, and to mitigate the negative impacts from unforeseen events. This goal was pursued with the proposal of an optimization model following a re-Timetabling approach. The model performs improvements on already existing timetables according to their historic records of deviations observed, while considering the independent operation of each route. Chapter 6 also proposes a set of quantitative measures to evaluate the robustness of Public Transport timetables, i.e., the ability of timetables to absorb deviations from the plan and prevent their propagation during operations. Chapter 7 includes final remarks and considerations for future research.

2 Review of Public Transport Planning Problems and Terminology

2.1 Introduction

Public Transport planning encompasses all planning decisions prior to operation. It is normally divided into the following six main stages: Network Design, Frequency Setting, Timetabling, Vehicle Scheduling, Driver Scheduling, and Driver Rostering. Each stage is usually solved separately, taking as input the information obtained from the previous stage. Outputs from each stage influence the solutions for all of its subsequent stages.

The main inputs and outputs of each Public Transport planning stage are schematized in Figure 2.1. Figure 2.1 also describes the terminology adopted in this work, which is aligned with the literature, while acknowledging that alternative terminologies also exist in the literature (Guihaire & Hao, 2008).

Some studies claim that it would be desirable to solve all Public Transport planning stages simultaneously to maximize capacity, productivity, and efficiency (Arbex & Cunha, 2015; Ceder, 2007). Indeed, the sequential solving of the Public Transport planning stages returns sub-optimal solutions. As a result, the overall set of decisions from this sequence of problems may not be optimal. These studies also identify the computational complexity as the main impediment to solving all Public Transport planning stages at once (even using heuristic processes).

However, computational complexity is not the only reason. The decision to solve Public Transport planning stages separately or in groups also has to do with different time horizons for specific decisions, namely at the strategic, tactical, and operational levels (each with specific planning needs).

The decisions at the strategic level are made for the long term, specifically in Public Trans-

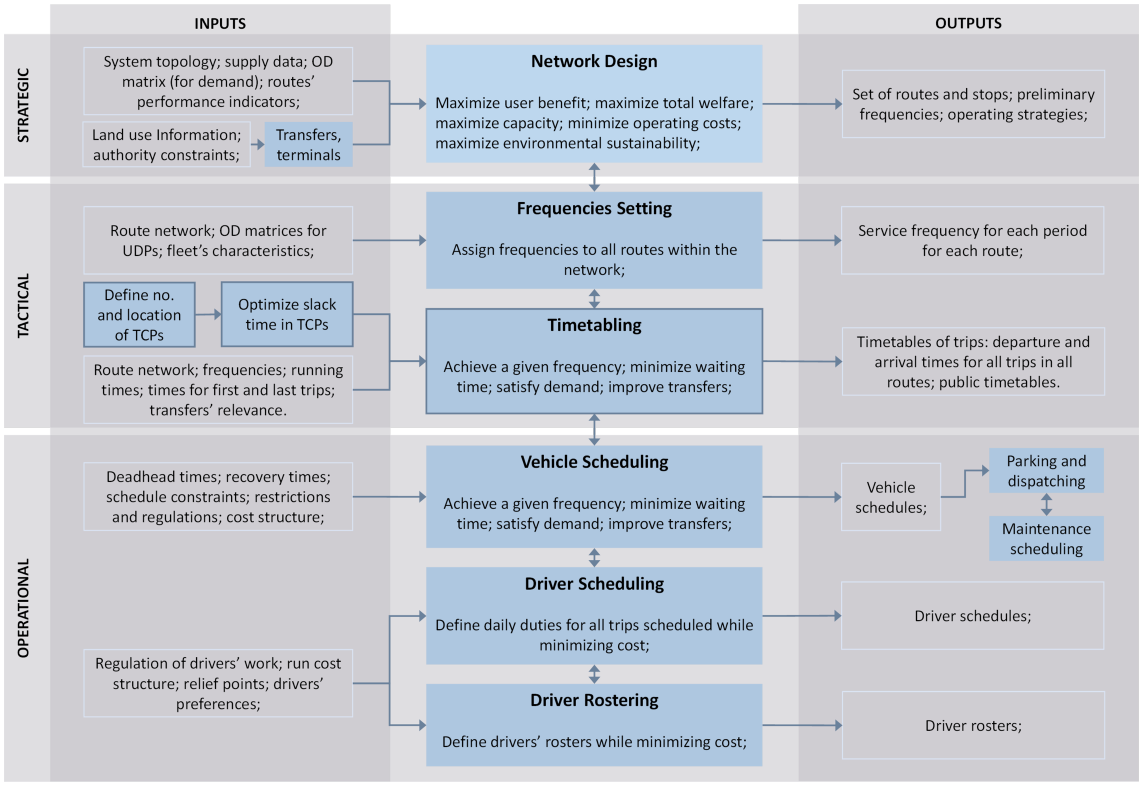


Figure 2.1: Public Transport planning main stages and their inter-relationships.

port this respect to Network Design. This includes the establishment and modification of Public Transport networks, routes and stops, as well as the evaluation of possible changes to the network and the assessment of their impacts (Farahani et al., 2013; Mesquita et al., 2011).

The decisions at the tactical level are made for the medium term. The Public Transport planning includes two stages at the tactical level: Frequency Setting and Timetabling. These decisions seek the adequate usage of Public Transport infrastructure and resources, in order to maximize the service quality for clients (Farahani et al., 2013; Mesquita et al., 2011).

Operational or short-term decisions apply to traffic flow control, the management of demand, scheduling of both the vehicles and the crews, and the rostering of drivers (Farahani et al., 2013; Ibarra-Rojas et al., 2014; Mesquita et al., 2011). These decisions are made under the Vehicle Scheduling, Driver Scheduling, and Driver Rostering problems.

The literature includes different formulations for each Public Transport planning stage, arising from the differentiated needs of each Public Transport system (Ibarra-Rojas & Rios-Solis, 2012). A growing number of studies integrate simultaneously two or more Public Transport planning stages, pursuing optimized overall solutions. These include: Network Design-Frequency Setting, Frequency Setting-Timetabling, Timetabling-Vehicle Scheduling, Vehicle Scheduling-Driver Scheduling, Driver Scheduling-Driver Rostering, Network Design-Frequency Setting-Timetabling, and Vehicle Scheduling-Driver Scheduling-Driver

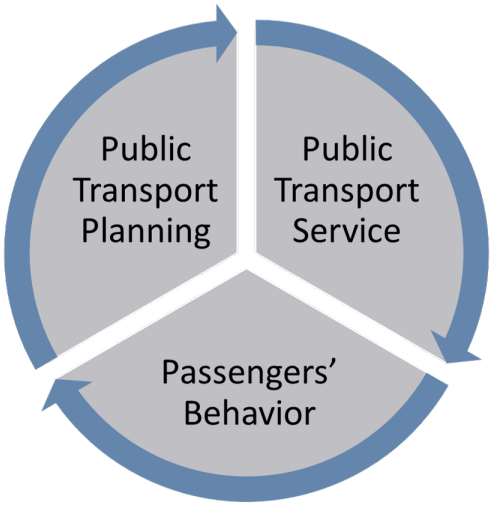


Figure 2.2: The *Public Transport planning - Public Transport service - passengers' behavior* cycle.

Rostering. Integrated approaches always involve ways multiple objectives, and are expected to produce better quality when compared with a traditional sequential solution approach, at the expense of increased complexity and processing time. The successful implementation of integrated approaches in real world cases depends, however, on the access to advanced computational means and optimization techniques.

In many cities, Public Transport planning is still done without access to optimization techniques, with reliance on manual tools, which presents a major opportunity for future improvement of service quality in Public Transport, mostly in under-developed contexts.

Changes in passengers' behavior are not deterministic and often unfold in unexpected ways, increasing the challenge of any Public Transport planning task. Public Transport planning decisions are based on assumptions about passengers' behavior, defined by historical data analysis and / or surveys. The implementation of Public Transport planning decisions impacts the Public Transport service delivered to passengers, e.g., with changes resulting from Network Design, Frequency Setting, or Timetabling.

Changing the Public Transport service, in its turn, affects passengers' behavior, especially in the choice of transportation means such as using Public Transport, private cars, or alternative means. Figure 2.2 represents this causal cycle interrelating Public Transport planning decisions, Public Transport service, and passengers' behavior. The conceptual idea of this cycle stems from a general view of Public Transport planning. Assumptions such as considering the demand unchanged by the planning decisions are usually necessary for planning decision making. Moreover, any demand shift will be detected and accommodated in the following cycle when addressing periodic planning decisions (Han & Wilson, 1982).

The chapter is organized as follows. Section 2.2 includes the literature review of the main

problems in Public Transport planning. Accordingly, the Network Design problem is reviewed in Section 2.2.1, Frequency Setting in Section 2.2.2, Timetabling in Section 2.2.3, Vehicle Scheduling in Section 2.2.4, Driver Scheduling in Section 2.2.5, and Driver Rostering in Section 2.2.6.

The chapter proceeds by introducing the terminology and concepts used in this work associated with space-time operation of runs from the perspective of the service provider, and trips from the perspective of passengers using the transportation service. Accordingly, the terminology associated with runs is detailed in Section 2.3.1 followed by the terminology for trips in Section 2.3.3. Final remarks are in Section 2.4.

2.2 Public Transportation Planning

2.2.1 Network Design

The Network Design problem delivers a Public Transport network configuration of routes that best satisfies the demand for the system, considering a set of constraints and an objective function to optimize.

Many cities have been designing their Public Transport networks based on empirical rules and the experience of experts and operators. This is not likely to result in economically and operationally efficient Public Transport networks (Kepaptsoglou & Karlaftis, 2009). Efficient Public Transport networks may be obtained through application of optimization techniques, which is the focus of the Network Design problem.

The Network Design problem have been applied in the literature with different objective functions, either separately or combined. These include: maximizing user benefit (e.g., reducing passengers' waiting-time or overall travel-time), maximizing total welfare, maximizing total capacity (e.g., reducing time of empty-seats and empty-space), minimizing operating costs (e.g., fleet size), minimizing operating costs plus passenger costs, or improving environmental sustainability.

The Network Design problem has three main inputs: system topology, Origin-Destination (OD) matrix, and land use characteristics. The system topology includes roads, possible locations for Public Transport stops and for transfer zones, and locations of depots serving as Public Transport terminals. The OD matrix, whose coordinates refer to Public Transport stops (possible Public Transport stops and transfer zones), stores the demand of passengers from each origin to each destination in a given period (Guihaire & Hao, 2008). The estimation of passenger volumes in OD matrices is reviewed in Chapter 3. The land use characteristics include constraints and regulators impositions, used for the preliminary determination of transfers and termini (Ceder & Tal, 2001).

The main output of the Network Design problem is the route network. The Public Transport route network includes the set of routes, with information regarding their directed-route paths and stops. Operational characteristics of each route, such as preliminary frequencies and vehicle types, are also determined through Network Design. This is necessary to ensure that the set of routes obtained not only connect locations strategically, but that they satisfy demand requirements, city regulations, and satisfy resources constraints.

The frequencies established for each route in this stage are preliminary and are adjusted at the Frequency Setting stage. They ensure frequency requirements, such as minimum and maximum allowed frequencies of each route to optimize the objective function, for example ensuring tolerable waiting-times or desired load factors.

The Network Design constraints adopted in the literature vary from system to system, depending on their specific needs. The most common constraints include: generalized cost (Agrawal & Mathew, 2004; Bagloee & Ceder, 2011; Bielli et al., 2002; Carrese & Gori, 2002; Ceder, 2007; Fan & Machemehl, 2006; Mandl, 1980; Pattnaik et al., 1998; Tom & Mohan, 2003); the existing network of Public Transport routes, when it is desirable to keep an existing service; number and length of Public Transport routes (goal to minimize costs associated with fleet size and crew size) (Baaj & Mahmassani, 1991, 1995; Cipriani et al., 2012; Fan & Machemehl, 2006); desirable route shapes (e.g., rectangular) (Guihaire & Hao, 2008); route directness (to return directed-route paths as straight as possible between consecutive stops); reduce route overlapping with other routes as much as possible; frequency feasibility (Pattnaik et al., 1998; Tom & Mohan, 2003); fleet size (Bagloee & Ceder, 2011; Ceder, 2007; Fan & Machemehl, 2006); load factor of vehicles (Agrawal & Mathew, 2004; Baaj & Mahmassani, 1991, 1995; Cipriani et al., 2012; Fan & Machemehl, 2006; Pattnaik et al., 1998; Tom & Mohan, 2003); demand satisfaction, counting with the distance between Public Transport stops and passengers' real OD (Agrawal & Mathew, 2004; Cipriani et al., 2012; Fan & Machemehl, 2006); the covered area, defined as the percentage of the demand served by the Public Transport network (Baaj & Mahmassani, 1991, 1995; Mandl, 1980); number of direct trips (to design routes to provide OD trips as direct as possible and counting with walking-distance to stops) (Ceder, 2007); number of transfers (Ceder, 2007; Ceder & Wilson, 1986; Rapp & Gehner, 1967); transfer time (Baaj & Mahmassani, 1991, 1995).

The assessment of candidate routes is a time consuming process and many potential solutions are rejected due to infeasibility. The Network Design problem is normally formulated as a combinatorial, highly constrained, multi-objective problem of Non-deterministic Polynomial-time hard (NP-hard) complexity (Arbex & Cunha, 2015). Real size Network Design problems are usually solved using heuristic approaches due to its computational complexity.

2.2.2 Frequency Setting

Increasing overall frequency in a Public Transport network would increase its operational costs, but it would also, most likely, attract more passengers and increase revenue (I. Ö. Verbas & Mahmassani, 2013). The inverse is also true. This phenomenon is well documented in the literature, with different names, such as the cumulative deterioration of Public Transport service (Mohring, 1972).

It is also well known and documented that Public Transport demand changes by season, weekday, time of day, location and direction of the route (Ceder, 1984; İ. Ö. Verbas et al., 2015). Plus, resources of each Public Transport system are limited, such as fleet size and crew size, or the available budget. Deciding on the best allocation of resources to the entire system is not straightforward, such as increasing or decreasing routes' frequencies. Which routes should operate most often, and when? Are there enough resources to meet the demand across the network?

The Frequency Setting stage aims to allocate Public Transport resources to match demand variations, increasing the system's overall operational efficiency and Public Transport social benefit (Ceder, 1984; Furth & Wilson, 1981; I. Ö. Verbas & Mahmassani, 2013). To that end, the Frequency Setting problem optimizes the frequency of each route for each operation period, considering an objective function and a set of constraints to satisfy. Reviews on the literature of this problem include Desaulniers and Hickman (2007), Guihaire and Hao (2008), Ibarra-Rojas, Delgado, et al. (2015).

Frequency Setting impacts the system in the medium term, i.e., at the tactical level. Whereas Network Design outputs remain unchanged for years, Frequency Setting is executed multiple times per year (Furth & Wilson, 1981; I. Ö. Verbas & Mahmassani, 2013). Applying Frequency Setting range from building timetables from scratch to the accommodation of demand variations in existing timetables (Ceder, 1984). Revising existing timetables means to improve the allocation of resources, by increasing the frequency in some parts of the network and decreasing it in others.

The Frequency Setting problem specifies only the number of runs that each route should execute per Uniform Demand Period (UDP). The precise departure-time and arrival-time of each run are set in the Timetabling stage. The time aggregation to adopt in Frequency Setting varies from system to system, but is usually applied to the daily operation of each route, dividing the day into its UDP. The solution then includes the number of runs to perform in each UDP.

UDPs refer to periods of time with expected low variability of the demand and running-times. UDPs are used to build similar patterns throughout the operation, and often support the establishment of assumptions for deterministic parameters. Typically, a UDP relates to periods within the day, such as morning peak, normal hours (off-peak hours),

afternoon peak, or night hours. UDPs can also relate to days of the week, such as weekend or holiday days.

Determining the frequency of each route is equivalent to determining its headway (van Oudheusden & Zhu, 1995), since the headway is the inverse of the frequency over a specified period. Therefore, a shorter headway corresponds to more frequent service. Headway accounts for the time elapsed between consecutive departure-times of runs operated in the same directed-route path (i.e., the time it will take for the trailing vehicle to reach the position of the next vehicle). Headway can also be quantified as a distance, measured from the tip of one vehicle to the tip of the next one behind it.

The Frequency Setting stage needs the following input information: network of Public Transport routes previously defined in the Network Design stage, detailed OD matrices for each UDP, Public Transport fleet information, since frequencies will often be constrained by the fleet size and its characteristics.

The main objective functions adopted in the literature for the Frequency Setting problem are as follows: i) Minimizing operating costs or maximizing profit (including features such as number of runs, fleet size, or revenue) Ceder, 1984; Hurdle, 1973; Y. Li et al., 2013; Salzborn, 1972; van Oudheusden and Zhu, 1995; ii) Improving Public Transport efficiency Ceder, 1984; van Oudheusden and Zhu, 1995; iii) Minimizing total waiting-time of passengers Furth and Wilson, 1981; Han and Wilson, 1982; Hurdle, 1973; Y. Li et al., 2013; Newell, 1971; Salzborn, 1972; Schéele, 1980; I. Ö. Verbas and Mahmassani, 2013; İ. Ö. Verbas et al., 2015; iv) Minimizing total running-time Ibarra-Rojas, Delgado, et al., 2015; v) Maximizing ridership Furth and Wilson, 1981; van Oudheusden and Zhu, 1995; I. Ö. Verbas and Mahmassani, 2013; İ. Ö. Verbas et al., 2015; vi) Minimizing empty seats and demand not served Hadas and Shnaiderman, 2012; and vii) Minimizing the maximum crowding level on any route Han and Wilson, 1982.

The most common constraints used in Frequency Setting applications are detailed as follows: i) Satisfy the demand Hadas and Shnaiderman, 2012; Han and Wilson, 1982; Ibarra-Rojas, Delgado, et al., 2015; Schéele, 1980; van Oudheusden and Zhu, 1995; ii) Accessibility (reaching every destination from every origin) Schéele, 1980; iii) Operating costs and available budget Furth and Wilson, 1981; I. Ö. Verbas and Mahmassani, 2013; İ. Ö. Verbas et al., 2015; iv) Headway regulations Furth and Wilson, 1981; I. Ö. Verbas and Mahmassani, 2013; İ. Ö. Verbas et al., 2015; v) Fleet size Furth and Wilson, 1981; Han and Wilson, 1982; Ibarra-Rojas, Delgado, et al., 2015; Schéele, 1980; van Oudheusden and Zhu, 1995; I. Ö. Verbas and Mahmassani, 2013; İ. Ö. Verbas et al., 2015; vi) Vehicle load (flows of passengers) Furth and Wilson, 1981; I. Ö. Verbas and Mahmassani, 2013; İ. Ö. Verbas et al., 2015; vii) Vehicle capacity Newell, 1971; Schéele, 1980; İ. Ö. Verbas et al., 2015; viii) Route capacity (passengers can board their desired route even if not on the first vehicle available) Han and Wilson, 1982; ix) Running-time Hadas and Shnaiderman, 2012; van Oudheusden and Zhu, 1995; x) Parking spaces van Oudheusden and Zhu, 1995;

and xi) Vehicles and crews pre-assignment rules van Oudheusden and Zhu, 1995.

To satisfy the demand relates to offering the best transport service possible. This constraint is usually aligned with the mitigation of overcrowding problems and the minimization of overall waiting-time and transfer-time. It is inter-connected with other constraints, for example noting that the inbound and outbound demand flows change over the day (van Oudheusden & Zhu, 1995). This constraint grounds the Frequency Setting problem, as it is also one of the main goals to achieve: to serve society through public transportation, as well as possible.

The running-time of each run and its fluctuations throughout the day considering traffic conditions and demand of passengers. Depending on the Public Transport system, the running-time can be stable or unstable. For example, inbound and outbound runs typically have distinct running-times for the same period (van Oudheusden & Zhu, 1995).

This problem returns the capacity level and waiting-times for each route. From these elements, it is possible to calculate the fleet size needed for the network to operate. Frequencies will directly impact the operation cost (by determining the fleet size required), the quality of service (higher frequencies allow for reduced waiting-times for passengers), and overall attractiveness of Public Transport. A Public Transport system with optimized frequencies attracts more passengers, since it is able to better satisfy public needs for transportation. Frequency Setting provides a preliminary number of runs for each route.

Research on Frequency Setting started with the seminal work of Newell (1971), proposing a method that would come to be known as the *square root method*, and rooted in Queuing Theory. This method assumes that fleet size and capacity of vehicles are both infinite. It models the arrival rate of passengers as a non-constant function, with some peaks. The model minimizes the total waiting-time of passengers. In these conditions, the optimal dispatching times of vehicles, i.e., frequencies, vary as the square root of passengers' arrival rate (Newell, 1971). When adding a constraint on vehicles' capacity, the dispatching time changes to release vehicles as soon as they are full (uneven headways).

Variations of the Newell's *square root method* were later proposed by Salzborn (1972) and by Hurdle (1973). Salzborn (1972) first sought to minimize the number of vehicles, and then passengers' waiting-time, considering a single bus route. The work by Salzborn (1972) is the first Frequency Setting method modeling the usage of vehicles on various trips, showing that with these additional considerations, the *square root method* only applies in off-peak periods. Hurdle (1973) considered a directed-route of continuous and deterministic passengers' arrival rate, minimizing both operational costs and passengers' waiting-time. The novelty of Hurdle (1973) work is using a linear cost structure to accommodate costs for owning vehicles (fixed costs), costs for performing runs (variable costs), and costs of passengers' waiting-time.

Prior to using optimization techniques to estimate frequencies, this problem was mainly addressed by empirical rules. A summary of empirical rules widely used for this purpose is provided in Furth and Wilson (1981). One important empirical rule in this context is the *Peak Load Factor*, which estimates frequencies at peak periods. Peak periods are those with maximum demand, as opposed to off-peak periods with lower demand.

The *Peak Load Factor* rule estimates the frequency of each peak period as the ratio between the maximum number of on-board passengers (in the entire route) by the *desired occupancy* on each vehicle. The *desired occupancy* on each vehicle is the product of its *load factor* (vehicle occupancy percentage) and its *maximum capacity* (number of seats plus the number of standees). The *desired occupancy* stands for what would be comfortable and efficient at peak periods. For example, occupancy of 80% could be desirable, to avoid the unpleasant experience of overcrowding in-vehicles and at-stops. Therefore, the *Peak Load Factor* ensures Public Transport capacity at peak periods (for off-peak periods, the minimum frequency imposed by regulation usually rules (Vuchic et al., 1978)). This rule would be incorporated in some Frequency Setting optimization models.

A significant contribution to the Frequency Setting literature is the optimization model of Furth and Wilson (1981). This model is the first alternative to the *square root method*. It includes constraints on subsidy, fleet size, policy headway, and *Peak Load Factor*, and it optimizes waiting-time savings and ridership. This formulation brings the best of all worlds: it includes the *Peak Load Factor* constraint acknowledged by operators, it counts with the cost of operators in a comprehensive way as well as all concerns that were covered in the works based on *square root method*. Overall, this was a seminal work in the Frequency Setting literature, and is still a must read in this area.

Worthy to mention the formulation by Han and Wilson (1982), designed for networks with overlapping routes and operating close to maximum capacity. It minimizes passengers' waiting-time and vehicles' crowding. In addition to including constraints on fleet size and capacity, it considers passenger route choice behavior.

Other works followed. Ceder (1984) proposed four formulations for this problem, including a method to reduce the number of runs (i.e., reduce operating costs) by relaxing its *desired occupancy*, and at the same time, avoid overcrowding problems. Additional constraints include the total route distance having loads greater than the *desired occupancy* (Ceder, 1984). Another work by Ceder (1991) considers a re-Frequency Setting problem that improves the frequencies already defined for a network. The rationale is that passengers' waiting-time is longer in the segments of maximum headway (i.e., lower frequency). This approach minimizes the maximum headway, called the *minmax headway problem*, while complying with a bunch of constraints such as the required number of runs. Ceder also shows how to estimate the number of working vehicles as a range of expected values instead of a single value (Ceder, 2007, p. 53).

More recently, some studies started to formulate the Frequency Setting problem acknowledging uncertainty in some features. Hadas and Shnaiderman (2012) considered stochastic demand and travel time, while Y. Li et al. (2013) considered stochastic passenger arrivals, boarding and alighting processes, and travel time. I. Ö. Verbas and Mahmassani (2013), İ. Ö. Verbas et al. (2015) consider demand variation along time and line route.

2.2.3 Timetabling

The Timetabling problem returns the specific departure-time of all runs on all routes, aiming at maximizing overall service efficiency and quality (Wu et al., 2016). It is desirable that Public Transport timetables encompass both passenger comfort (efficiency) and service cost (cost-effective) (Ceder, 2007).

The Timetabling stage returns the timetables with the departure-time and arrival-time of all runs on each route, typically with detail at the Time Control Point (TCP) or stop.

There are different techniques used for Timetabling, depending on the experience and resources of planners and companies (Ceder, 2007). These are differentiated by the methods employed, by the objectives and constraints conceptualized, and by the assumptions taken. The methodology adopted to build timetables is made considering operators goals and the specific Public Transport network, including the decision to build timetables for some routes independently, or to consider the interaction between several routes.

Computation tools have been increasingly applied to aid the Timetabling process, helping the decision-making process. These include the GIST system (Galvão et al., 2001), the GIRO HASTUS software (Salicrú et al., 2011), ROUTELOGIC, Routematch, Optibus or Trapeze (Ceder, 2016).

There are two main measures to assess timetables: i) the number of runs for each route, that will determine the required fleet size; ii) the estimated fleet size required considering each route separately (including interlining and deadheading runs).

The main inputs used in the Timetabling stage include: i) the network of Public Transport routes; ii) the running-times associated with each run-piece of each route in the network; iii) the frequencies of each route previously determined in Frequency Setting; iv) departure-times of the first and last runs; v) the relevance of each transfer deduced from OD matrices; vi) the optimal slack time to allocate to each TCP for each route - obtained from a preliminary optimization problem;

The main objective functions used in the Timetabling stage are as follows: i) To attain a periodic frequency (i.e., even headway), usually by applying Periodic Event Scheduling Problem (PESP) formulations; ii) Minimize total transfer waiting-time; iii) Satisfy demand with even loads; iv) Synchronize transfers or maximizing the number of well timed trans-

fers, usually by applying *Synchronization Timetabling techniques* such as Timed Transfers, Transfers Optimization or Bunching Mitigation; v) Trade-off between the overall transfer waiting-time and operating costs (Bruno et al., 2009).

The outputs obtained with the Timetabling stage are: i) a timetable with runs' information for each route in the network. ii) the departure-time and arrival-time for all runs on each route along the entire day. iii) the departure-time from the initial depot and arrival-time at the final depot. Public Transport systems typically consider identical planning periods for all routes. Some studies also suggest specific planning periods for each route (Ibarra-Rojas, López-Irarragorri, et al., 2015).

One challenge addressed in Timetabling is finding a balance between vehicle supply (through departure-time) and passenger demand (dynamic process over time). This balance occurs when a timetable satisfies the demand while minimizing the fleet size (thus minimizing the company costs related to drivers and vehicles).

Four major guidelines can be highlighted to achieve cost-effective timetables: i) to optimize required resources; ii) to find an adequate correspondence between vehicle supply and passenger demand; iii) during the timetable development and under the supervision of the planner, authorize vehicle-frequency changes for potential exceptions not relying on passenger demand data; iv) employment of alternative techniques for developing timetables, such as headway-smoothing techniques (concerning transition segments between adjacent time periods), or frequency-setting methods (Ceder, 1987, 2007).

The main constraints applied to Timetabling in the literature are: i) to satisfy passengers' demand, by computing the travel-time that passengers spend performing trips. This constraint has impacts on traffic, dwell-time and on the overall efficiency of the Public Transport system. When the demand is underestimated, the Public Transport system becomes slow and more vulnerable to bunching. When the demand is overestimated, vehicles can execute their itineraries earlier than originally planned. The optimum situation is the one returning low variability from the planned schedule to the performed one; ii) Coordination of passengers' transfers considering transfer zones and their connected Public Transport routes, in order to return a global network timetable with improved transfers in time and space. Transfers among routes can be given higher priority according to specified criteria (e.g., number of passengers expected for each transfer); iii) fleet size; iv) historical background; (Guihaire & Hao, 2008). v) The general case: build timetables for each UDP of the day, respecting its specific frequency, and merge the solutions to obtain the entire day timetables.

PESP

The PESP approach returns periodic timetables which are easily perceived by passengers. PESP was firstly addressed by Serafini and Ukovich (1989) with a mathematical model. The PESP builds timetables satisfying a set of periodic interval constraints. It considers events as the combination of (vehicle, node/station, arrival) and (vehicle, node/station, departure). Events are scheduled for one cycle (e.g. one hour) and further repeated in following cycles. Safety requirements are included in the form of a set of cyclic constraints, such as imposing a given time interval between the end and the start of two consecutive events (this time interval can be fixed or a time window) or a minimum headway time between every pair of vehicles using the same path.

Different approaches to solve PESP include implicit enumeration methods (Serafini & Ukovich, 1989), cutting plane method (Odijk, 1996), or constraint propagation.

Nachtigall (1996) optimized a periodic railway network. The concept of waiting time at all junctions (transfer stations) is formulated and PESP is generally predicted to be NP-hard. Nachtigall and Voget (1996) applied a genetic algorithm to a large railway network.

Liebchen and Mohring (2002) used the PESP framework to construct timetables for the Berlin underground with consideration of many criteria, including maximizing the number of crosswise correspondences (the meeting frequency of feeder vehicles and connecting vehicles).

Liebchen (2008) proposed a directed-graph mechanism with several extended models as a comprehensive foundation for solving PESP. Based on the compression of the periodic timetable in practice, it turns out that periodic timetabling can be suboptimal for short time horizons. However, periodic timetabling can always be done for sufficiently long time horizons – e.g., in different time buckets.

Bunching Mitigation

Another group of Synchronization Timetabling techniques address the mitigation of vehicles' bunching, either exclusively or combined with other goals. These models include the reduction of vehicles' bunching at stops as a goal in their objective function. Bunching can occur in two undesirable situations: i) when vehicles running in the same route end up in the same location at the same time due to severe delays, and ii) the case where different routes share portions of their paths, and vehicles bunch due to lack of schedule coordination or delays.

2.2.4 Vehicle Scheduling

There are two variants frequently considered in Vehicle Scheduling regarding the number of depots of the problem: Single Depot Vehicle Scheduling problem (SDVS) and Multi Depot Vehicle Scheduling Problem (MDVS). The complexity of SDVS is polynomially solvable with minimum cost flow problem (Haase et al., 2001). MDVS has NP-hard complexity (Desaulniers & Hickman, 2007; Haase et al., 2001).

Vehicle Scheduling can be formulated as a SDVS problem when the fleet operates from a single depot, which usually occurs in small cities. Moreover, Vehicle Scheduling can be formulated as a MDVS problem, by considering several depots in a multi-commodity flow problem, usually using one directed graph for each depot (Desaulniers & Hickman, 2007; Ribeiro & Soumis, 1994).

The main goals pursued in Vehicle Scheduling approaches are: i) To assign Public Transport vehicles to cover a set of timetabled runs; ii) To minimize operational costs (the total cost of a schedule is the sum of the cost of all its runs); iii) To minimize waiting-time of passengers; iii) To comply with constraints of the system: number of depots, capacity of depots, fleet size, type of vehicles, fixed run timetable, manpower capacity, other in-company restrictions (Bunte & Kliewer, 2009; Daduna & Paixão, 1995; Kliewer et al., 2006).

The constraints ensure that each active run is covered exactly once, and ensure that the schedules obtained are feasible in the sense that they comply with the number of vehicles available (Desaulniers & Hickman, 2007; Ribeiro & Soumis, 1994).

If the Vehicle Scheduling problem is infeasible or its solutions are excessively expensive, the timetable or route frequencies may have to be revised. Moreover, the problems of vehicle parking and dispatching and maintenance scheduling are solved in this stage, as they are dependent on the vehicles schedules obtained in the Vehicle Scheduling problem (Desaulniers & Hickman, 2007).

Public Transport schedules are created normally under the assumption that vehicles arrive and leave from each stop without disturbances (Kliewer et al., 2006; G. Liu & Wirasinghe, 2001). This problem also considers specific constraints of each system such as the coordination of vehicle schedules (Hill, 2003), demand and topology of each geographic area (Mulley & Ho, 2013; Szeto & Wu, 2011; van Oudheusden & Zhu, 1995).

The main inputs of Vehicle Scheduling approaches are: i) the fixed timetable of runs previously determined in Timetabling; ii) the set of depots where vehicles are housed; iii) the number of vehicles stationed at each depot.

Each run is performed between two TCPs, with defined departure-time and arrival-time. The problem includes four types of runs: i) an active run carries passengers on board; ii)

a deadhead run does not carry passengers on board; iii) a pull-out run corresponds to the drive between the depot and the starting terminus of an active run; iv) a pull-in run occurs when a vehicle leaves the ending terminus of an active run and returns to the depot.

The main output from the Vehicle Scheduling problem are vehicle schedules. The Vehicle Scheduling problem assigns exactly one vehicle to each run. The travel time of a vehicle between the end of a run and the start of the next run is considered including layover. A pair of consecutive active runs is compatible if both runs can be covered by the same vehicle. Costs are incorporated exclusively for deadhead runs, pull-out runs and pull-in runs. No cost is associated with active runs, since their cost is fixed for any feasible solution.

2.2.5 Driver Scheduling

The main goals of Driver Scheduling include: i) To define daily duties for all runs scheduled; ii) Minimize cost. The Driver Scheduling can be formulated as a multi-objective set-covering problem, of NP-hard complexity (Lourenço et al., 2001).

Driver Scheduling techniques take as inputs the vehicle schedules defined at the previous stage and return a set of generic drivers' daily duties to cover all runs or vehicle blocks scheduled, whilst minimizing the total cost from driver's wages (Ibarra-Rojas, Delgado, et al., 2015; Lourenço et al., 2001).

A vehicle block is the path traveled by a vehicle between its departure and return to the depot. Blocks can be split into units of work at relief points if the itinerary includes change-over points (places where changes of drivers are possible) at compatible time. A driver's duty is a set of consecutive units of work that can be assigned to a driver (Lourenço et al., 2001).

The set of daily duties obtained from Driver Scheduling is constrained by drivers' labor and other regulation applied to the transportation system under analysis (e.g., regulations of drivers' length of work and rest) (Ibarra-Rojas, Delgado, et al., 2015). All regulations have to be considered, from international to local rules (some rules are unwritten and soft rules may be broken in some cases), including maximum daily work time, maximum work time without a meal break or the maximum duration between the start and end of a shift.

The complexity of regulation influences the ease in obtaining feasible solutions for each case study. For example, European community allows a single meal break, or two or three smaller breaks, or a shift without breaks but whose cumulative slack complies with other requirements. This type of regulation increases the number of possible solutions as well as the complexity in finding the best one. These challenges are increasingly solved with computational optimization methods in order to obtain efficient schedules complying with

all regulations.

2.2.6 Driver Rostering

The Driver Rostering stage has the following main goals: i) To define rosters of driver through the assignment of the generic daily crew duties obtained in Driver Scheduling to the real drivers working in the company; ii) To minimize operating costs, particularly wages of drivers.

The allocation of real drivers to crew duties can be implemented with different procedures. For example, the drivers can be organized into small groups, so that each group can be scheduled independently on a cyclic basis. Another example is the sequential assignment of duties to drivers by some criterion (e.g., seniority) (Mesquita et al., 2011).

Driver Rostering is constrained by the time horizon that each driver is assigned to each depot (e.g., a month) and by labor regulations (Mesquita et al., 2011). There is little published research devoted to Driver Rostering. This problem is difficult to solve mainly due to the challenge of defining an objective function to optimize. Frequently Driver Rostering is applied with the target of satisfying constraints for a feasible solution (i.e., ensuring the solution obtained complies with all drivers' constraints) (Ernst et al., 2004).

2.3 Space-time terminology for runs and trips

2.3.1 Space-time terminology for runs

The Public Transport service delivered by buses, metro, rail and other collective vehicles, is usually organized using routes accessed by passengers at stops. The vehicles providing the service on each route execute several runs over a day.

Routes can operate either in one (e.g., a circle route) or two directions (e.g., with round trips). This work uses the concept of directed-route to refer to the transportation service delivered by a route in one defined direction. Accordingly, routes operating in two directions can be analyzed for each direction separately, therefore divided into two separate directed-routes. Moreover, routes which operate in one direction can be directly analyzed as directed-routes.

The term *route* will be used to refer to route activity covering both directions of travel and possible ramifications. For example, *routes*' information is disclosed to the public by identifying color codes, including predefined paths and schedules.

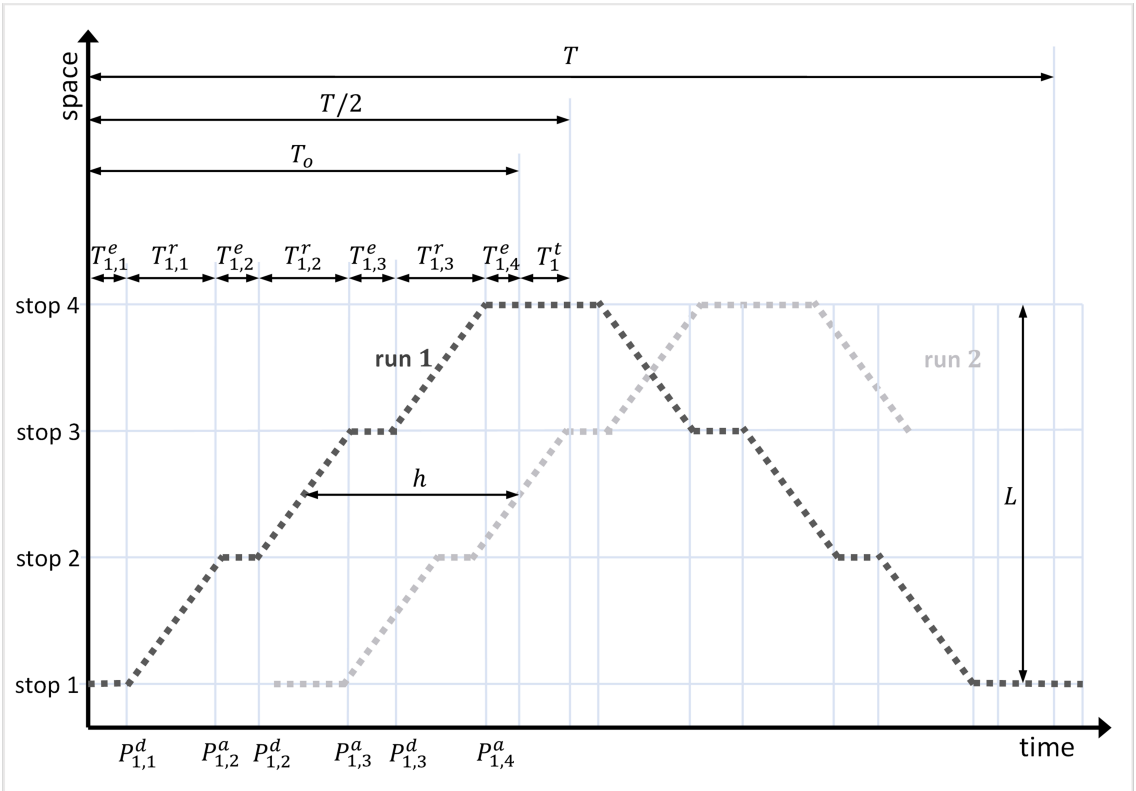
The *directed-route path* is the one-way geographic path that vehicles on that directed-

route have to take, starting and ending at termini, and visiting an ordered sequence of intermediate stops. Some directed-route paths may have branches in order to increase the geographical scope of the transportation service provided. Moreover, the traveling distance of a directed-route path is referred to as directed-route length (L, in km).

It is desirable to distinguish stops from stations. Stops are the places where passengers board and alight from Public Transport vehicles. Stations refer to places with some infrastructure and are typically associated with large volumes of passengers, and which may incorporate several stops.

The acronym *TCP* refers to a stop on a directed-route where the Public Transport operator monitors the actual time of each run.

Figure 2.3 shows a space-time diagram representing the generic operation of runs.



Where:

- T is the cycle-time (in minutes)
- T_o is the operating time (in minutes)
- h is the headway
- L is the directed-route length
- $T^e_{u,s}$ is the dwell-time of run u at stop s (in minutes)
- $T^r_{u,s}$ is the running-time between consecutive stops s and $s+1$ in run u (in minutes)
- T^t_u is the terminus-time of run u (in minutes)
- $P^d_{u,s}$ is the departing-time of run u from stop s (point in time)
- $P^a_{u,s}$ is the arrival-time of run u at stop s (point in time)

Figure 2.3: Space-time diagram illustrating key concepts associated with runs.

In each UDP, each directed-route path can be covered by several vehicles at different times. The concept of run distinguishes each time a specific vehicle covers a directed-route path. Each run is unique. In Figure 2.3, the gray dashed line illustrates a run covering the four stops of its directed-route path (i.e., run 1), followed by a second run represented with the light gray dashed line (i.e., run 2).

The specific departure-time of a run from a stop ($P^d_{f,s}$, point in time) can be calculated by cumulative inference, taking the run departure-time from terminus (or other stop where that information is available) as a reference and adding the expected running-time and dwell-time at the consecutive stops the vehicle visits. This inference process is represented for the case of two consecutive stops in Equation (2.1).

Departure-time of a run from a stop

$$P^d_{u,s+1} = P^d_{u,s} + T^r_{u,s} + T^e_{u,s+1} \tag{2.1}$$

Where:

- s identifies a stop
- f identifies a run
- $P^d_{u,s}$ is the departure-time of run u from stop s (point in time)
- $T^r_{u,s}$ is the running-time between consecutive stops s and $s+1$ in run u (in minutes)
- $T^e_{u,s}$ is the dwell-time at stop s in run u (in minutes)

The time spent by a vehicle to travel between two consecutive stops in the same run is referred to as *running-time* ($T^r_{u,s}$, in minutes).

Dwell-time refers to the time a vehicle spends without moving at a stop to allow boarding and alighting of passengers ($T^e_{u,s}$, in minutes). Dwell-time can be divided into five stages: door-unblocking, opening doors, passenger boarding and alighting, closing doors and vehicle dispatching. Dwell-time is frequently used as an efficiency measure of Public Transport, where shorter dwell-times are desirable. Passengers' in/out flows relate to passengers' alighting and boarding. Variability of dwell-times is due to many factors, such as the size of vehicle doors, the number of passengers boarding and alighting, and the step height between platform and vehicle.

Analogously, the arrival-time of a run at a specific stop $s+1$ ($P^a_{u,s+1}$, point in time) can be calculated with reference to the corresponding run's departure-time from the previous stop s, to which the expected running-time is added. This inference process is represented for the case of two consecutive stops in Equation (2.2).

Arrival-time of a run

$$P^a_{u,s+1} = P^d_{u,s} + T^r_{u,s} \tag{2.2}$$

Where:

- s identifies a stop
- u identifies a run
- $P^a_{u,s+1}$ is the arrival-time of run u at stop $s+1$ (point in time)
- $P^d_{u,s}$ is the departure-time of run u from stop s (point in time)
- $T^r_{u,s}$ is the running-time between consecutive stops s and $s{+}1$ in run u (in minutes)

Operating-velocity (V_o, in km/h) is the average velocity a vehicle travels between termini (not including terminus-time). The operating-velocity can be calculated by dividing directed-route length by operating-time, as shown by Equation (2.3)

Operating-velocity

$$V_o = (L \cdot 60)/T_o \tag{2.3}$$

Where:

- V_o is the operating-velocity (in km/h))
- L is the directed-route length (in km)
- T_o is the operating-time (in minutes)

The operating-time (T_o, in minutes) refers to the required time for a vehicle to travel its directed-route path, starting and ending at its terminus.

Cycle-time (T, in minutes) is the time spent by a vehicle to perform the complete journey of a route, defined as the time between two successive departures of the same vehicle from the same terminus. When a route operates in two directions and under equal operating-time and terminus-time, the cycle-time is calculated as shown in Equation (2.4).

Cycle-time

$$T = 2 \cdot (T_o + T_t) \tag{2.4}$$

Where:

- T is the cycle-time (in minutes)
- T_o is the operating-time (in minutes)
- T_t is the terminus-time (in minutes)

Terminus-time (T^t_u, in minutes) is the time spent by a vehicle at a terminus between the

end of run u and the start of the next run. It includes time for vehicle checkup, turnaround time, and slack time. Slack time at termini is often planned to allow drivers to take rest breaks.

A headway separates two consecutive runs on the same directed-route. Accordingly, a headway h is the time elapsing between consecutive run departure-times (i.e., the time it will take for the trailing vehicle to reach out the position of the next vehicle). A shorter headway corresponds to more frequent service, since headway is the inverse of the frequency over a determined period. Its determination considers passenger demand, capacity of vehicles, and the desired Level of Service (LOS) (i.e., load factor and policy headway). Most systems have regulation for minimum and maximum headway thresholds, to ensure Public Transport service quality.

Frequency

$$f = 60/h \tag{2.5}$$

Where:

- f is the frequency (in hour^{-1})
- h is the headway (in minutes)

Headway

$$h = T/f \tag{2.6}$$

Where:

- h is the headway (in minutes)
- T is the cycle-time (in minutes)
- f is the frequency (in hour^{-1})

Frequency (f, in hour^{-1}) is the number of vehicle departures on a route during one hour. The inverse of headway.

Even headway refers to equally spaced run departure-times, while uneven headway refers to variably spaced run departure-times.

Policy headway is the minimum headway that operators have to offer so to ensure a specified LOS (instead of defining the headway by a capacity requirement).

Fleet size (N in vehicles) is the number of vehicles required in a route's operation so to comply with the specified frequency or headway. Usually calculated as shown in Equation (2.7).

Fleet size

$$N = T/h \tag{2.7}$$

Where:

- N is the fleet size (in vehicles)
- T is the cycle-time (in minutes)
- h is the headway (in minutes)

In summary, for a specified UDP, the service of a directed-route is fully defined in space and time by the following parameters: (1) the sequence of stops, in this work called directed-route path, and (2.a) when the service is non-periodic, the run departure-times of all runs, or (2.b) when the service is periodic, the run departure-time of the first run and the headway for the following runs.

Run departure-times are defined at the Timetabling stage of Public Transport planning. Timetables of even headway only require information on the first run departure-time and headway. Timetables of uneven headway require information on the first run departure-time plus the sequence of headways to operate or equivalently the sequence of all runs' departure-times.

2.3.2 Space-time terminology for runs considering a higher level perspective of the system

When pursuing the goal of synchronization, the system can be analyzed from a higher-level perspective. The system can be formulated by considering run-pieces, transfer-nodes and termini as elements.

Run-pieces refer to segments of runs. Transfer-nodes refer to the the geographic area where two or more directed-routes meet, cross, or merge, and where passengers can transfer between those directed-routes. In a system formulated with these elements, the transfer-nodes are used as connection points between the run-pieces. Therefore, a run-piece always starts and ends at termini or transfer-nodes.

Figure 2.4 shows a space-time diagram representing the generic operation of runs considering a higher-level perspective of the system. The main difference of this approach when compared to the previous approach is that the departure-times and arrival-times are now estimated for each run-piece (whereas in the previous approach they were estimated for each pair of consecutive stops).

The departure-time of a run-piece p (P_p^d, point in time) can be calculated by cumulative inference, taking the departure-time of the previous run-piece as a reference and adding

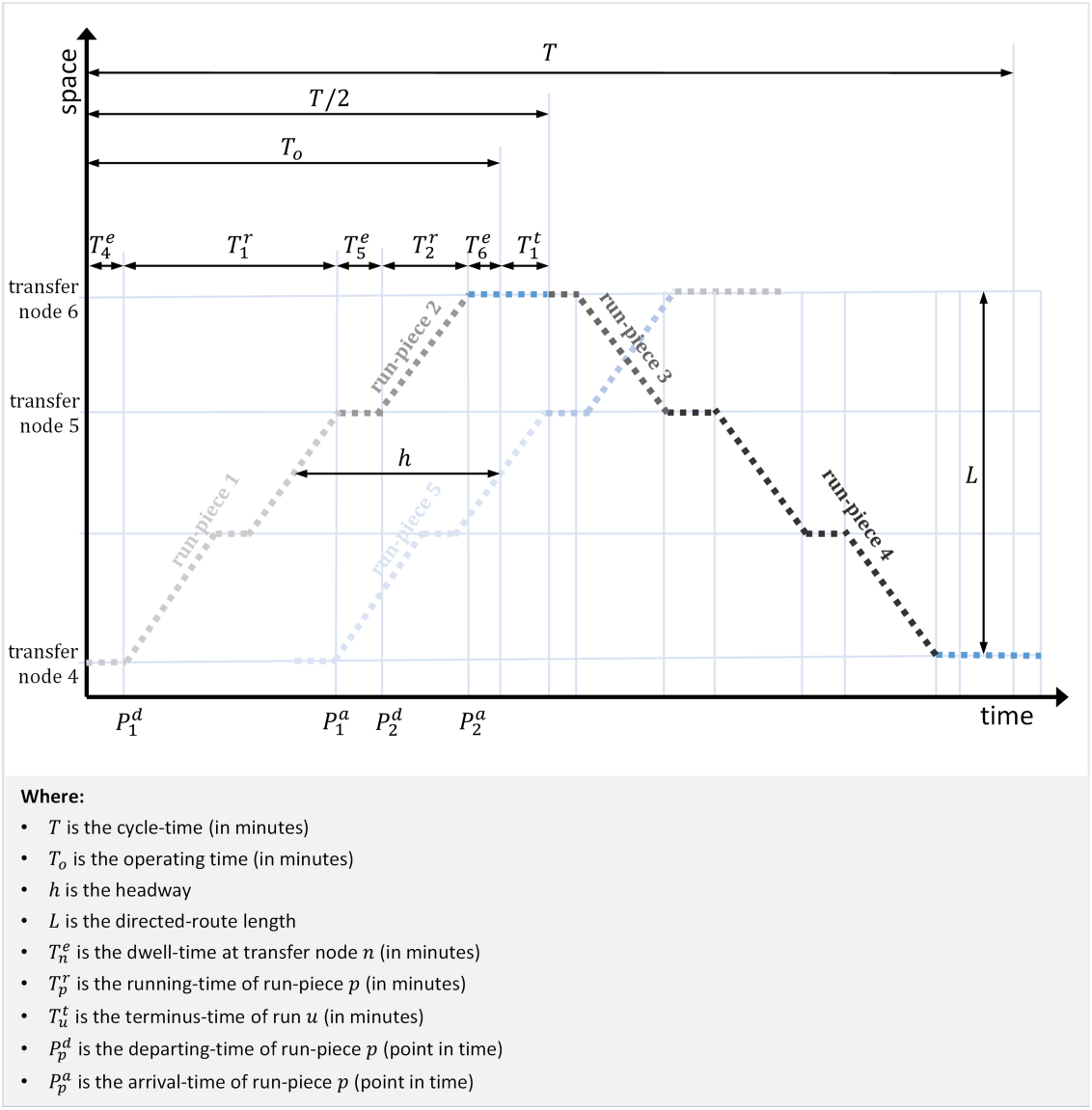


Figure 2.4: Space-time diagram illustrating key concepts associated with runs considering a higher-level perspective of the system.

the corresponding expected running-time and dwell-time. This inference rationale is only valid for consecutive run-pieces within the same run, detailed in Equation (2.8).

Departure-time of a run-piece

$$P_{p+1}^d = P_p^d + T_p^r + T_{p+1}^e \tag{2.8}$$

Where:

- p identifies a run-piece
- P_p^d is the departure-time of run-piece p (point in time)
- T_p^r is the running-time of run-piece p (in minutes)
- T_p^e is the dwell-time of run-piece p (in minutes)

Arrival-time of a run

$$P_p^a = P_p^d + T_p^r \tag{2.9}$$

Where:

- p identifies a run-piece
- P_p^a is the arrival-time of run-piece p (point in time)
- $P_{u,s}^d$ is the departure-time of run-piece p (point in time)
- $T_{u,s}^r$ is the running-time of run-piece p (in minutes)

Analogously, the arrival-time of a run-piece (P_p^a, point in time) can be calculated with reference to the corresponding run-piece's departure-time, to which the expected running-time is added. This inference rationale is represented in Equation (2.9).

2.3.3 Space-time terminology for passengers' full-trip

Public Transport passengers take full-trips prompted to activities such as work, school, shopping, or returning home. Each full-trip starts at an origin and ends at a destination. The sequence of geographic locations a passenger travels from origin to destination is referred to as passenger itinerary.

Figure 2.5 shows the main locations and times over a generic passenger itinerary comprising three trip-legs and two transfers, organized as a space-time diagram.

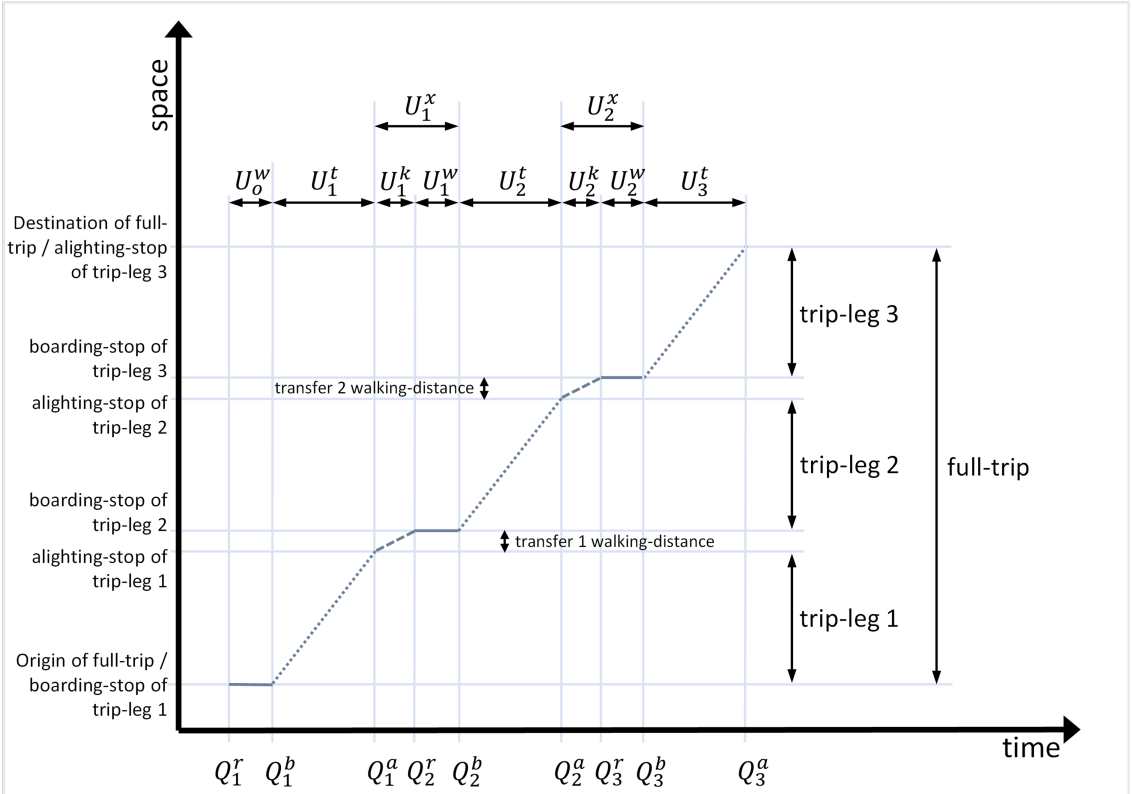
A full-trip may entail one or more trip-legs. Each pair of consecutive trip-legs within the same full-trip is linked by a transfer. Therefore, a transfer refers to a passenger interchanging between two trip-legs, in order to complete a full-trip. Moreover, a direct-trip indicates a full-trip made by a single trip-leg, i.e., without any transfer.

A boarding-stop is a stop where a passenger boards to start a trip-leg. An alighting-stop is a stop where a passenger alights from a trip-leg. Therefore, the term *origin* refers to the passenger's first boarding-stop of a full-trip, while the term *destination* refers to the passenger's last alighting-stop of a full-trip.

The readiness to board (Q_j^r, point in time) refers to the time at which a passenger is ready to start a trip-leg, i.e., the passenger is ready to board at a specified boarding-stop.

The time a passenger waits between his readiness to board and boarding-time is referred to as waiting-time. Passengers experience waiting-time at the origin of full-trips (i.e., origin waiting-time) and at transfers (i.e., transfer waiting-time).

The boarding-time Q_j^b (point in time) refers to the time when a passenger boards to start



Where:

- U_o^w is the passenger's waiting-time at the origin of a full-trip (in minutes)
- U_j^t is the passenger's travel-time in the trip-leg j (in minutes)
- U_i^x is the passenger's transfer time at transfer i (in minutes)
- U_i^k is the passenger's transfer walking-time at transfer i (in minutes)
- U_i^w is the passenger's transfer waiting-time at transfer i (in minutes)
- Q_j^r is the moment from which the passenger is ready to start trip-leg j (point in time)
- Q_j^b is the passenger's boarding-time on trip-leg j (point in time)
- Q_j^a is the passenger's alighting-time from trip-leg j (point in time)

Figure 2.5: Space-time diagram of a generic passenger itinerary.

trip-leg j. The alighting-time Q_j^a (point in time) refers to the time when a passenger alights from trip-leg j.

Travel-time in a trip-leg

$$U_j^t = Q_j^a - Q_j^b \tag{2.10}$$

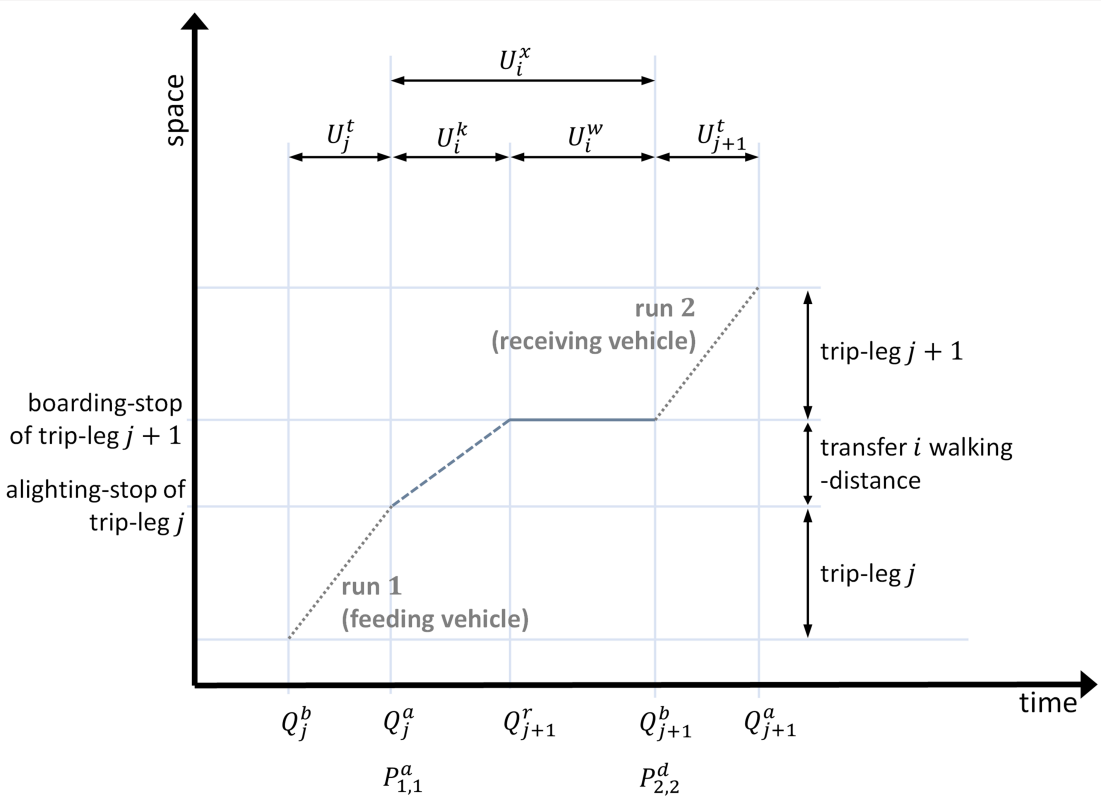
Where:

- j identifies a trip-leg within a full-trip
- U_j^t is the passenger's travel-time on the trip-leg j (in minutes)
- Q_j^a is the passenger's alighting-time from trip-leg j (point in time)
- Q_j^b is the passenger's boarding-time on trip-leg j (point in time)

The travel-time U_j^t (in minutes) refers to the time a passenger spends on the trip-leg j,

defined as the difference between the associated alighting-time Q_j^a and boarding-time Q_j^b, as detailed in Equation (2.10).

Transfers are unpopular for passengers. First, they require a physical transfer between two vehicles, which often implies aspects such as weather conditions, the transfer walking-distance, carrying luggage or the need to cross barriers such as roads or stairs. Second, transfers often involve unnecessary transfers' waiting-time. The perception of transfer waiting-time varies from passenger to passenger. Overall short transfers' waiting-time are perceived as comfortable, and long transfers' waiting-time as annoying and distressing. Finally, transferring is associated with the risk of missing the connection from the Feeding-Vehicle to the Receiving-Vehicle due to delays or service disruptions.



Where:

- U_j^t is the passenger's travel-time in the trip-leg j (in minutes)
- U_i^x is the passenger's transfer time at transfer i (in minutes)
- U_i^k is the passenger's transfer walking-time at transfer i (in minutes)
- U_i^w is the passenger's transfer waiting-time at transfer i (in minutes)
- Q_j^r is the moment from which the passenger is ready to start trip-leg j (point in time)
- Q_j^b is the passenger's boarding-time on trip-leg j (point in time)
- Q_j^a is the passenger's alighting-time from trip-leg j (point in time)
- $P_{u,s}^a$ is the arrival-time of run u at stop s (point in time)
- $P_{u,s}^d$ is the departing-time of run u from stop s (point in time)

Figure 2.6: Schematic of a transfer.

Figure 2.6 provides a schematic of a transfer. Figure 2.6 shows that, in a transfer, the alighting-time of the passenger from a trip-leg is coincident with the arrival-time of the

corresponding Feeding-Vehicle (running on the Feeding-Route), and that the boarding-time of the passenger on the next trip-leg is coincident with the departure-time of the corresponding Receiving-Vehicle (running on the Receiving-Route).

Moreover, Figure 2.6 also shows the four main times of a transfer: (1) the alighting-time from a trip-leg, (2) the transfer walking-time between the alighting-stop and the next boarding-stop (when the two stops do not coincide), (3) the transfer waiting-time at the boarding-stop, and (4)the boarding-time on the next trip-leg.

The transfer walking-time U_i^k (in minutes) is the time the passenger has to walk to make transfer i. The time required to walk the distance between the alighting-stop of the Feeding-Route and the boarding-stop of the Receiving-Route.

The transfer waiting-time U_i^w (in minutes) is the time the passenger has to wait to make transfer i. The time elapsed between the passenger arrival at the boarding-stop and the arrival of the next Receiving-Vehicle.

The transfer time U_i^x (in minutes) is the sum of transfer walking-time and transfer waiting-time of a specified transfer, as detailed in Equation (2.11).

Transfer time

$$U_i^x = U_i^w + U_i^k \tag{2.11}$$

Where:

- i identifies a transfer made by the passenger within a full-trip
- U_i^x is the passenger's transfer time at transfer i (in minutes)
- U_i^w is the passenger's transfer waiting-time at transfer i (in minutes)
- U_i^k is the passenger's transfer walking-time at transfer i (in minutes)

Transfer wait-time on full-trip

$$U_l^y = \sum_{i=1}^{N} U_i^w \tag{2.12}$$

Where:

- l identifies a full-trip
- $i = 1, ..., N$ includes all transfers performed by the passenger over full-trip l
- U_l^y is the passenger's transfer wait-time on full-trip l (in minutes)
- U_i^w is the passenger's transfer waiting-time at transfer i (in minutes)

Wait-time on full-trip

$$U_l^z = U_o^w + \sum_{i=1}^{N} U_i^w = U_o^w + U_l^y \tag{2.13}$$

Where:

- l identifies a full-trip
- $i = 1, ..., N$ includes all transfers performed by the passenger over full-trip l
- U_l^z is the passenger's wait-time on full-trip l (in minutes)
- U_o^w is the passenger's waiting-time at the origin of the full-trip l (in minutes)
- U_i^w is the passenger's transfer waiting-time at transfer i (in minutes)

The Transfer wait-time on full-trip (U_l^y, in minutes) is the sum of all transfers' waiting-time within it, as detailed in Equation (2.12). The Wait-time on full-trip (U_l^z, in minutes) is the sum of origin waiting-time and all transfers' waiting-time made by a passenger during a full-trip, as shown in Equation (2.13).

2.4 Final remarks

This chapter has reviewed the literature on Public Transport planning. The traditional approach to Public Transport planning involves the sequential solution of six stages, from the design of Public Transport routes to the rostering of drivers. These stages have been widely studied during recent decades. Their implementation in real world cases is always challenging due to the specifics inherent to each system. This review summarizes the main characteristics of each problem, referring their inputs, outputs, and highlights the interconnections and information flows occurring between them. It highlighted difficulties intrinsic to Public Transport planning such as the potential gap between models and reality, and the main policy trends influencing decision makers and planners.

The planning of Public Transport systems is continuously challenging the operations research community. More recently, the advent of Intelligent Transportation System (ITS) along with the significant improvements in computers' processing capacity fomented new research opportunities. The implementation of ITS in transportation systems allowed more accurate data collection and storage procedures, enhancing the historic analysis of transportation systems' and supporting the development of improved planning solutions. The use of ITS was also determinant in the field of dynamic re-planning approaches. The technological improvement in processing capacity empowered researchers to develop and implement more complex algorithms, boosting research on integrated Public Transport planning approaches.

Future research directions include the development of improved algorithms for larger prob-

lems, particularly with focus on the integration of several stages of Public Transport planning. The implementation of these approaches in real systems is expected to improve the overall quality of Public Transport planning solutions and consequently the quality on the Public Transport service provided to passengers.

The quality enhancement of Public Transport service can only be achieved when Public Transport planning solutions are conceived following the holistic perspective provided by regulating authorities on mobility and inter-modality integration. This implies cooperation between Public Transport planners, the operators of different transportation means, as well as with the other activities closely related to Public Transport.

This chapter also included an overview of terminology adopted in this work regarding the perspective of runs performed by operators and trips performed by passengers. This terminology is adopted and consistently applied in this thesis.

3 Estimating Origin-Destination Matrices from Automated Fare Collection Data

This chapter addresses the inference of OD matrices from entry-only AFC data. This research goal is pursued with two main tasks: the inference of alighting-stops for each AFC record using the Trip Chaining Method (TCM) - further associated with trip-legs, and the subsequent identification of transfers between trip-legs to identify full-trips. The work includes a literature review on these topics, followed by the description of the methodology implemented in the case of Porto. The case study includes all AFC records for a set of 19,999 smart cards in 2013. The results were analyzed through a quantitative approach, complemented by the visualization of OD matrices built at two geographic levels: a detailed perspective at the stop level, and an aggregate perspective at the Public Transport geographic zones. Data were segmented by type of day, seasonality, and user frequency.

3.1 Introduction

OD matrices are an essential source of information for Public Transport planning. OD matrices quantify Public Transport demand by summarizing the number of passengers traveling between each Origin-Destination (OD) pair. This source of information supports Public Transport planning in different decision-making processes, including Public Transport infrastructure planning, the geographic scope of the Public Transport service to be provided (i.e., Network Design), and its frequency (i.e., Frequency Setting). Consequently, when the actual OD matrices are unknown, the overall accuracy of the estimated OD matrices is critical for the successful Public Transport planning.

Until recently, data for the inference of OD matrices was mainly gathered through manually-collected surveys or combining different sources of data. With the technological advances

of the last few decades, Public Transport operators started to invest in Intelligent Transportation System (ITS) technologies, facilitating the collection of data and its use for Public Transport planning and decision-support. The work by Zalewski et al. (2019) provides an overview of up-to-date survey methods for estimating OD matrices, including the role played by ITS and new technologies in this context.

New methods have been developed for the inference of OD matrices using data from cell-phones, Global Positioning System (GPS), Automatic Passenger Counter (APC), and Automated Fare Collection (AFC), providing nearly complete spatial and temporal coverage at minimal marginal cost (Sánchez-Martínez, 2017) and leading some operators to abandon traditional surveys (Zalewski et al., 2019). An overview of AFC technology and related data collection processes is provided in Bagchi and White (2004).

Nowadays, AFC systems are widely used in Public Transport systems (Pelletier et al., 2011). Operators have been investing in AFC mainly to improve the efficiency of revenue collection and management. AFC systems encompass many other advantages, including ease of passenger use, ease of inter-modal integration, ease of cooperation between different operators, systematic data collection and gathering tools (Barry et al., 2009; Nunes et al., 2016). AFC can be used in several applications to improve the planning process of Public Transport systems, such as the inference of OD matrices, passenger miles and load profiles (Navick & Furth, 2002). Regarding the inference of OD matrices, using AFC data is considered to be more accurate, cheaper and of faster availability than using data retrieved from manual surveys (Barry et al., 2002).

Despite these advantages, there are some challenges in using AFC data for Public Transport planning. These include privacy concerns (Trépanier & Chapleau, 2006), and the failure to provide the information needed to sustain Public Transport planning decisions due to the design of data structures tailored for revenue management analysis, which may not be appropriate to support decision making related with strategic issues. All studies addressing this line of research require tremendous efforts to clean and correct missing and erroneous information (Trépanier & Chapleau, 2006). Plus, some data fields that could be collected directly with this technology, are not recorded at all in some cities (e.g., boarding-stop or route).

The research on the estimation of OD matrices from AFC is continuously evolving, with the increasing use of sophisticated methods supported by the new technologies and computational advances. The potential of these new resources is still being explored, and will certainly continue to improve the quality of Public Transport demand estimation in the years to come.

Depending on the characteristics of the AFC system, different tasks may be required. These include (a) the estimation of boarding-stop, (b) the estimation of alighting-stop, (c) the estimation of boarding route, and (d) the identification of transfers (Nassir et al.,

2011).

The estimation of boarding-stop (a) is required in some systems where the AFC devices store only the time of the trip, and not its boarding-stop. In these cases it might be possible to join Automated Vehicle Location (AVL) and AFC data to retrieve the vehicle position at the time of each AFC record, thus estimating its boarding-stop (Gordon et al., 2013; Wang et al., 2011). This approach is only accurate for cases where passengers tap a smart card in-vehicle (frequently in buses and trams).

The estimation of alighting-stop (b) is necessary in entry-only AFC systems. In these cases, passengers tap a smart card only when boarding, and there is no information regarding their alighting-stop or time. The Trip Chaining Method (TCM) is the most popular method dealing with this problem, although some alternative approaches are now emerging. A literature review on TCM applications is included in Section 3.2.

The estimation of boarding route (c) is necessary in cases where entry-only AFC data is recorded at boarding stations with multiple possible boarding routes (frequently in metro stations). In these cases, the AFC records store information on the boarding-stop and time, but not on the route taken. An example of using AFC data to this problem can be found in Kusakabe et al. (2010).

Transfers (d) are identified using criteria tailored for each system. This task allows for the aggregation of trip-legs into full-trips, which in turn is central to OD flow estimation. There are some differences in systems where passengers must re-tap their smart card on each trip-leg (such as is the case of Porto), and other systems where passengers only need to tap once at their origin, and then can travel freely in the system. A review on the criteria used to identify transfers in the literature is provided in Section 3.3.

The work reported in this chapter focuses on the inference of OD matrices using entry-only AFC data. This topic arises considering the state-of-the-art of this research area, and simultaneously the resources available from the Public Transport operators in the city of Porto (i.e., entry-only AFC data).

Considering the characteristics of the AFC system used in the Porto Metropolitan Area (PMA), along with the data available for the present work, the inference of OD matrices reported in this study encompasses the estimation of alighting-stops for each trip-leg, and the subsequent identification of transfers. The TCM was chosen for the process of estimating alighting-stops because it is the most recognized method for this task in the literature. Furthermore, a set of criteria was established for the identification of transfers, for this particular case study, and aligned with the state-of-the-art in the topic.

The main goal of this chapter is the estimation of alighting-stops and the identification of transfers from entry-only AFC data, applied to the case study of Porto. This work includes a literature review on applications of the TCM in Section 3.2, and on the identification of

transfers in Section 3.3. The methodology adopted to implement the TCM and transfers identification is detailed in Section 3.4.

The implementation of the TCM (Section 3.4.1) requires four assumptions: The majority of passengers will start the next trip at or near the alighting-stop of their previous trip; The majority of passengers end the last trip of the day at or near the boarding-stop of the first trip of the day; Passengers travel outside of the Public Transport system when the walking-distance between consecutive AFC records exceeds a specified threshold; Passengers can alight only in the sequence of downstream stops on the directed-route boarded.

The identification of transfers (Section 3.4.2) is made under four assumptions: Passengers do not walk more than a specified distance to transfer; Passengers do not wait more than a specified time to transfer; Passengers do not transfer to the same route; When an alighting-stop is not estimated, the next AFC record starts a new full-trip.

The case study is presented in Section 3.5. The results obtained are detailed in Section 3.6, which includes the quantitative analysis by type of day, seasonality, and user frequency, and the visualization of OD matrices at the stop and geographic area levels. Final remarks are provided in Section 3.7.

3.2 TCM Literature Review

The TCM is an algorithm to infer alighting-stops from entry-only AFC data. Each AFC record is associated with a trip-leg. The TCM considers the sequence of trip-legs made by each passenger in each day along with a set of assumptions to infer the alighting-stop of each trip-leg separately.

The TCM has been applied to Public Transport systems worldwide: to the metro system of New York City (Barry et al., 2002); to the joint operation of metro, bus, ferry, and tram of New York City (Barry et al., 2009); to rail and bus of Illinois (Zhao et al., 2007); to the bus network of Minneapolis-Saint Paul, Minnesota (Nassir et al., 2011); to bus operations in Gatineau, Canada (Trépanier & Chapleau, 2006); to the bus network of Québec, Canada (Trépanier et al., 2007); to the bus network of São Paulo, Brazil (Farzin, 2008); to metro and bus operations in Santiago, Chile (Munizaga & Palma, 2012); to the bus network of London, UK (Gordon et al., 2013; Wang et al., 2011); to buses in Bradford and Southport, UK (Bagchi & White, 2004); to bus and metro operations in Porto, Portugal (Hora et al., 2017; Nunes et al., 2016); to bus, metro and ferry operations in Brisbane, Australia (Alsger et al., 2016; Alsger et al., 2015; He et al., 2015); to bus operations in Jinan city, China (D. Li et al., 2011), among others.

The TCM can be used to infer OD matrices from aggregate or disaggregate perspectives on trip-legs. In the disaggregate perspective, trip-legs are analyzed without identifying

transfers (and therefore trip-legs are treated as full-trips). Studies following this approach include Barry et al. (2002), Hora et al. (2017), Nunes et al. (2016), Trépanier and Chapleau (2006), Zhao et al. (2007).

The aggregate perspective includes an additional step to identify transfers connecting trip-legs, subsequently obtaining full-trips. Studies applying this approach include Alsger et al. (2016), Alsger et al. (2015), Barry et al. (2009), Munizaga and Palma (2012), Nassir et al. (2011), Trépanier et al. (2007).

The body of literature applying the TCM differs mainly through the set of assumptions implemented. The main assumptions adopted in the literature are reviewed in the following sections, and summarized in Tables 3.1–3.5. Data preparation and cleaning procedures are not considered as assumptions, such as removal of duplicate AFC records, and strategies for missing or illogical AFC records.

3.2.1 Estimating the Alighting-Stop

Although TCM studies incorporate differences in some assumptions and approaches adopted, they share the grounding assumptions 3.1 and 3.4 for estimating the alighting-stop, proposed in the seminal work of Barry et al. (2002), or its variants, as summarized in Table 3.1.

Table 3.1: Overview of TCM assumptions to infer alighting-stops.

No.	Description
3.1	The majority of passengers will start the next trip-leg at or near the alighting-stop of their previous trip-leg
3.2	The majority of passengers will start the next trip-leg in the same geographic zone of the alighting-stop of their previous trip-leg
3.3	The majority of passengers will start the next trip-leg at the minimum generalized time distance to the alighting-stop of their previous trip-leg
3.4	The majority of passengers end the last trip-leg of the day at or near the boarding-stop of the first trip-leg of the day
3.5	The majority of passengers end the last trip-leg of the day in the same geographic zone of the first trip-leg of the day
3.6	Assumption 3.4 only applies when assumption 3.13 is also satisfied, otherwise the first boarding-stop of the next day is used instead

Assumption 3.1 considers that the majority of passengers start their next trip-leg at or near the alighting-stop of their previous trip-leg. Assumption 3.1 is also referred to as *the closest stop assumption* (Gordon et al., 2013). Applying assumption 3.1 results in chaining all daily trip-legs of each passenger, which is the source of the algorithm's name. Studies applying assumption 3.1 include Alsger et al. (2015), Barry et al. (2009), Barry et al. (2002), Gordon et al. (2013), Hora et al. (2017), D. Li et al. (2011), Munizaga and

Palma (2012), Nassir et al. (2011), Nunes et al. (2016), Trépanier and Chapleau (2006), Trépanier et al. (2007), Wang et al. (2011), Zhao et al. (2007).

Variants of assumption 3.1 include assumptions 3.2 and 3.3. Assumption 3.2 infers OD at the geographic zone level instead of stops (Farzin, 2008). Assumption 3.3 considers a minimum generalized time distance instead of a plain distance (Munizaga & Palma, 2012).

Assumption 3.4 follows the same principle as assumption 3.1 but uses the first boarding-stop of the day to infer the last alighting-stop of the day. Assumption 3.4 is also referred to as the *assumption of symmetry* (Navick & Furth, 2002), following the idea of mirrored daily patterns between alighting-stops in one direction and boarding-stops in the opposite direction. Studies applying assumption 3.4 include Alsger et al. (2015), Barry et al. (2009), Barry et al. (2002), Gordon et al. (2013), Hora et al. (2017), D. Li et al. (2011), Munizaga and Palma (2012), Nassir et al. (2011), Nunes et al. (2016), Trépanier and Chapleau (2006), Trépanier et al. (2007), Wang et al. (2011), Zhao et al. (2007).

Variants of assumption 3.4 include assumptions 3.5 and 3.6. Assumption 3.5 infers OD at the geographic zone level instead of stops (analogously to assumption 3.2) (Farzin, 2008). Assumption 3.6 infers the alighting-stop of the last trip-leg of the day regarding the boarding-stop of the first trip-leg of the day (assumption 3.4) only if it relates to the route taken (assumption 3.13) – otherwise, the first boarding-stop of the next day is used instead (Trépanier et al., 2007).

Assumptions 3.1 and 3.4, and their variants, may include some errors, because some passengers might travel outside the Public Transport system or end the day at other locations.

Assumptions 3.1 and 3.4 were validated in Barry et al. (2002) using New York Metropolitan Transportation Council information, and were found to be true for 90% of passengers. This analysis compared the inferred and real count of passengers exiting each station and compared the passenger volumes inferred with the corresponding values retrieved from a trip assignment model. The joint validation of assumptions 3.1 and 3.4 was also conducted by D. Li et al. (2011), through the comparison of real entry-exit AFC data in Jinan city, where the TCM returned an accuracy of inference above 75% considering the full data set, and above 85% during peak periods.

Studies by Alsger et al. (2016), Alsger et al. (2015) used the entry-exit AFC data from Brisbane, Australia, to validate some TCM assumptions, by comparing TCM inference to the corresponding real values. 82% of passengers returned to the first boarding-stop of the day and 88% of passengers had the last alighting-stop of the day within 800 meters from the first boarding-stop of the day (assumption 3.4) (Alsger et al., 2015). Constraining possible alighting-stops to downstream stops on the route boarded (i.e., adding assumption 3.13) improved the alighting-stop inference in the last trip-leg of the day (assumption 3.4) from

66.4% to 72.4% (Alsger et al., 2016).

Assumption 3.4 was tested by Navick and Furth (2002), aggregating the daily trips of each route. They tested the symmetry pattern of daily boarding and alighting on ten separate routes. The results showed that nine of the ten routes had a strong symmetric pattern, with a maximum variation in the cumulative distribution of less than 5%.

3.2.2 Traveling outside the system

Assumptions related to passengers traveling outside the Public Transport system under analysis are summarized in Table 3.2.

Table 3.2: Overview of TCM assumptions regarding traveling outside the Public Transport system.

No.	Description
3.7	By default, passengers travel within the Public Transport system
3.8	When there is a single AFC record on a day, passengers are assumed to have traveled outside the Public Transport system
3.9	When the walking-distance between consecutive AFC records exceeds a specified threshold, passengers are assumed to have traveled outside the Public Transport system

Assumption 3.7 means that, by default, passengers travel within the Public Transport system being analysed. This means that the TCM algorithm does not consider links on any other transportation means beyond those considered in the Public Transport system being analysed. AFC records not complying with assumption 3.7 are discarded. Assumption 3.7 is considered implicitly by most studies, while its explicit statement can be found for example in Farzin (2008), Nassir et al. (2011), Zhao et al. (2007).

Assumption 3.8 addresses the case of single AFC records on a day, which does not comply with assumption 3.4 (i.e., there is no reverse trip). These AFC records are usually discarded since they most likely relate to passengers traveling outside the Public Transport system on their reverse trips.

Assumption 3.9 was firstly proposed by Nassir et al. (2011). It means that, when a maximum walking-distance threshold is exceeded, the inferred alighting-stop cannot be kept (i.e., it is discarded). Exceeding this threshold implies a violation of assumption 3.7, since it identifies situations where passengers most likely traveled outside the system (i.e., using transportation means other than the ones being analysed). Studies applying assumption 3.9 include He et al. (2015), Hora et al. (2017), Nassir et al. (2011), Nunes et al. (2016).

The walking-distance in assumption 3.9 is defined between a) the inferred alighting-stop

and next boarding-stop or b) the last alighting-stop on a day and the first boarding-stop on a day. The lower the threshold considered, the more conservative the implementation. Different threshold were studied in He et al. (2015) for different scenarios using the entry-exit AFC data from Brisbane. Overall, a positioning in the value for this threshold is case-specific, and should be made considering the characteristics of each Public Transport system, such as Public Transport coverage area and stop density.

3.2.3 When an alighting-stop cannot be inferred

When an alighting-stop cannot be inferred, some assumptions can be made to guide the following analysis, as summarized in Table 3.3.

Table 3.3: Overview of TCM assumptions to use when an alighting-stop cannot be inferred.

No.	Description
3.10	When an alighting-stop cannot be inferred, the corresponding AFC record is discarded
3.11	When an alighting-stop cannot be inferred, an alternative inference is attempted assuming passengers often make the same trips throughout the month
3.12	When an alighting-stop cannot be inferred, an alternative inference is attempted assuming the traveling pattern of single-fare and multiple-fare card users to be identical for each boarding-stop

Assumption 3.10 stands to discard AFC records whose alighting-stop inference was not possible. It is present in all works, including cases of a single AFC record on a day and cases not complying with other constraints.

Assumptions 3.11 and 3.12 are applied when other assumptions fail in estimating an alighting-stop for a particular AFC record. Instead of immediately discarding those AFC records (assumption 3.10), these assumptions represent a final attempt to infer a suitable alighting-stop.

Assumption 3.11 considers an additional statistical analysis on all AFC records in the month of the smart card trip being analysed. The goal is to find another AFC record with a *similar pattern* (i.e., boarding in the same stop and route, and at a similar time of day) and with a successful alighting-stop inference (Trépanier & Chapleau, 2006; Trépanier et al., 2007).

Assumption 3.12 considers that the traveling pattern of single-fare card user is identical to the traveling pattern of multiple-fare card users for each boarding-stop (Barry et al., 2009). AFC records without a chained destination are randomly assigned to a destination. A stochastic distribution is used for this assignment, built from the successfully chained AFC records, and specific to each boarding-stop (Barry et al., 2009).

3.2.4 Network constraints

Table 3.4 summarizes TCM assumptions adopted in the literature which are associated with the constraints of the Public Transport network and its operating rules.

Table 3.4: Overview of TCM assumptions associated with network constraints.

No.	Description
3.13	Passengers can only alight in the sequence of downstream stops on the directed-route they boarded
3.14	The alighting-stop has to comply with the prepaid geographic fare (travel zones)
3.15	AFC records are discarded when associated with trip-legs traveling away from their next boarding-stop

Assumption 3.13 means that passengers can only alight in the sequence of downstream stops on the directed-route they boarded. Studies applying assumption 3.13 include Alsger et al. (2016), Hora et al. (2017), Nunes et al. (2016), Trépanier et al. (2007). Assumption 3.14 means that the alighting-stop must comply with the prepaid geographic fare (travel zones) of the AFC record (Nunes et al., 2016). Assumption 3.15 discards AFC records when its directed-route is traveling away from their next boarding-stop, i.e., when the next AFC record is closer to stops served before the boarding-stop (Gordon et al., 2013).

3.2.5 Inferring Alighting-Time

Table 3.5 summarizes assumptions applied in the TCM literature to infer the alighting-time.

Table 3.5: Overview of TCM assumptions to infer the alighting-Time.

No.	Description
3.16	Inferred alighting-stops are further crossed with AVL, APC with vehicle location, or other data, to search for a compatible vehicle whose recorded arrival-time is adopted
3.17	The inferred alighting-time of a trip-leg must precede the next trip-leg's boarding-time
3.18	Walking-time feasibility between the candidate alighting-stop and the next boarding-stop
3.19	The alighting-time is not be inferred

Inferring the alighting-time can consider strategies such as adding the expected travel-time to the boarding-time (retrieved from operators schedules), cross-checking the inferred alighting-stops with AVL data for compatible vehicles whose recorded arrival-times are adopted, as stated by assumption 3.16 (Gordon et al., 2013), cross-checking the inferred

alighting-stops and alighting-time with APC and AVL records (Nassir et al., 2011), or other sources of information depending on the data available in each system.

Assumptions 3.17 and 3.18 validate the inferred alighting-time. Assumption 3.17 means that the inferred alighting-time must precede the next trip-leg's boarding-time (Munizaga & Palma, 2012; Nassir et al., 2011). Assumption 3.18 ensures whether the passenger could have walked from the candidate alighting-stop to the following boarding-stop in the available time (i.e., walking-time feasibility) (Gordon et al., 2013).

Finally, assumption 3.19 covers for cases where the inference of alighting-time is not possible.

3.2.6 Alternative methods to TCM

An alternative approach to the TCM was proposed by Zhang et al. (2015), using a probabilistic model including monetary, temporal and geographic features. The data was analyzed by smart card Unique IDentifier (UID), mapping the historic pattern of each passenger over time. This approach does not include the analysis of each day separately, as implied by assumption 3.4. Instead, it searches for mobility patterns in each passenger, and groups passengers with similar mobility patterns (e.g., passengers living close to each other may frequently commute with on same routes). The time is analyzed for different Uniform Demand Period (UDP), including peak periods and off-peak periods, or different weekdays.

The work by Sánchez-Martínez (2017) reports a dynamic programming model that infers alighting-stops and identifies transfers from AFC and AVL data, thus returning full-trips. The model works on the basis of a generalized disutility minimization objective, and suits systems using a mix of gated stations and un-gated stops. The model is currently being used to support Public Transport planning in Boston.

3.3 Identifying Transfers Literature Review

This section presents the main assumptions used in the literature to identify transfers from AFC records, including assumptions summarized in Tables 3.6–3.8 and Assumption 3.20.

The order in which assumptions are implemented matters, mostly for reducing computational time. Assumptions on the feasibility of the network and the walking-distance threshold are usually applied first, while assumptions on the transfer time are usually the last to be applied. The reduction in computational time is because transfer time criteria usually require more calculations (i.e., alighting-time, walking-time, plus one or more time thresholds) than the other criteria.

3.3.1 Walking-distance

The main assumption applied in the literature to identify transfer walking-distance is *Assumption 3.20 : Passengers do not walk more than a specified distance to transfer.*

Assumption 3.20 means that passengers will only transfer between stops within a reasonable walking-distance of each other. The implementation of assumption 3.20 involves setting the maximum distance a passenger is willing to walk to transfer.

The walking-distance is calculated between the inferred alighting-stop and the boarding-stop of the next trip-leg. If the distance is over the threshold, the next trip-leg starts a new full-trip. If the distance is under the threshold, the next trip-leg is eligible to be classified as a transfer provided it complies with other criteria adopted.

Different values have been applied to implement assumption 3.20 in the literature: 400 m (Zhao et al., 2007), 750 m (Gordon et al., 2013), 800 m (Alsger et al., 2015; Nassir et al., 2011), 1 km (Munizaga & Palma, 2012; Wang et al., 2011), 1.1 km (Cui, 2006), and 2 km (Trépanier et al., 2007)

Alsger et al. (2015), using an entry-exit AFC data set, reported a sensitivity analysis of different values for the maximum walking-distance. It concluded that transfers are usually made with only a small walking-distance. The number of transfers identified in Alsger et al. (2015) were found to not significantly change for values of walking-distance equal to, or greater than, 800 m. Therefore, the value of 800 m was found to be adequate for the Brisbane network. The value for the maximum walking-distance is case-sensitive and should account for the specifics of each Public Transport system, for example through experts opinion or a sensitivity analysis as reported in Alsger et al. (2015).

3.3.2 Walking-time, waiting-time and activity-time

Assumptions applied in the literature to identify transfers based on walking-time, waiting-time and activity-time are summarized in Table 3.6.

Table 3.6: Overview of assumptions to identify transfers on walking-time, waiting-time and activity-time.

No.	Description
3.21	Walking-time feasibility, similar to assumption 3.18
3.22	Passengers do not wait more than a specified time to transfer
3.23	Passengers take some time to carry out an activity
3.24	Passengers embark on the first possible departure

The time elapsed between two consecutive trip-legs is an essential variable in the process

of transfer identification. Before identifying whether a transfer occurred or not, the time elapsed between two consecutive trip-legs is analyzed in two components: the walking-time and the non-walking time, as shown in Figure 3.1.

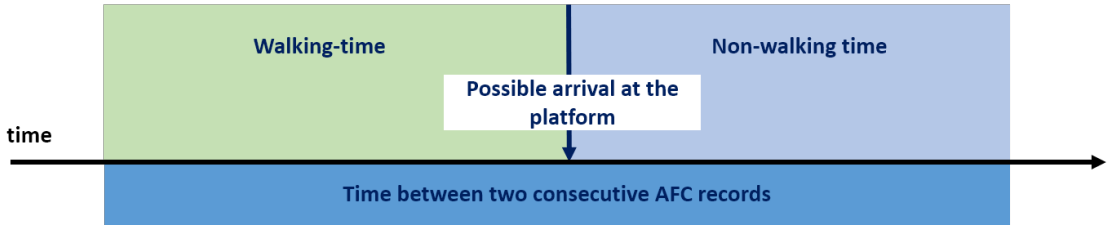


Figure 3.1: Walking-time and non-walking time between two consecutive trip-legs.

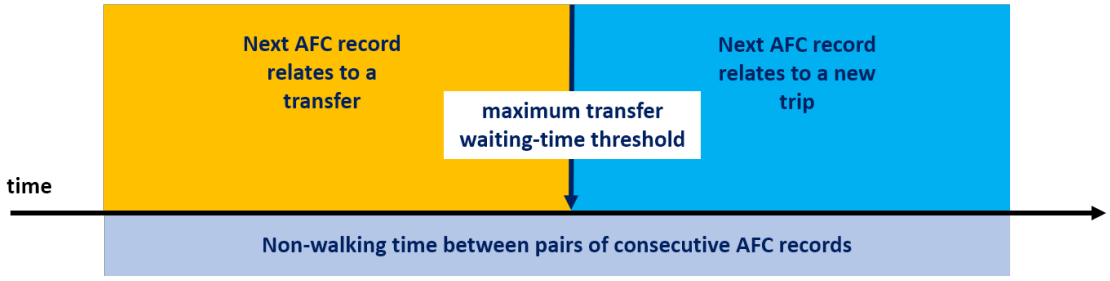


Figure 3.2: One waiting-time threshold to identify transfers.

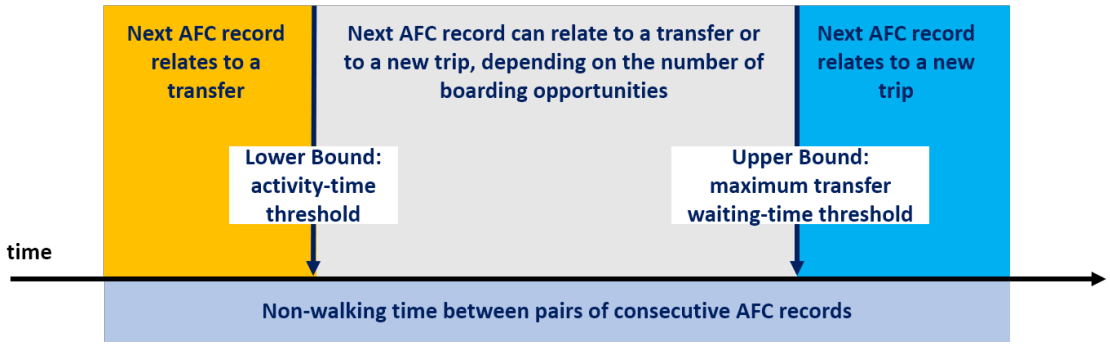


Figure 3.3: Two waiting-time thresholds to identify transfers.

The walking-time is the time a passenger needs to walk from the alighting-stop to the next boarding-stop. It is usually estimated using an average walking speed (e.g., 5 km/h in Alsger et al. (2015) or 3 km/h in Gordon et al. (2013)).

Assumption 3.21 verifies if passengers could have walked from the candidate alighting-stop to the following boarding-stop in the available time (Gordon et al., 2013; Nassir et al., 2011).

When a transfer occurs between two consecutive trip-legs, the non-walking time corresponds to transfer waiting-time at the platform. If the two consecutive trip-legs belong to different full-trips, the non-walking time corresponds to the time spent on an activity plus the subsequent waiting-time at the platform to start the next full-trip.

Alsger et al. (2015) reports a sensitivity analysis of walking-time and non-walking time. They found that, on average, the walking-time component accounts for three minutes or

less, independent of the non-walking time absolute value.

Assumption 3.22 means that passengers do not wait more than a specified time to transfer. This assumption can be implemented with a) one or b) two transfer waiting-time thresholds, or c) considering the time elapsed between consecutive boardings.

In cases using a single transfer waiting-time threshold (a), as illustrated in Figure 3.2, when the non-walking time is above a maximum transfer waiting-time threshold, the next trip-legs starts a new full-trip. Otherwise, the next trip-leg can relate to a transfer (provided it complies with all other criteria).

In cases using two transfer waiting-time thresholds (b), a maximum transfer waiting-time threshold relates to an upper bound, above which a new full-trip is identified, and below which other criteria are needed to identify transfers (such as verifying whether passengers board at the first opportunity). The approach of using two transfer waiting-time thresholds is illustrated in Figure 3.3.

The implementation of a maximum transfer waiting-time threshold implies the prior estimation of the alighting-time of each trip-leg. The alighting-time inference depends on additional information beyond the AFC data, namely the joint-checking of operators schedules from AVL and AFC data sets (i.e., it implies assumption 3.16 is met). Studies applying a maximum transfer waiting-time threshold include Zhao et al. (2007) with 5 min, Barry et al. (2009) with 18 minutes, Nassir et al. (2011) with 40 minutes, Gordon et al. (2013) with 45 min, and Alsger et al. (2015) with 60 min. Alsger et al. (2015) concluded, from a sensitivity analysis on the value for the maximum transfer waiting-time threshold, that 90% of passengers are not willing to wait more than 10 minutes to transfer.

Finally, implementing assumption 3.22 by considering a maximum threshold for the time elapsing between consecutive boarding-times (c) is usually adopted when the alighting-time cannot be inferred (assumption 3.19). Studies adopting this approach include Hofmann and O'Mahony (2005) with 90 minutes, and Bagchi and White (2004) with 30 minutes.

Assumption 3.23 defines a minimum activity-time threshold. When the non-walking time is above this threshold, the algorithm will identify potential activities performed by passengers. When the non-walking time is below this threshold, the algorithm identifies a transfer. This threshold is only used in studies using two waiting-time thresholds, and corresponds to the lower bound, as shown in Figure 3.3. This threshold was implemented with a value of 30 min in Munizaga and Palma (2012), Nassir et al. (2011).

Assumption 3.24 is incorporated in studies using two waiting-time thresholds. When the waiting-time at the platform is in between the Upper and Lower Bounds, the algorithm identifies a transfer only if the passenger boards at the first opportunity, which is the first accessible vehicle performing the same route of the next AFC record. Otherwise, the algorithm identifies a new trip (Nassir et al., 2011), as shown in Figure 3.3.

3.3.3 Transfer feasibility in the network

Assumptions applied in the literature to Identify Transfers on Transfer feasibility in the network are summarized in Table 3.7.

Table 3.7: Overview of assumptions to identify transfers on transfer feasibility in the network.

No.	Description
3.25	A transfer occurs between consecutive trip-legs
3.26	A transfer occurs between trip-legs on the same smart card
3.27	Passengers do not transfer to the same route

Assumption 3.25 defines that transfers can only be identified between consecutive trip-legs, while assumption 3.26 defines that those trip-legs must belong to the same smart card. Overall these two assumptions work together in defining that a transfer can only be identified in between consecutive AFC records by the same passenger (Hofmann & O'Mahony, 2005). Although most works do not explicitly define these two assumptions, its implementation implicitly grounds the necessary logic for the identification of transfers in this context.

Assumption 3.27 considers that passengers will not transfer to another vehicle on the same route in which they are traveling, regardless of its direction. When two consecutive trip-legs occur in the same route, regardless of its direction, they belong to different full-trips (Hofmann & O'Mahony, 2005; Munizaga & Palma, 2012).

3.3.4 When the alighting-stop is not inferred

Assumptions applied in the literature to identify transfers when the alighting-stop is not inferred are summarized in Table 3.8.

Assumptions 3.28 and 3.29 establish the rules to apply when an alighting-stop can not be inferred (i.e., when all efforts to infer an alighting-stop using the TCM failed). These cases refer mainly to situations in which passengers travel outside the Public Transport system, using alternative transportation means. Assumption 3.28 considers that the next trip-leg starts a new full-trip. Assumption 3.29 considers that the next trip-leg starts a

Table 3.8: Overview of assumptions to identify transfers when the alighting-stop is not inferred.

No.	Description
3.28	The next trip-leg starts a new full-trip
3.29	The next trip-leg starts a new full-trip only if it occurs after a time threshold

new full-trip only if it occurs after a time threshold (Munizaga & Palma, 2012).

3.4 Methodology

This section describes the methodology used in this work to infer alighting-stops and identify transfers from AFC records.

All AFC records are firstly sorted by smart card UID and then chronologically. Therefore, AFC records are analyzed sequentially in chronological order.

Figure 3.4 shows the main steps of the methodology, where the TCM is represented within the shaded area labeled *TCM to infer alighting-stops* and the identification of transfers within the shaded area labeled *Distinguishing transfers from trip ends*. Each procedure is described in the following sections, Section 3.4.1 relating to the TCM and Section 3.4.2 to the identification of transfers.

3.4.1 TCM

When a smart card has at least two trip-legs in the same day, the methodology infers the corresponding alighting-stops by applying the TCM and proceeds to the identification of transfers following a set of criteria. When a smart card has only one trip-leg in the same day, the methodology does not infer any alighting-stop and moves forward to the next trip-leg of that smart card. When all trip-legs on a smart card have been analyzed, the methodology moves to the next smart card in the data set.

The summary of the assumptions adopted in this work to implement the TCM is provided in Table 3.9.

The two TCM grounding assumptions proposed in Barry et al. (2002) seminal work are adopted, i.e., the *closest stop assumption* (assumption 3.1) and the *assumption of symmetry* (assumption 3.4). Accordingly, from the set of possible alighting-stops, the TCM infers the alighting-stop as the one with the shortest walking-distance regarding (1) the boarding-stop of the subsequent trip-leg if it exists (assumption 3.1), or (2) the boarding-stop of the first trip-leg of the day for the last daily trip-leg (assuming the passenger would

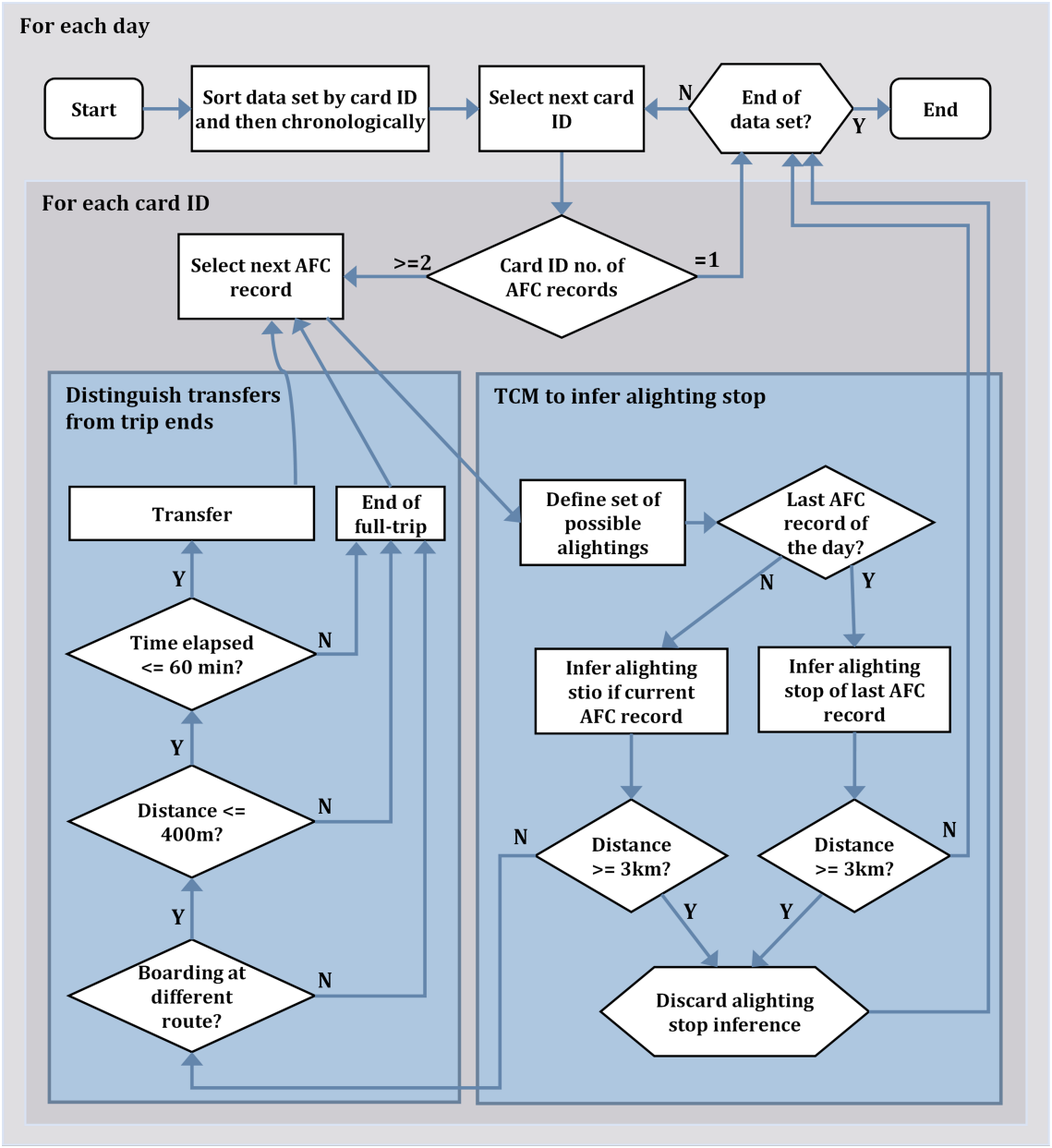


Figure 3.4: Methodology to infer alighting-stops and to identify transfers.

travel back home at the end of the day) (assumption 3.4).

This work does not consider any premises connecting the Public Transport system under analysis with trips made on other transportation means. Thus, the assumption that by default passengers travel within the Public Transport system under analysis is adopted, i.e., assumption 3.7.

There are two situations in which passengers are considered to have traveled outside the system (i.e., using an alternative transportation mean). One case is identified under assumption 3.9, when the inferred walking-distance is higher than a specified threshold. Assumption 3.9 is adopted both for consecutive trip-legs and for the case of the last trip-leg of the day. The second case is identified with assumption 3.8, when there is only

Table 3.9: Assumptions adopted to infer alighting-stops using the TCM.

No.	Description
Assumption 3.1	The majority of passengers will start the next trip-leg close to the alighting-stop of their previous trip-leg
Assumption 3.4	The majority of passengers end the last trip-leg of the day close to the boarding-stop of the first trip-leg of the day
Assumption 3.7	By default, passengers travel within the Public Transport system
Assumption 3.8	Passengers travel outside the Public Transport system when there is a single trip-leg on a day
Assumption 3.9	Passengers travel outside the Public Transport system when the walking-distance between consecutive trip-legs exceeds a specified threshold
Assumption 3.10	When an alighting-stop cannot be inferred, the corresponding trip-leg is discarded
Assumption 3.13	Passengers can only alight in the sequence of downstream stops on the directed-route boarded
Assumption 3.19	The alighting-time is not inferred

one daily trip-leg. The algorithm cannot infer the alighting-stop when either assumption 3.9 or assumption 3.8 is verified. Therefore, in those cases, the algorithm discards the corresponding trip-legs (assumption 3.10).

With assumption 3.13, the TCM algorithm considers for each AFC record that the possible alighting-stops will be in the set of downstream stops in the corresponding run. Accordingly, knowing the boarding-stop and directed-route, the algorithm specifies all downstream stops as possible alighting-stops.

This work does not perform any inference regarding the alighting-time (assumption 3.19). The non-adoption of this particular assumption arises from the impossibility of obtaining AVL or APC records for the transport operations analyzed in this work. Such information would be essential to associate the AFC data with the runs provided by the Public Transport system, therefore allowing to the inference of trips' boarding-time (especially those made with metro where passengers tap the smart card at the station).

The TCM has linear complexity, with execution time proportional to the input size.

3.4.2 Identifying transfers

The main assumptions adopted to identify transfers between trip-legs are detailed in Table 3.10.

Table 3.10: Assumptions adopted to identify transfers.

No.	Description
Assumption 3.20	Passengers do not walk more than a specified distance to transfer
Assumption 3.22	Passengers do not wait more than a specified time to transfer
Assumption 3.25	A transfer occurs between consecutive trip-legs
Assumption 3.26	A transfer occurs between trip-legs on the same smart card
Assumption 3.27	Passengers do not transfer to the same route
Assumption 3.28	When passengers travel out of the Public Transport system, the next trip-leg starts a new full-trip

The algorithm distinguishes if the alighting-stop of a trip-leg is part of a transfer within two trip-legs, or if it corresponds to the destination of a full-trip.

The identification of transfers can only be made between consecutive AFC records (assumption 3.25) performed by the same passenger (assumption 3.26). Assumption 3.27 means that passengers who have two consecutive trip-legs on the same route are making two distinct full-trips. That is, a passenger does not perform a transfer to board the same route he was already traveling in, even if in its opposite direction, unless by mistake. Thus, when a passenger boards the same route in consecutive AFC records, the algorithm considers the passenger to be starting a new full-trip, and not making a transfer. For example: (a) a passenger travels from home to bank, and then from bank to home, using the same route, in less than 60 minutes; (b) a passenger travels from home to school, pick up the kids, and goes back home using the same route, in less than 60 minutes. In these examples, there was an activity that took less than 60 minutes, and the walking-distance between the two full-trips is lower than 400 meters.

3.4.3 Building full-trips

Table 3.11 lists four basic rules for inferreing full-trips after the TCM and identification of transfers processes.

Table 3.11: Assumptions adopted to build full-trips.

No.	Description
3.30	A full-trip starts at a boarding-stop and ends at an alighting-stop
3.31	A full-trip containing transfers starts at the boarding-stop of the first trip-leg, and ends at the alighting-stop of the last trip-leg
3.32	The boarding-stop of the first trip-leg of the day starts a full-trip
3.33	The alighting-stop of the last trip-leg of the day ends a full-trip

Assumption 3.30 provides a positioning at the level of geographic aggregation to build full-trips, at the stop level. This positioning is relevant to stress that the last-mile problem is not covered in this work. Therefore, the resulting data set includes OD flows at the stop level. Assumption 3.31 specifies that when transfers are identified, the full-trip is built between the boarding-stop of the first trip-leg and the alighting-stop of the last trip-leg.

Assumptions 3.32 and 3.33 establish basic rules for the first and last trip-legs in each day. Assumption 3.32 considers that the boarding-stop of the first trip-leg of the day is always the start of a full-trip. Analogously, assumption 3.33 states that the alighting-stop of the last trip-leg of the day is always the end of a full-trip.

3.5 Case Study

The PMA has an entry-only AFC system, whose smart cards are called *Andante*. This case study was selected considering the data made available for this research, which included entry-only AFC records on the joint activity of the bus and tram operator Sociedade de Transportes Colectivos do Porto, S.A. (STCP) and of the metro operator Metro do Porto (MP), for 2013. All trips performed in this system were recorded in the AFC data set, even passengers willing to pay cash in-vehicles were provided with a smart card to swipe. Furthermore, this AFC system allows any number of free transfers within one hour of the first transaction.

In 2013, the PMA was divided into geographic areas, as shown in the map in Figure 3.5. These geographic areas were organized into three groups: areas to the North were identified by an *N*, areas at the Center by a *C*, and areas at the South by an *S*.

Night transportation service was provided by bus and metro, with routes and frequencies adapted to the demand. This study considers that each day starts at 00h00 and ends at 23h59. Removing no generality to the methodology presented, when the algorithm identifies transfers amid trip-legs on different days, they are kept together to build the corresponding full-trip.

The Public Transport network considered in this study includes 2,672 stops. The metro system had six routes and 81 stops, the bus system 71 routes, and the tram system three routes. Stops used by trams were shared with buses. Moreover, this study analyzes each directed-route separately.

3.5.1 AFC data

All AFC records include information on smart card UID, date, time, boarding-stop, and Public Transport operator. AFC records relating to trips by bus and tram, additionally

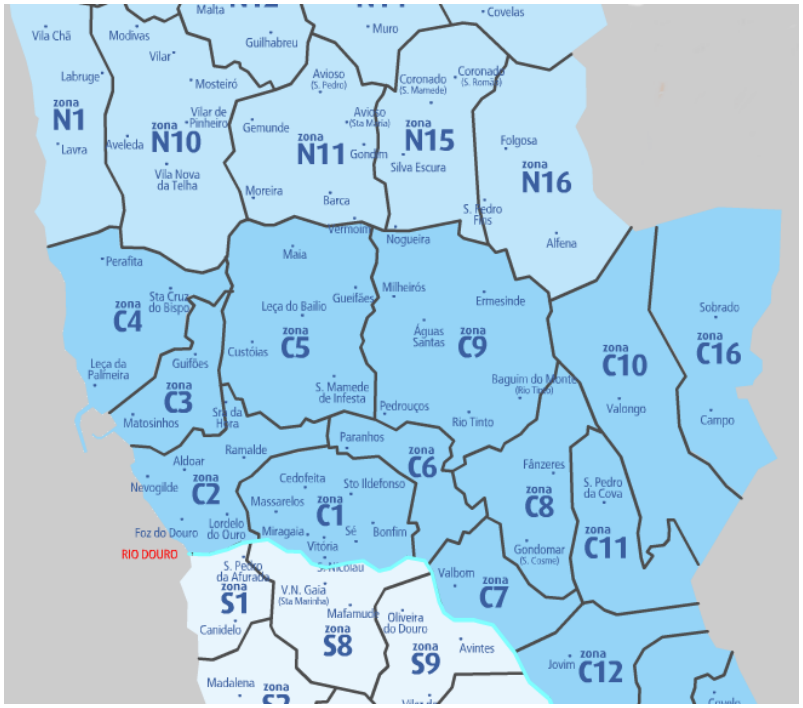


Figure 3.5: AMP geographic areas. Retrieved from STCP, 2017.

contain the information on the boarding directed-route, as they are recorded in-vehicle. Trips made by metro, however, do not include information on the boarding directed-route, since AFC records are created at the gates or platforms of metro stations, with multiple boarding possibilities. Even in stations served by only one route, there is the possibility of boarding in two directions. Since metro AFC records do not include information on the directed-route, the entire metro system was treated as one route.

Cleaning data procedures included the identification and removal of error readings, inconsistent, noisy, and duplicated AFC records. Passengers can tap the smart card more than once while waiting for a metro vehicle, or when boarding a bus or tram, leading to repeated AFC records. A duplicated AFC record is identified when the same smart card has another AFC record at the same boarding-stop within 15 minutes.

3.5.2 Walking-distance data

This study measures the distance between each pair of stops with the Manhattan distance. Walking-distances were provided by Dr. Thiago Sobral, a fellow researcher with the Institute for Systems and Computer Engineering, Technology and Science (INESC TEC).

Due to the road network layout of Porto, the application of the Manhattan distance was considered as more realistic than the haversine metric (shortest distance). Moreover, the distance between two geographic coordinates was computed using the haversine metric instead of the orthodromic (great-circle) due to the possible rounding errors that might

occur when two stops are too close to each other (e.g., 1km) Sinnott, 1984, as presented in Equation (3.1).

$$D_{ij} = \begin{cases} 2 \cdot R_e \cdot atan2(\sqrt{a(i,j)}, \sqrt{1-a(i,j)}) \text{ , if } i \neq j \\ 0, \text{otherwise} \end{cases} \tag{3.1}$$

Where: • R_e is the Earth radius, in meters;
• $atan2$ returns the arctangent of the quotient of its parameters;
• $a(i,j) = hav(\Delta\phi) + cos(\phi_i) \cdot cos(\phi_j) \cdot hav(\Delta\lambda)$;
• (ϕ, λ) are the latitude-longitude coordinates for each stop, previously converted to radians;
• $hav(x) = \sin^2(x/2)$ is the haversine function.

3.5.3 Thresholds adopted

Assumption 3.9 was applied adopting a threshold value of 3 km. This value was considered as a distance sufficiently large that most passengers are not willing to walk between full-trips. The incorporation of this assumption makes it possible to identify cases in which passengers have traveled by another transportation mean apart from the Public Transport system under analysis.

Assumption 3.20 was applied in this case study considering a threshold for transfer walking-distance of 400 meters. This value was selected from the literature review and also because it is considered as adequate regarding the reality of the city Porto.

Assumption 3.22 was applied in this case study with a threshold of 60 minutes. The value of 60 minutes was adopted as it is the period adopted by operators in this Public Transport system to allow passengers to transfer without an additional payment. The time is counted as the boarding-time difference between consecutive trips, since it was not possible to infer the alighting-time of trips in this case study.

3.6 Results

This section presents the results obtained by implementing the methodology described in the case study of Porto. This study considered a sample of 19,999 randomly selected smart cards. All AFC records from this data set were analyzed over the entire year of 2013. The open-source database software PostgreSQL was used to select and sort data. The TCM algorithm was implemented in C++, using a 3.4 GHz Intel Core i7 processor and 16 Gigabytes of Random Access Memory (RAM).

Table 3.12: Results from applying the methodology to the case study of Porto, by month. All proportions calculated with reference to the total number of AFC records analyzed (i.e., 902,819 records).

	All AFC records		Ass. 3.8		Ass. 3.9 (3km)		Transfers	
Month	No.	%	No.	%	No.	%	No.	%
1	78,455	8.69	7,023	0.78	2,085	0.23	15,813	1.75
2	68,930	7.63	6,176	0.68	1,843	0.20	13,404	1.48
3	74,444	8.25	6,925	0.77	1,903	0.21	14,676	1.63
4	80,984	8.97	7,222	0.80	2,136	0.24	16,010	1.77
5	86,985	9.63	8,180	0.91	2,146	0.24	16,871	1.87
6	70,800	7.84	7,165	0.79	1,898	0.21	13,568	1.50
7	76,169	8.44	6,882	0.76	1,946	0.22	15,452	1.71
8	61,745	6.84	5,874	0.65	1,547	0.17	12,806	1.42
9	73,551	8.15	6,569	0.73	1,843	0.20	14,694	1.63
10	86,323	9.56	7,136	0.79	2,087	0.23	16,762	1.86
11	76,169	8.44	6,521	0.72	1,816	0.20	13,820	1.53
12	68,264	7.56	6,407	0.71	1,761	0.20	12,209	1.35
Total	902,819	100.00	82,080	9.09	23,011	2.55	176,085	19.50

Table 3.12 provides a summary of the results obtained for the set of 19,999 smart cards, totaling 902,819 AFC records. All proportions presented in Table 3.12 were calculated with reference to the total number of AFC records analyzed (i.e., 902,819 records).

The application of the methodology led to the exclusion of 82,080 AFC records from Assumption 3.8, corresponding to cases of a single AFC record on a day (see total values in columns *Single AFC record* in Table 3.12). Moreover, 23,011 AFC records were removed from Assumption 3.9, corresponding to cases where the walking-distance between consecutive AFC records exceeds 3 km (see total values in columns *Ass. 3.9 (3km)* in Table 3.12).

There was a total of 176,108 identified transfers (see total values in columns *Transfers* in Table 3.12). A transfer is identified between two AFC records, but its accounting is not duplicated. For example, one trip-leg from A to B, followed by a trip-leg from B to C, and with a transfer identified at B, results in a full-trip from A to C. In this implementation, the methodology identified 700,180 full-trips.

Table 3.12 also provides detail on the proportion of AFC records for each month. It is possible to see that August presents the lowest volume of AFC records, followed by February and by December, which relates to summer and other holidays such as Carnival and Christmas, noting, however, that February is a shorter month. Months with the highest volume of records are May followed by October.

The OD flows data set was further analyzed considering its segmentation by type of day, seasonality, and passenger frequency. The results of this analysis are described in Sections 3.6.1–3.6.3.

Figures 3.6–3.12 include the OD matrices obtained for each segmentation analysis. Two OD matrices are analyzed for each category, one corresponding to a perspective at the level of the geographic area (left), and the second corresponding to a perspective at the level of the stop (right).

The OD matrices built by geographic area follow the same labeling system shown in Figure 3.5, and are organized N-C-S for ease of understanding, even knowing that OD matrices can never replicate the complexity of geographic maps.

In order to allow for a direct comparison between all OD matrices shown in this section, they were all built over the same scale ratio, which is as a proportion to the total of 621,666 full-trips inferred. Accordingly, all OD matrices share the same scale of proportional dots, where the smallest dot indicates that at least 0.01% of total full-trips (around 70 full-trips in the year) were made on that OD pair, and the largest dot indicates at least 25% of total full-trips (around 155,416 full-trips in the year) were made on that OD pair.

All OD matrices in Figures 3.6–3.12 follow a symmetric pattern towards the diagonal, which is consistent with regular daily commuting patterns from an overall perspective.

OD matrices at the stop level show a higher density of full-trips in the first 800 stops, resulting in the visualization of a denser square positioned in the lower-left corner of these OD matrices. These stops are almost all positioned within the geographic area C1, which is the city center. From these set of stops, it is worth mentioning that stops from the metro are at the first positions, which translates to a small but even denser zone within the referred square. In parallel, we can see that the corresponding OD matrices built at the geographic area level always have the most significant dot in the area C1. This larger dot encompasses all full-trips with origin and destination within C1.

All full-trips starting within another zone and finishing within C1 are visualized in the dots vertically aligned to C1 in these matrices. Analogously, all full-trips starting within C1 and finishing within other areas are visualized in the dots aligned horizontally to C1. The size of these dots aligned vertically and horizontally with C1 is significant in all categories, showing that area C1 not only is the densest regarding internal travel; it is also the area with the most significant flows to other zones.

3.6.1 Analysis by type of day

The first segmentation classifies days into three categories: workdays, Sundays & holidays, and Saturdays.



Figure 3.6: OD matrices for the category of workdays, segmentation by type of day. At the stop level (right) and at the geographic area level (left). Proportions calculated on the total number of full-trips.

Table 3.13 shows that workdays encompass most full-trips in this segmentation, accounting for 84.77% of total full-trips. It was expected to observe a considerably larger number of full-trips in workdays as they encompass most days in the year (251 days out of 365). We can also see from Table 3.13 that there is a more significant number of average daily full-trips made on workdays, around 2,100 full-trips per day, while Saturdays have an average of 1,034 full-trips per day, and Sundays & holidays an average of 665 full-trips per day.

Figures 3.6–3.8 include the OD matrices obtained for this segmentation of full-trips. Workdays show much denser OD matrices, as was expected, when compared with the other two categories.

3.6.2 Analysis by seasonality: regular service vs. reduced service

The service provided by the Public Transport system in Porto has two modalities translated in different schedules over the year: regular service and reduced service. The regular service has higher frequency, and operates throughout the entire year, provided some exceptions of reduced service. Reduced service has a lower frequency and operates during summer and school holidays (Carnival, Easter, and Christmas), which are lower demand periods.

Table 3.13: Summary of the segmentation by type of day: workdays vs. Sundays and Holidays vs. Saturdays. Proportions calculated on the total number of full-trips (i.e., 621,666).

Category	Days/year	full-trips/day	full-trips/year	
	No.	Average No.	No.	%
Workdays	251	2,100	526,998	84.77
Sun. & Hol.	63	665	41,921	6.74
Saturdays	51	1,034	52,747	8.48

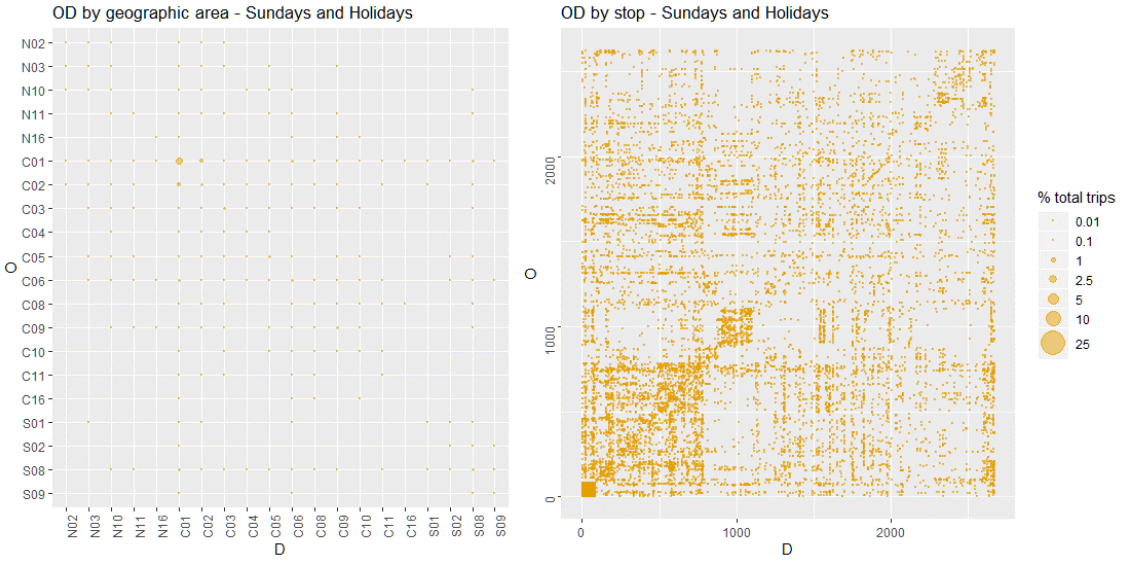


Figure 3.7: OD matrices for the category of Sundays & holidays, segmentation by type of day. At the stop level (right) and at the geographic area level (left). Proportions calculated on the total number of full-trips.

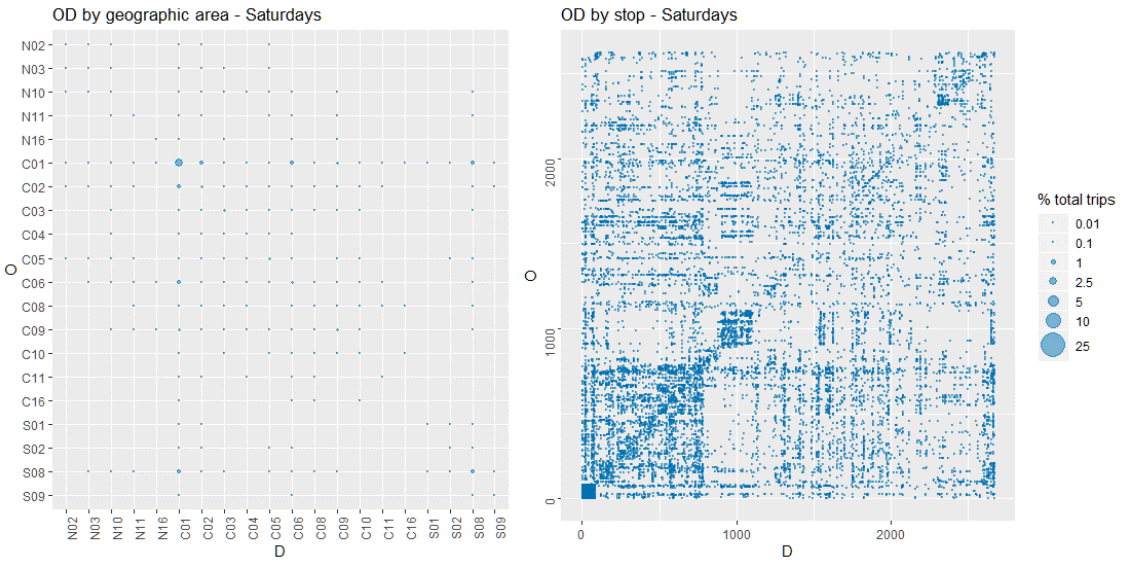


Figure 3.8: OD matrices for the category of Saturdays, segmentation by type of day. At the stop level (right) and at the geographic area level (left). Proportions calculated on the total number of full-trips.

Table 3.14: Summary of the segmentation by seasonality: regular service vs. reduced service. Proportions calculated on the total number of full-trips (i.e., 621,666).

Category	Days/year	full-trips/day	full-trips/year	
	No.	Average No.	No.	%
Regular	257	1,807	464,377	74.70
Reduced	108	1,456	157,289	25.30



Figure 3.9: OD matrices for the category of regular service, segmentation by seasonality. At the stop level (right) and at the geographic area level (left). Proportions calculated on the total number of full-trips.



Figure 3.10: OD matrices for the category of reduced service, segmentation by seasonality. At the stop level (right) and at the geographic area level (left). Proportions calculated on the total number of full-trips.

Table 3.15: Summary of the segmentation by passenger frequency: frequent passengers vs. occasional passengers. Proportions calculated on the total number of full-trips (i.e., 621,666).

Category	smart cards	full-trips/year	
	No.	No.	%
Frequent	1,354	497,123	79.97
Occasional	13,227	124,543	20.03



Figure 3.11: OD matrices for the category of frequent passengers, segmentation by passenger frequency. At the stop level (right) and at the geographic area level (left). Proportions calculated on the total number of full-trips.

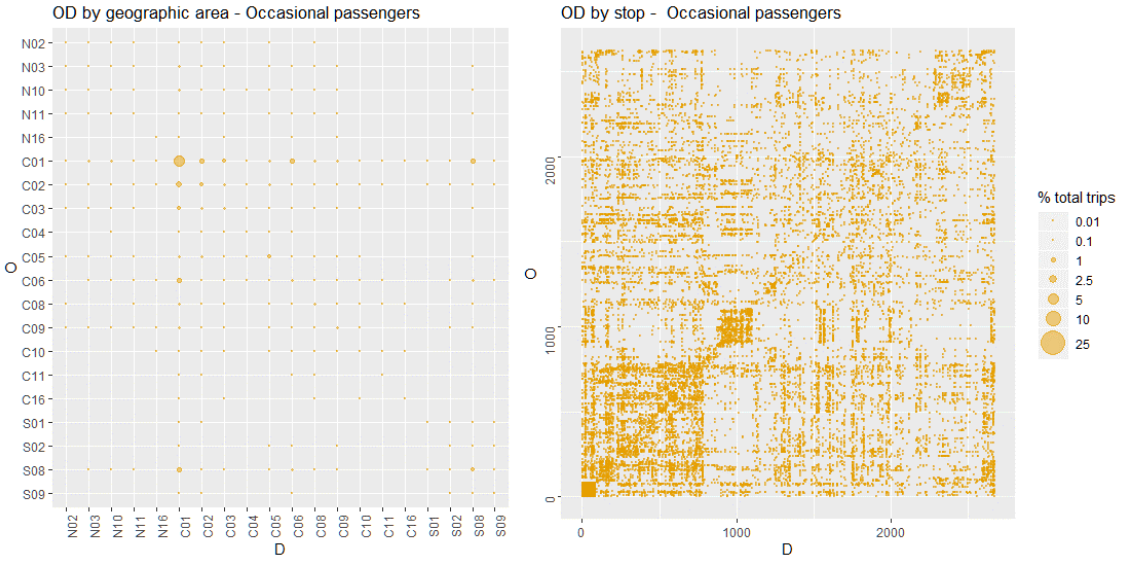


Figure 3.12: OD matrices for the category of occasional passengers, segmentation by passenger frequency. At the stop level (right) and at the geographic area level (left). Proportions calculated on the total number of full-trips.

Table 3.14 shows that in 2013, the reduced service operated for 108 days, while regular service operated for 257 days. It also shows that, the average number of full-trips per day performed during regular service (1,807) is only 351 higher than during the reduced service (1,456). Nevertheless, the annual number of full-trips made during the regular service accounts for around 75% of total, while the reduced service accounts for around 25%. The differences in magnitude are visible in the OD matrices shown in Figures 3.9 and 3.10, with much higher density for the regular service when compared to the reduced service.

3.6.3 Analysis by passenger frequency: frequent and occasional passengers

The annual number of full-trips of each smart card was used to classify passengers as frequent or occasional. We considered that a smart card is classified as a frequent passenger when it has at least 50 annual full-trips. Analogously a smart card is classified as an occasional passenger when it has 49 or fewer annual full-trips. This number was obtained after a statistical analysis of this variable, and assuming that a frequent passenger would use the Public Transport system regularly for more than two months.

As Table 3.15 details, the number of occasional passengers (13,227) was much higher than the number of frequent passengers (1,354). The missing 5,418 smart cards (i.e., 19,999 total minus 1,354 frequent minus 13,227 occasional smart cards) relate to those AFC records discarded due to not complying with criteria for estimating OD matrices, as described in Table 3.15. Even with a significantly smaller number of smart cards, frequent passengers performed almost 80% of all full-trips, while occasional passengers performed around 20%. This discrepancy in the volume of full-trips performed in the two categories is visible in Figures 3.11 and 3.12.

3.7 Conclusions

This chapter proposed a two-step methodology to infer OD flows from entry-only AFC data. The first step applied the TCM to infer the alighting-stops for each AFC record.

The main assumptions adopted were: (1) the majority of passengers will start the next trip-leg at or near the alighting-stop of their previous trip-leg; (2) the majority of passengers end the last trip-leg of the day at or near the boarding-stop of the first trip-leg of the day; (3) by default, passengers travel within the Public Transport system; (4) passengers travel outside the Public Transport system when there is a single trip-leg on a day; (5) passengers travel outside the Public Transport system when the walking-distance between consecutive trip-legs exceeds a specified threshold; (6) when an alighting-stop cannot be

inferred, the corresponding trip-leg is discarded; (7) passengers can only alight in the sequence of downstream stops on the directed-route boarded; and (8) the alighting-time is not inferred;

The second step identified transfers using the following assumptions: (1) passengers do not walk more than a specified distance to transfer; (2) passengers do not wait more than a specified time to transfer; (3) a transfer occurs between consecutive trip-legs; (4) a transfer occurs between trip-legs on the same smart card; (5) passengers do not transfer to the same route; (6) when passengers travel out of the Public Transport system, the next trip-leg starts a new full-trip.

This methodology was applied in the case of Porto, integrating metro, bus, and tram trips. The data covered all AFC records from 19,999 randomly selected smart cards for the entire year of 2013. The results showed that around 9% of all AFC records were discarded from being a single record on the day, around 2.5% of all AFC records were discarded by not complying with the threshold of maximum walking distance, and around 19.5% of all AFC records were identified as transfers.

The methodology allowed the inference of OD flows for the data analyzed and to build the corresponding OD matrices. Three segmentation analyses were conducted: (1) by type of day considering the categories of workdays, of Sundays and holidays, and of Saturdays; (2) by seasonality considering the categories of regular service days and of reduced service days; (3) by passenger frequency considering the categories of frequent and occasional passengers (these categories were defined after a statistical analysis of the data).

The visualization of OD matrices was provided for each category at the stop level and at the geographic area level (considering the geographic zones currently used by the operators). The segmentation analyzes showed significant differences in the volume of trips of the different categories, while a similar OD pattern was observed across all cases.

Future work could include the quantitative validation of this methodology. One way to perform this validation for the case of Porto would be to use data of trips made with the ANDA cell phone app (which is operating since 2018), as one could compare the inferences made with entry-exit records.

Future work could also include a comparison of the results obtained with this methodology with other literature on this topic, and the use of statistical methods to identify mobility patterns at the level of UDPs.

4 Identifying Synchronization Networks

The synchronization of Public Transport systems usually considers a simplified network to optimize the flows of passengers at the principal transfer-nodes of the network. This chapter proposes a methodology to discover synchronization networks in a Public Transport system using the following information: assessment by experts, routes' frequency, routes' geographic information, and the transfer walking-distance and transfer-flow at each transfer-connection. The methodology starts by identifying transfer-connections whose synchronization would most benefit the Public Transport system, aggregating them into transfer-nodes and subsequently synchronization networks. The value of the methodology is demonstrated with its implementation to the case study of Porto. The results include a set of synchronization networks that can be optimized with synchronization techniques.

4.1 Introduction

Public Transport networks can only offer a limited set of direct Origin-Destination (OD) connections. Many passengers need to transfer between different directed-routes to complete their full-trips. Well-designed Public Transport systems provide transfer opportunities for flexible trip planning, while Public Transport systems lacking transfer planning, are overall, less effective. Public Transport planning decisions that change the effectiveness of transfers will impact passengers' choice of routes, especially in networks with multiple options for some OD pairs.

Due to the association of transfers with Public Transport's lack of attractiveness, some Public Transport systems attempt to provide as many direct OD trips as possible (i.e., long routes without transfers) (Ceder et al., 2013). Although recognizing that transfers always impose some inconvenience on passengers, providing routes between every conceivable OD pair is economically and logistically impossible for any Public Transport network (Ceder et al., 2013). Such systems would result in dysfunctional networks consisting of routes disconnected from each other. Adding to this, the accumulation of new routes over time

without making changes to the existing network can cause many problems.

In contrast, Public Transport systems could provide fully optimized networks. These Public Transport systems adopt Network Design strategies to satisfy demand through interconnecting routes, leading to integrated multimodal Public Transport networks. A key component is the planning of smooth, safe, and reliable transfers. We thus obtain efficient and attractive Public Transport systems not by removing transfers from the plan, but by planning for quality transfer opportunities at strategic locations.

The *demand for transfers* on a particular system is associated with the type of *transfer policy adopted* (Nelson et al., 1981). However, the causal relationship between these two aspects is not clear. Applying Synchronization Timetabling techniques (and consequently reducing overall transfer waiting-time) may increase transfer ridership. However, the opposite is also true, i.e., locations with high transfer demand are more likely to be targeted for tailored transfer policies. This way, it is not straightforward to conclude either that implementing transfer policies increases the demand for transfers, or that significant demand for transfers forces the adoption of transfer policies. In the estimation of OD flows performed in Chapter 3, transfers accounted for around 20% of all AFC records in Porto in 2013. Studies of other cities show that transfers can account for much higher percentages of all trips (e.g., a survey in Frankfurt concluded that around 30% of daily commuters had to make at least one transfer (Clever, 1997)).

Public Transport systems where transfers are free encourage passengers to undertake flexible itineraries, facilitating their trip planning. Free transfers policies also work as a marketing strategy to attract more passengers by avoiding charging passengers more for less convenient trips.

The reduction of transfer waiting-time, especially at high demand transfer-connections, has a significant impact on the overall quality of the service provided by the Public Transport system: i) From the operators perspective, reduced transfer waiting-time is essential for effective network coverage and connectivity, and to stimulate passenger flow within the Public Transport network, by minimizing crowding at stops and in-vehicles; ii) From the passengers perspective, reduced transfer waiting-time allows for trip planning flexibility, reduces transfer inconvenience and ultimately enhances the attractiveness of the Public Transport system (retaining passengers and attracting new passengers).

The reduction of overall transfer waiting-time can be achieved by increasing the frequency of strategic routes at the Frequency Setting stage of Public Transport planning. To that end, it is essential to verify the Frequency Setting solution feasibility regarding resources available and interrelated operating elements (see Sections 2.3.1 and 2.3.3).

The reduction of transfer waiting-time can also be addressed at the Timetabling stage of Public Transport planning through Synchronization techniques. Synchronization tech-

niques focus on the optimization of transfers by minimizing transfer waiting-time and reducing bunching. There are two main groups of Synchronization Timetabling techniques: Timed Transfers and Transfer Optimization. Timed Transfers seek to coordinate routes by vehicle meeting simultaneously at focal-points, while Transfer Optimization seek the coordinated operation of routes to optimize transfer-flows.

Synchronized transfer-nodes are expected to increase the flow of passengers: i) retaining current passengers (when passengers find efficient transfer-connections in their itinerary, the likelihood of traveling on that itinerary increases), ii) attracting new passengers (from alternative and less effective itineraries).

The best solutions obtained with Synchronization Timetabling techniques may prove to be sub-optimal at the Vehicle Scheduling and Driver Scheduling stages of Public Transport planning. This can be overcome by integrating Synchronization Timetabling with the following planning stages, or through the iterative solution of these planning stages until an acceptable equilibrium is found. In any case there is a need to consider the trade-off between user convenience and cost efficiency.

Synchronization Timetabling is usually applied to simplified, yet realistic, networks. This simplification is employed due to the complexity of the algorithms used in Synchronization Timetabling (e.g., the algorithm used in Ibarra-Rojas and Rios-Solis (2012) was NP-hard), because some Synchronization Timetabling techniques may imply increased operating costs, and also because increasing the size of the network significantly reduces the flexibility of the solutions obtained, which is critical for finding compatible solutions in the Public Transport planning downstream stages, especially in Vehicle Scheduling.

The literature applying Synchronization Timetabling techniques usually has the networks to synchronize given as inputs. There is a literature gap on methodologies suited to define the network to optimize with Synchronization Timetabling techniques. This work proposes a methodology to identify Public Transport networks whose Timetabling Synchronization would most benefit the entire Public Transport system. If we consider the set of all routes within a Public Transport system as the entire network, the networks to identify with this methodology are subsets of the entire network, but whose integrated scheduling would benefit the whole system by optimizing passengers' flows.

Section 4.2 analyzes the relationship between the frequency of routes and their suitability for applying synchronization techniques. Section 4.3 presents the concepts and terminology used in this work, in particular transfer-connection, transfer-flow, and transfer-node.

Section 4.4 presents the methodology adopted in this work. The methodology identifies the most important transfer-connections in a Public Transport system considering a set of criteria, including: i) assessment by experts, ii) the operation frequency of each route (i.e., Low-Frequency or High-Frequency), iii) the geographic information of each route (i.e., its

directed-route path), iv) the transfer walking-distance for each transfer-connection, and v) the transfer-flow of each transfer-connection. Once the set of relevant transfer-connections is known, it is used to identify key transfer-nodes and subsequently synchronization networks.

Section 4.5 describes the application to Porto. This study used entry-only AFC data of the system to identify transfers and quantify transfer-flows. The assessment of transfer-connections through experts' opinions and route' frequencies was not available. Section 4.6 presents the results of applying the methodology to Porto. Section 4.7 summarizes findings.

4.2 Which Frequencies to Synchronize?

Without loss of generality, the operating frequency of a route in a specified Uniform Demand Period (UDP) can be classified as High-Frequency, Low-Frequency or Medium-Frequency. The frontier values for each of these categories are specific to each Public Transport system.

High-Frequency routes usually operate periodically during peak periods and are the most crowded routes. Vehicles pass by each stop at short intervals (e.g., 5 minutes or less). The information provided to passengers is the frequency at which vehicles pass each stop. Passengers show up and go, with no plan in advance, since the maximum waiting-time should not exceed the headway on the route. The capacity of High-Frequency routes to satisfy the demand is usually the most critical feature to optimize. Operators' main challenges occur during operations, in particular, to avoid bunching of vehicles and to minimize the variability of headway. These routes can be optimized separately from the network (i.e., they do not need synchronization with other routes).

Low-Frequency routes are characterized by longer time between consecutive vehicles at each stop (e.g., one vehicle per hour). They are suitable for lower passenger demand services. Low-Frequency services operate during specific periods of the day (i.e., off-peak periods) or for the entire day (such as in sparsely populated areas), depending on the demand. Low-Frequency services usually do not need capacity optimization. Low-Frequency services are usually planned with a schedule-based approach. Passengers are provided with a well-defined schedule, which incorporates detailed information on departure-time and arrival-time for all runs. Schedules are of utmost importance for passengers, conditioning them to shape routines around the Public Transport service availability.

Synchronization Timetabling techniques are especially important when applied to UDP of Low-Frequency, where lack of transport connection can lead to long transfer waiting-time, consequently increasing the overall passenger travel-time.

In-between High-Frequency and Low-Frequency, are Medium-Frequency services. The

Table 4.1: Transfer-connections cases where synchronization is most relevant to apply, considering the frequency of the corresponding Feeding-Route and Receiving-Route.

Feeding-Route frequency	Receiving-Route frequency	Relevance for synchronization
High-Frequency	High-Frequency	No need to synchronize
High-Frequency	Low-Frequency	Passengers need to check the Receiving-Route timetable in advance
Low-Frequency	High-Frequency	No need to synchronize
Low-Frequency	Low-Frequency	Strong need for synchronization of timetables using Timed Transfers or Transfer Optimization

boundaries that define Medium-Frequency vary across each system. The solutions to adopt in these cases are not straightforward and many times are case-sensitive. This is the context in many Portuguese cities.

While in some cases, Synchronization is not necessary, in others, it can be beneficial. Its implementation, however, requires careful study of the achievable benefits and possible inconvenience. Table 4.1 summarizes the transfer-connection cases where Synchronization is most relevant in terms of the frequency of the corresponding Feeding-Route and Receiving-Route.

It should always be convenient to transfer to a High-Frequency Receiving-Route, regardless of the frequency of the Feeding-Route. Routes operating with High-Frequency do not need to be synchronized with other routes since their associated waiting-time should not exceed their scheduled headway.

Transferring from a High-Frequency Feeding-Route to a Low-Frequency Receiving-Route requires passengers to plan by checking the timetable of the Receiving-Route.

The Synchronization of transfers significantly impacts the quality of the Public Transport service at transfer-connections between Low-Frequency routes. This includes routes operating with medium or low demand, usually during off-peak periods and in low demand density areas (Bookbinder & Desilets, 1992; Daduna & Voss, 1995; Desilets & Rousseau, 1992; Vuchic et al., 1981). First studies on Synchronization aimed to cope with the very long waiting-times of passengers living in low-density areas (Vuchic et al., 1981), and only more recently this concept has been implemented in high-density areas, during off-peak periods.

4.3 Transfer-connections, Transfer-flows and Transfer-nodes

A transfer-connection refers to the possibility for passengers to transfer between two specific directed-routes (i.e., a Feeding-Route and a Receiving-Route) that meet at a transfer-node. A transfer-flow relates to the number of passengers making a specific transfer-connection in a specified UDP. A transfer-node refers to the geographic location at which passengers can transfer between two (or more) directed-routes.

Transfer-nodes can take many different configurations. A common type of transfer-node occurs when two directed-routes cross or merge, as illustrated in Figure 4.1. In both situations, the resulting transfer-node always includes eight transfer-connections, as identified in Figure 4.1. This analysis deliberately excludes transfers between runs of the same route, regardless of route direction. The main reasoning is that passengers would only board on the same route on consecutive trip-legs by mistake, or to start a new full-trip which takes place after an activity (even when the two consecutive trip-legs occur shortly after each other). Either way, they do not reflect a transfer and therefore are not included in this analysis.

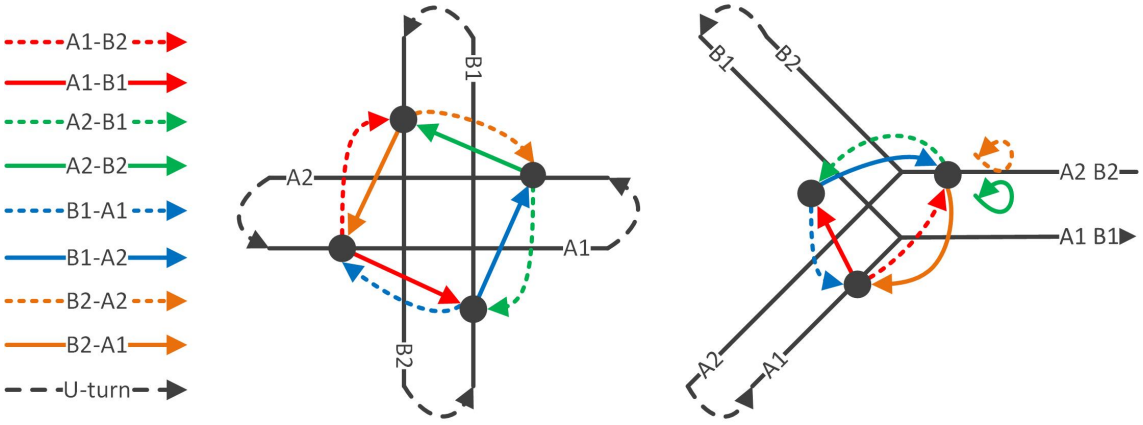


Figure 4.1: Possible transfer-connections when two routes cross or merge.

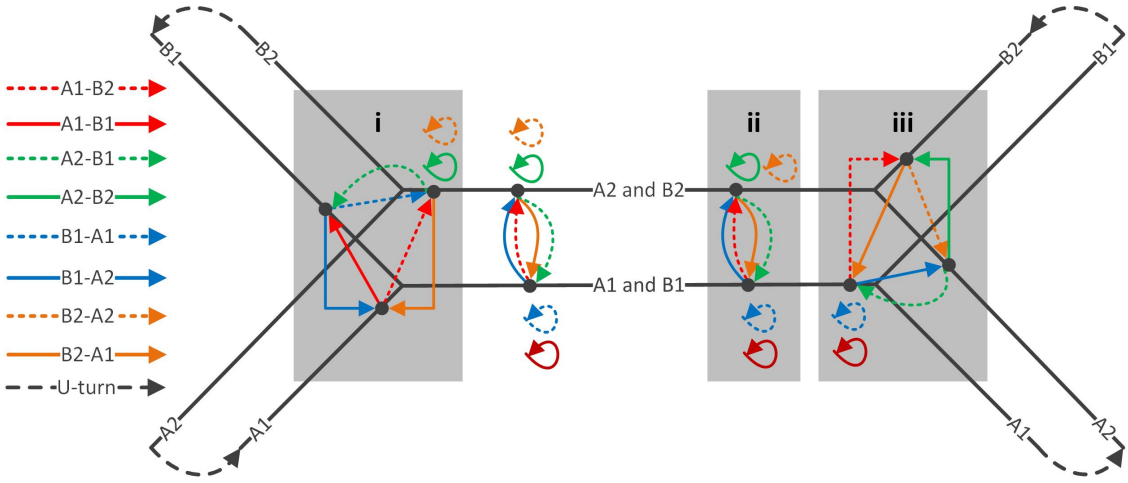


Figure 4.2: Merging and splitting of two routes sharing an overlapping path.

Figure 4.2 represents the case of two routes with a portion of their paths overlapping, with their merging and splitting transfer-nodes. Possible transfer-connections at the merging/splitting transfer-nodes are represented by boxes (i) and (iii), while possible transfer-connections at the shared path are represented by box (ii).

Table 4.2: Possible transfer-connections when four routes intersect at a transfer-node.

	A1	A2	B1	B2	C1	C2	D1	D2
A1	NA	NA	•	•	•	•	•	•
A2	NA	NA	•	•	•	•	•	•
B1	•	•	NA	NA	•	•	•	•
B2	•	•	NA	NA	•	•	•	•
C1	•	•	•	•	NA	NA	•	•
C2	•	•	•	•	NA	NA	•	•
D1	•	•	•	•	•	•	NA	NA
D2	•	•	•	•	•	•	NA	NA

The number of transfer-connections when three or more routes intersect or merge in the same geographic area can be understood with a matrix approach, such as the one exemplified in Table 4.2. For example, a transfer-node with three intersecting routes has 24 possible transfer-connections, and a transfer-node with four intersecting routes has 48 possible transfer-connections. The calculation of the number of transfer-connections for any number of intersecting routes at a given transfer-node is defined in Equation (4.1) (Vuchic et al., 1981, p. 34).

$$N_{tc} = 4 \cdot N_{cr} \cdot (N_{cr} - 1) \tag{4.1}$$

Where:

- N_{tc} is the number of transfer-connections
- N_{cr} is the number of intersecting routes

Another case of a transfer-node occurs when the termini of two (or more) routes meet. A simple case is illustrated in Figure 4.3, where the terminus of one route is in the same geographic area as the terminus of another route. This type of transfer-node is commonly found in peripheral areas of cities, aiming to connect Public Transport service from the suburbs to strategic routes into cities. In this particular case, the transfer-node encompasses only two possible transfer-connections.

The calculation of the number of transfer-connections for any number of routes with termini at the same transfer-node is defined in Equation (4.2) (Vuchic et al., 1981, p. 32).

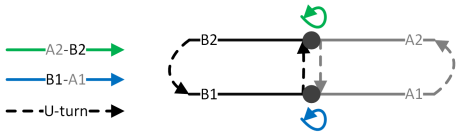


Figure 4.3: Possible transfer-connections when two routes' termini meet.

$$N_{tc} = N_{rt} \cdot (N_{rt} - 1) \tag{4.2}$$

Where:

- N_{tc} is the number of transfer-connections
- N_{rt} is the number of routes' termini

Considering the two situations simultaneously, intersecting (or merging) routes and route termini, allows the analysis of any transfer-node. This way, the calculation of the number of transfer-connections for any number of crossing routes and routes' termini is defined in Equation (4.3) (Vuchic et al., 1981, p. 34).

$$N_{tc} = (N_{rt} + 2 \cdot N_{cr})^2 - (N_{rt} + 4 \cdot N_{cr}) \tag{4.3}$$

Where:

- N_{tc} is the number of transfer-connections
- N_{rt} is the number of routes' termini
- N_{cr} is the number of intersecting routes

Table 4.3 shows all transfer-connection possibilities for a transfer-node ranging from none to five intersecting routes and none to five routes' termini. For example, a transfer-node with two intersecting routes and one route's terminus has 16 possible transfer-connections, while a transfer-node with five intersecting routes and two route termini has 122 possible transfer-connections. This shows the complexity faced by Synchronization Timetabling techniques for a single transfer-node, and how the complexity escalates by considering the case of multiple transfer-nodes.

While a transfer-node refers to an area where passengers can transfer between two (or more) routes, a congestion-node refers to an area served by two or more routes and where vehicle congestion can occur (Fouilhoux et al., 2016). Both types of nodes can be relevant for optimization, and are usually referred to as *synchronization nodes*.

Table 4.3: Number of transfer-connections in one transfer-node with 0 to 5 intersecting routes (N_{cr}) and 0 to 5 routes' termini (N_{rt}).

N_{cr}	N_{rt}					
	0	1	2	3	4	5
0	0	0	2	6	12	20
1	0	4	10	18	28	40
2	8	16	26	38	52	68
3	24	36	50	66	84	104
4	48	64	82	102	124	148
5	80	100	122	146	172	200

4.4 Methodology for Identifying Synchronization Networks

This section presents the methodology adopted to determine Public Transport networks suitable for optimization using Synchronization Timetabling techniques. The methodology has two main steps: first identifying transfer-connections suitable for synchronization in the Public Transport system from the full set of all possible transfer-connections in the system; and second, using the identified transfer-connections, to determine and join transfer-nodes into synchronization networks. These two steps are described in the following two sections.

4.4.1 Identifying Transfer Connections Candidate for Synchronization

The identification of transfer-connections suitable for synchronization is grounded on the four main assumptions summarized in Table 4.4. These assumptions are not seen as rigid criteria, but instead as a framework supporting the selection process.

Assumption 4.1 means that the expertise and knowledge of stakeholders should be considered to identify key transfer-connections, even though it is not a quantitative criterion. This includes cases such as providing service in areas with lower population density, maintaining a transfer-connection that has existed for many years and therefore is relied on by passengers, or ensuring the transfer-connection between the last runs of specific routes (allowing late evening passengers to get home).

Assumption 4.2 considers situations where two (or more) routes have an overlaping portion of their paths. In these cases, preference should be given to selecting transfer-connections at strategic stops such as route meets, merges, or intersections. Considering the case in Figure 4.2, although passengers can transfer over the shared path represented in box (ii),

Table 4.4: Set of assumptions chosen to identify transfer-connections suitable for synchronization.

No.	Description
4.1	A transfer-connection is a candidate for synchronization when so identified by experts, considering social, historical, and service quality aspects
4.2	When two directed-routes have an overlapping path segment, favor the selection of transfer-connections at their merging and splitting transfer-nodes
4.3	A transfer-connection must be within a specified transfer walking-distance
4.4	Select transfer-connections whose constituent directed-routes are Low-Frequency
4.5	Select the transfer-connections with the highest demand (i.e., with high transfer-flows)

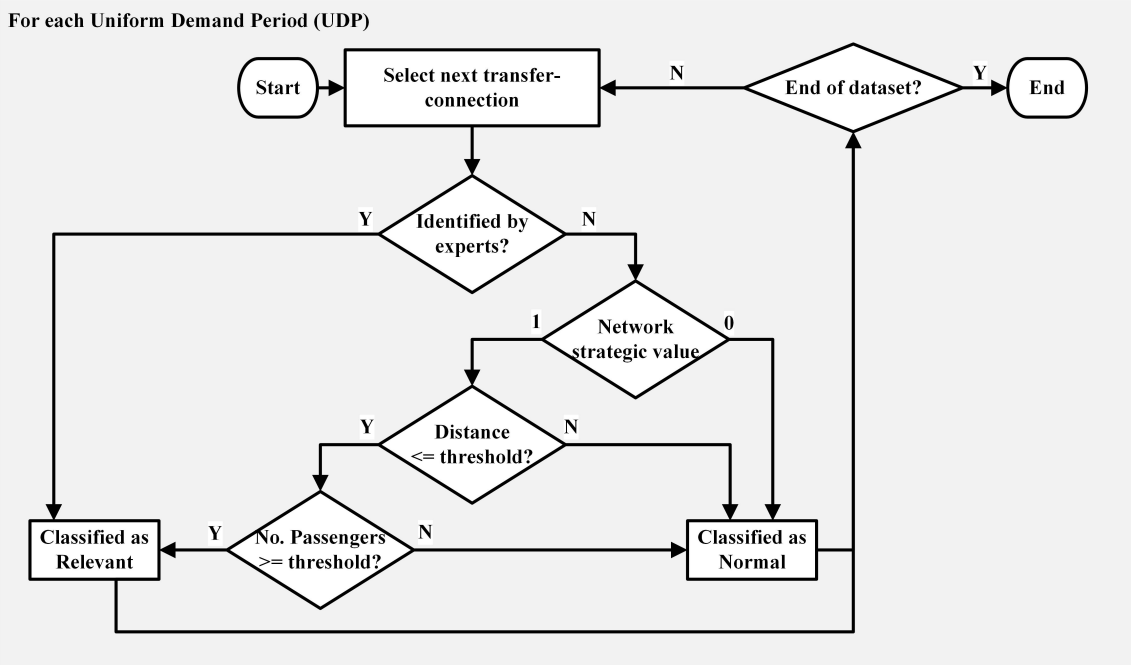


Figure 4.4: Schema showing the process to identify transfer-connections candidate for synchronization.

the methodology followed in this work considers that transfer-connections positioned at the merging and splitting transfer-nodes (boxes i and iii) should be given priority over any stop on the shared path (box ii). The goal is to minimize overall transfer waiting-time and vehicle congestion, which is achieved more efficiently by concentrating transfers at a limited number of strategic stops.

Assumption 4.3 ensures the walkability of each transfer-connection by applying a maximum threshold for transfer walking-distance.

Assumption 4.4 ensures the selection of transfer-connections linking routes of Low-Frequency. From the analysis of Table 4.1, we could conclude that the synchronization is most valuable for Low-Frequency routes, both Feeding-Route and Receiving-Route.

Assumption 4.5 considers that the importance of transfer-connections is associated with the number of passengers using them. This assumption can be implemented with a minimum demand threshold that a transfer-connection must comply with to be selected or considering a cutoff to the set of admissible transfer-connections ordered by demand values.

Figure 4.4 provides the schema with all steps in the process of identifying transfer-connections candidate for synchronization. The process starts with the set of all possible transfer-connections in the system. Each transfer-connection is considered once.

If the connection is considered suitable by experts, it is classified as *relevant* (i.e., assumption 4.1). Otherwise, the next criteria are applied.

Assumptions 4.2 and 4.4 were translated into the binary variable called *Network strategic value* in Figure 4.4. When both assumptions are verified, the *Network strategic value* assumes the value one, otherwise it is zero. Therefore, if both assumptions 4.2 and 4.4 are verified, the transfer-connection under evaluation proceeds to the following criteria. Otherwise it is classified as *normal* and not considered for further synchronization.

The process proceeds in verifying if the transfer walking-distance is within the threshold. If this threshold is respected, the transfer-connection proceeds to the final criterion. Otherwise, it is classified as *normal*.

The final criterion considers the transfer-flow value of the transfer-connection under evaluation. The transfer-flow value can be compared to a threshold value or used to order the data set and apply a cutoff. If the transfer-connection satisfies this criterion, it is classified as *relevant*. Otherwise, it is classified as *normal*.

The input information required by this process include: i) the data set of all possible transfer-connections in the system; ii) if available, the identification of relevant transfer-connections by experts; iii) the *network strategic value* of each transfer-connection (binary). This variable is calculated considering the frequency of each route (i.e., if they are Low-Frequency or High-Frequency) and the geographic information of each route (i.e., its directed-route path). iv) the transfer walking-distance of each transfer-connection. v) the transfer-flow of each transfer-connection analyzed.

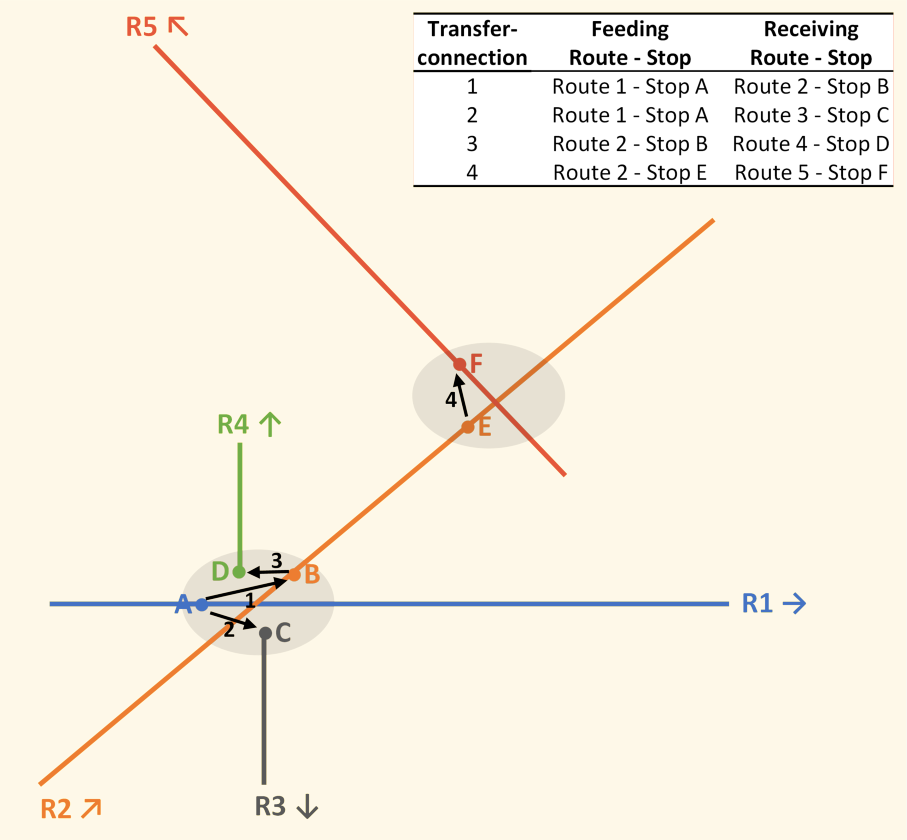
4.4.2 Identifying Networks Candidate for Synchronization

The second part of the methodology is twofold: first, to discover transfer-nodes by grouping transfer-connections with common pairs of route/stop; and second, to form networks by joining the transfer-nodes with common routes while considering the size of the resulting networks.

Each transfer-connection involves two directed-routes at two specific stops: the Feeding-

Route at the alighting-stop (the *route/stop* pair) and the Receiving-Route at the boarding-stop (the second *route/stop* pair).

Figure 4.5 provides an illustrative example with information regarding four relevant transfer-connections, and their position in the system map. For example, the first transfer-connection refers to the transfer-flow of passengers from Route 1 at stop A (i.e., pair Route 1 - Stop A) to Route 2 at Stop B (i.e., pair Route 2 - Stop B).



Transfer-connection	Feeding Route - Stop	Receiving Route - Stop
1	Route 1 - Stop A	Route 2 - Stop B
2	Route 1 - Stop A	Route 3 - Stop C
3	Route 2 - Stop B	Route 4 - Stop D
4	Route 2 - Stop E	Route 5 - Stop F

Figure 4.5: Example including four transfer-connections, which are grouped into two transfer-nodes and subsequently joined into one synchronization network.

Transfer-nodes are identified by grouping the transfer-connections (previously identified as candidate for synchronization) whenever they share at least one common *route/stop* pair. This grouping process considers the *route/stop* pairs of the transfer-connections regardless of their direction in the transfer (i.e., feeding or receiving).

In the example in Figure 4.5, transfer-connections one and two share the *route/stop* pair Route 1-Stop A, while transfer-connections one and three share the *route/stop* pair Route 2-Stop B. Therefore, transfer-connections one, two, and three are grouped within the same transfer-node.

The routes composing each transfer-node are included in the same synchronization network. The analysis of all transfer-nodes will then allow determination of the networks to synchronize. When two or more transfer-nodes share the same route, one possibility is to join those transfer-nodes into the same network. However, when the resulting network

is too large, decision-makers may split it by discarding one or more relevant transfer-connections. These decisions are made on a case-by-case basis.

In the example shown in Figure 4.5, there are two transfer-nodes, one containing transfer-connections one, two, and three, and the other containing transfer-connection four. Since Route 2 is common to both transfer-nodes, then the two transfer-nodes are included in the same synchronization network. Accordingly, the resulting network includes routes 1, 2, 3, 4, and 5 which could be an input to the Synchronization Timetabling problem.

4.5 Application to Porto

The methodology described in Section 4.4 was applied to the Public Transport operations of buses, metro, and tram in Porto in 2013. The Public Transport system under analysis encompasses 2673 stops and 156 directed-routes. Figure 4.6 shows a map of all directed-routes.



Figure 4.6: Visualization of the 156 directed-routes considered in Porto.

The data set used in this case study considered the travel activity recorded in 4,000 randomly selected smart cards throughout 2013, which account for 191,938 AFC records. The identification of transfers in this data set was performed by applying the Trip Chaining Method (TCM) and a subsequent process to identify transfers following the methodology described in sections Section 3.4.1 and Section 3.4.2.

The database software PostgreSQL was used to select and sort the data. The TCM algorithm was implemented in C++, using a 3.4 GHz Intel Core i7 processor and 16 GB of Random Access Memory (RAM). The computational effort to solve the TCM in this

Table 4.5: Summary of the application of the methodology to the case study of Porto, by month. All proportions were calculated with reference to the total number of Automated Fare Collection (AFC) records analyzed (i.e., 191,938 records).

	All AFC records		Ass. 3.8		Ass. 3.9 (3km)		Transfers	
Month	No.	%	No.	%	No.	%	No.	%
1	16,783	8.74	1,458	0.76	447	0.23	1,830	0.95
2	15,080	7.86	1,243	0.65	417	0.22	1,632	0.85
3	15,965	8.32	1,452	0.76	409	0.21	1,664	0.87
4	17,160	8.94	1,481	0.77	475	0.25	1,866	0.97
5	18,460	9.62	1,607	0.84	494	0.26	2,076	1.08
6	15,088	7.86	1,434	0.75	428	0.22	1,668	0.87
7	16,349	8.52	1,465	0.76	404	0.21	1,864	0.97
8	12,891	6.72	1,091	0.57	357	0.19	1,479	0.77
9	15,232	7.94	1,327	0.69	381	0.20	1,677	0.87
10	17,851	9.30	1,449	0.75	464	0.24	1,912	1.00
11	16,360	8.52	1,363	0.71	450	0.23	1,587	0.83
12	14,719	7.67	1,311	0.68	458	0.24	1,337	0.70
Sum	191,938	100.00	16,681	8.69	5,184	2.70	20,592	10.73

application was low, less than 10 seconds. The performance of this algorithm in larger instances was reported in Hora et al., 2017.

This implementation considered the following thresholds: 3 km in assumption 3.9 (i.e., passengers travel outside the Public Transport system when the walking-distance between consecutive trip-legs exceeds a specified threshold), 200 meters in assumption 3.20 (i.e., passengers do not walk more than a specified distance to transfer), and 30 minutes in assumption 3.22 (i.e., passengers do not wait more than a specified time to transfer) (Hora et al., 2020).

Table 4.5 shows the summary of the application of the TCM and transfer identification processes to this data set, where each row provides the information by month, and the last row the aggregate information for the entire year.

In Table 4.5, the 2nd and 3rd columns provide the information on the total number of AFC records analyzed (*All records*), including the absolute number of AFC records and the corresponding proportion calculated with reference to the total number of AFC records analyzed (i.e., 191,938 records).

The information regarding cases for which it was not possible to estimate alighting-stops are given in two groups: *Ass. 3.8* (corresponding to the 4th and 5th columns) and *Ass. 3.9 (3km)* (corresponding to the 6th and 7th columns). The first group includes the cases

where there was only one daily AFC record and to which the Assumption 3.4 of returning home could not be applied. The second group refers to the cases where the estimated distance between consecutive trip-legs (calculated as the distance between the estimated alighting-stop and the corresponding chained boarding-stop) was greater than 3 km - those inferences were discarded since the passenger is assumed to have traveled out of the system.

Finally, the process of identifying transfers was applied to the AFC records with successful estimations of alighting-stops. Table 4.5 shows the number of transfers that were identified, and its proportion with reference to the total number of AFC records analyzed in the last two columns. For a yearly aggregate perspective, transfers accounted for around 11% of total AFC records. Note that a transfer is identified with two AFC records, but its accounting is not duplicated. Therefore, each transfer is counted just once - making them comparable to the total number of AFC records.

The procedures described in this section produced the data set for this case study, composed of the set of transfers performed by 4,000 passengers, and to which the methodology described in section Section 4.4 was applied, and whose results are presented in the next section.

4.6 Results

The methodology described in Section 4.4 was applied to the case of Porto. The data includes all transfers identified during the travel activity of a set of 4,000 smart cards throughout 2013.

4.6.1 Transfer-connections

The identification of relevant transfer-connections was implemented as described in Section Section 4.4.1. In this particular case study, there was no expert consultation to identify candidate transfer-connections. Moreover, it was not possible to obtain information regarding the operation frequencies of the different routes under analysis, which prevented their classification regarding High-Frequency or Low-Frequency. Even though the lack of this information prevented the application of two assumptions foreseen in the methodology (i.e., assumption 4.1 and assumption 4.4), the methodological process remains viable without their inclusion.

Assumption 4.5 was implemented by considering a cut-off line with the 20 highest demand transfer-connections, selected as candidates. Figure 4.7 shows the total number of transfers for the 20 transfer-connections with the highest demand. Taken together, the transfer-connections identified as candidates represent 36.40% of the total transfers under analysis.

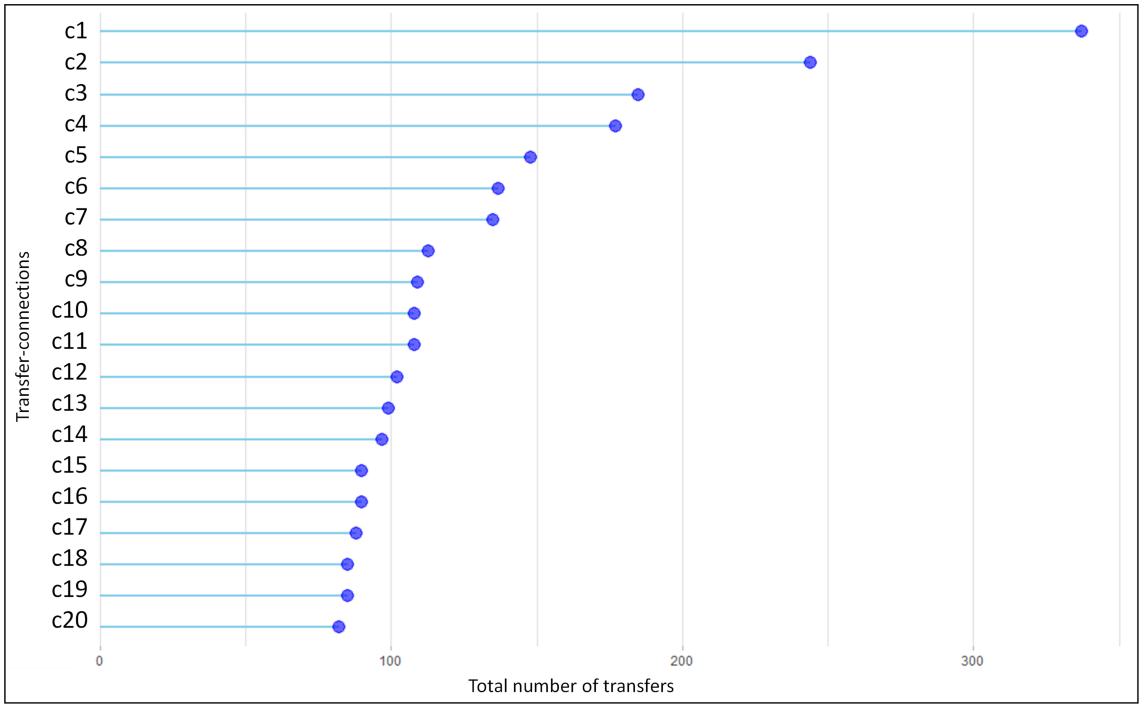


Figure 4.7: Visualization of the 20 highest demand transfer-connections as candidates.

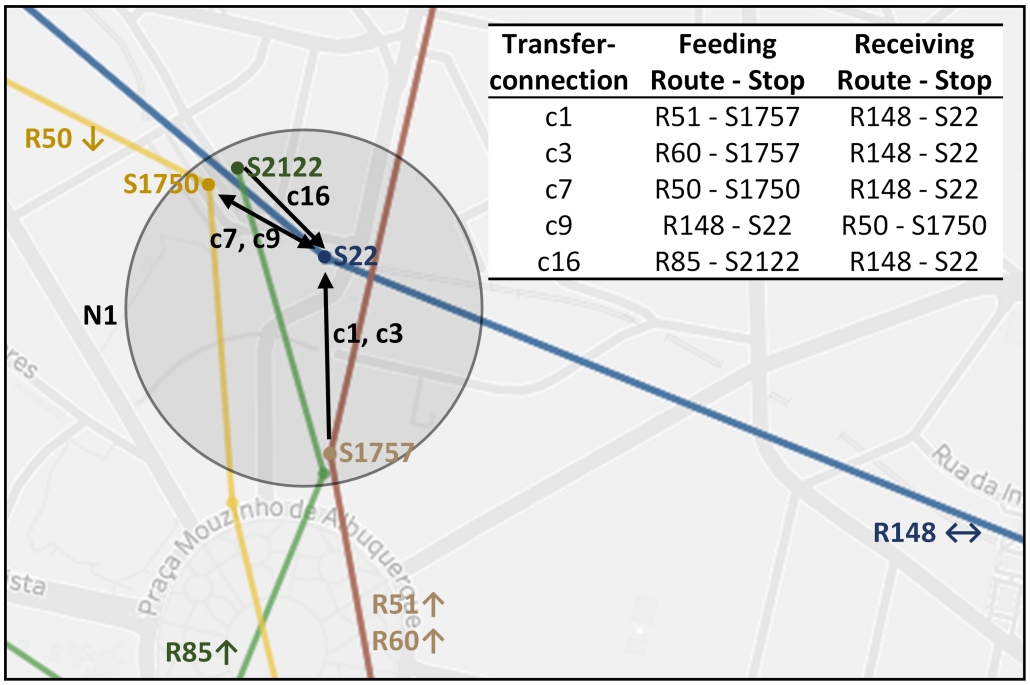
The threshold adopted regarding assumption 4.3 was 200 meters, following similar values in the literature to identify transfers and because this threshold is considered appropriate for Porto. The implementation of assumption 4.2 led to the discarding of two candidate transfer-connections (i.e., c8 and c19). This process resulted in the identification of 18 candidate transfer-connections.

4.6.2 Transfer-nodes

Transfer-nodes were identified by grouping the candidate transfer-connections when they share (at least) one route/stop pair (regardless of whether they are feeding or receiving routes in the transfer-connection). This process resulted in the identification of 13 transfer-nodes. The visualization of all transfer-nodes is provided in Appendix A.

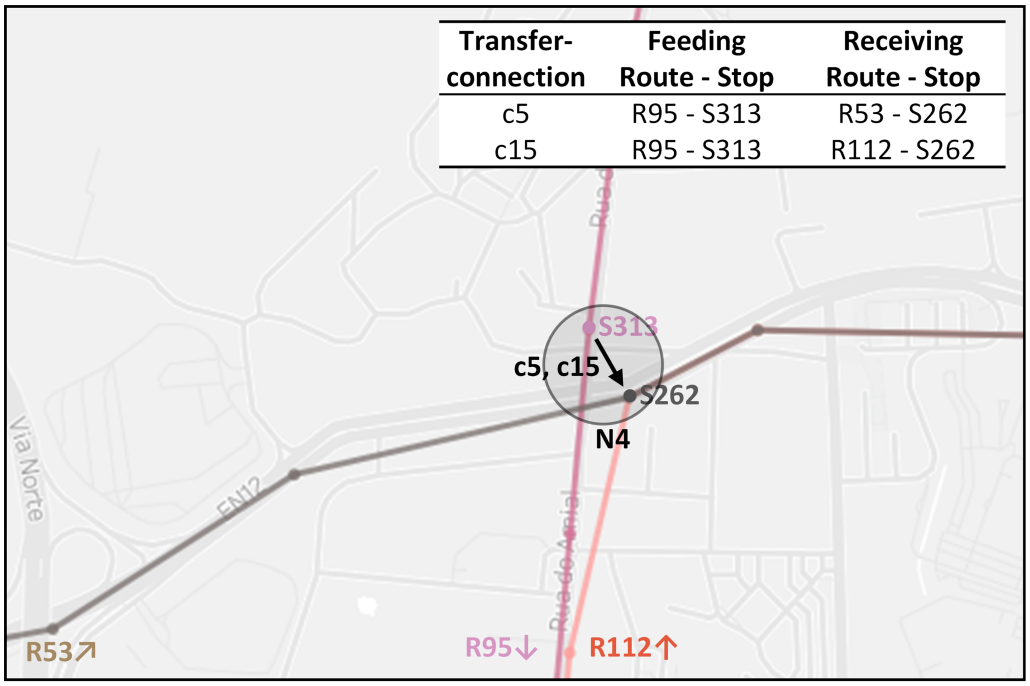
Figure 4.8 shows the visualization of transfer-node N1, which includes transfer-connections c1, c3, c7, c9 and c16. Figure 4.8 also details, for each transfer-connection, the information regarding its Feeding-Route and alighting-stop followed by its Receiving-Route and boarding-stop, with stops preceded by S, and routes by R.

Figure 4.9 shows the detail of transfer-node N4, which includes transfer-connections c5 and c15. Both c5 and c15 connect stops S313 and S262, but they are distinct transfer-connections since the Receiving-Routes are different.



Transfer-connection	Feeding Route - Stop	Receiving Route - Stop
c1	R51 - S1757	R148 - S22
c3	R60 - S1757	R148 - S22
c7	R50 - S1750	R148 - S22
c9	R148 - S22	R50 - S1750
c16	R85 - S2122	R148 - S22

Figure 4.8: Transfer-node N1 (including transfer-connections 1, 3, 7, 9, and 16).



Transfer-connection	Feeding Route - Stop	Receiving Route - Stop
c5	R95 - S313	R53 - S262
c15	R95 - S313	R112 - S262

Figure 4.9: Transfer-node N4 (including transfer-connections 5 and 15).

4.6.3 Synchronization networks

The final step of the methodology refers to the identification of synchronization networks by grouping transfer-nodes which have at least one route in common. This process resulted in five synchronization networks, shown in Figures 4.10 and 4.13–4.16.

Figure 4.10 shows the visualization of synchronization network 1, grouping eight transfer-nodes: N1, N2, N3, N5, N7, N8, N12, and N13. All transfer-nodes in synchronization network 1 share route R148. Transfer-node N1 incorporates routes R50, R51, R60, R85, and R148 (see Figures A.1 and A.2), transfer-node N2 incorporates routes R44 and R148 (see Figures A.3 and A.4), transfer-node N3 incorporates routes R147 and R148 (see Figures A.5 and A.6), transfer-node N5 incorporates routes R71 and R148 (see Figures A.9 and A.10), transfer-node N7 incorporates R148 and R70 (see Figures A.13 and A.14), transfer-node N8 incorporates routes R73 and R148 (see Figures A.15 and A.16), transfer-node N12 incorporates R148 and R44 (see Figures A.23 and A.24), and transfer-node N13 groups R148 with R52 (see Figures A.25 and A.26).

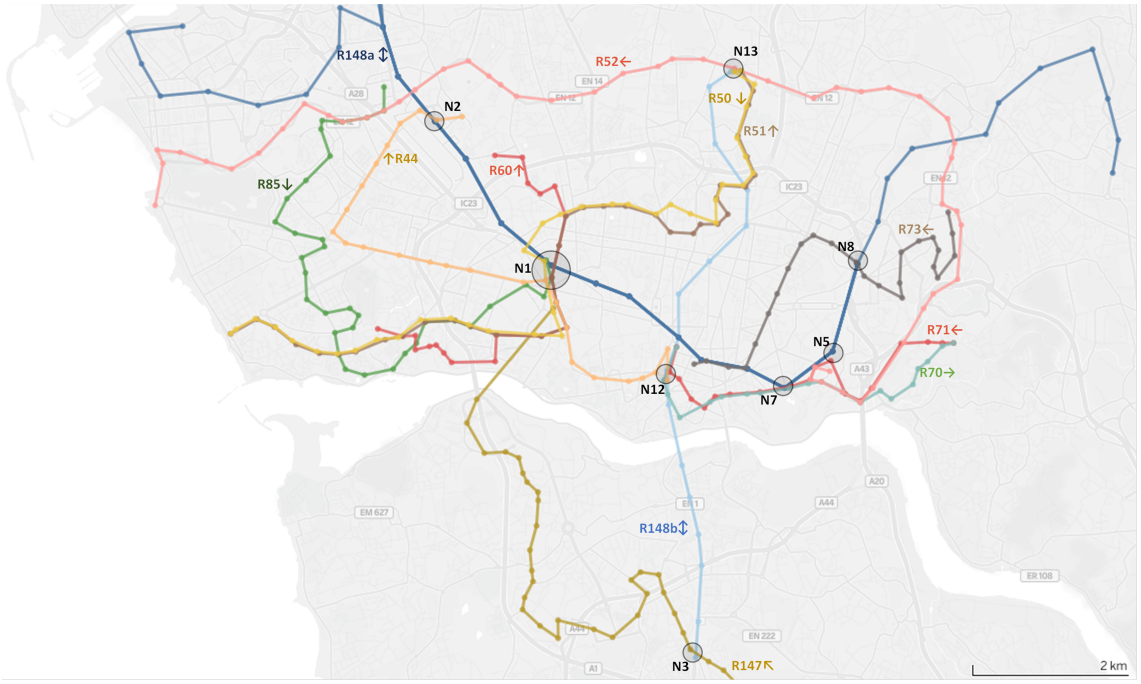


Figure 4.10: Synchronization Network 1 (including transfer-nodes N1, N2, N3, N5, N7, N8, N12, and N13).

Route R148 refers to the operation of all metro routes in Porto (i.e., it aggregates metro routes A, B, C, D, E, and F). This study analyzes all metro routes as a single route due to the impossibility of estimating the specific boarding route from AFC records made at metro stations. By considering all metro routes as a whole, the TCM considers all stops that make up the set of metro routes as possible destinations, regardless of direction. In the case of bus routes, since each AFC record's boarding route is known, the TCM considers as possible destinations the set of all downstream stops in that run.

By considering the activity of all metro routes as a single route and taking into account that the metro has a significant share of all Public Transport trips in Porto, it was expected to obtain a more complex synchronization network with all metro connections to other routes in the system. It is possible to divide the synchronization network represented in Figure 4.10 into two less complex ones by discarding transfer node N12 and separating the metro operation of route D from the remainder metro routes, as shown in Figures 4.11 and 4.12.

Figure 4.11 shows synchronization network 2, linking metro routes A, B, C, E, and F to bus routes at transfer-nodes N1, N2, N5, N7, and N8. Figure 4.12 shows synchronization network 3, linking the activity of metro route D to bus routes at transfer-nodes N3 and N13.

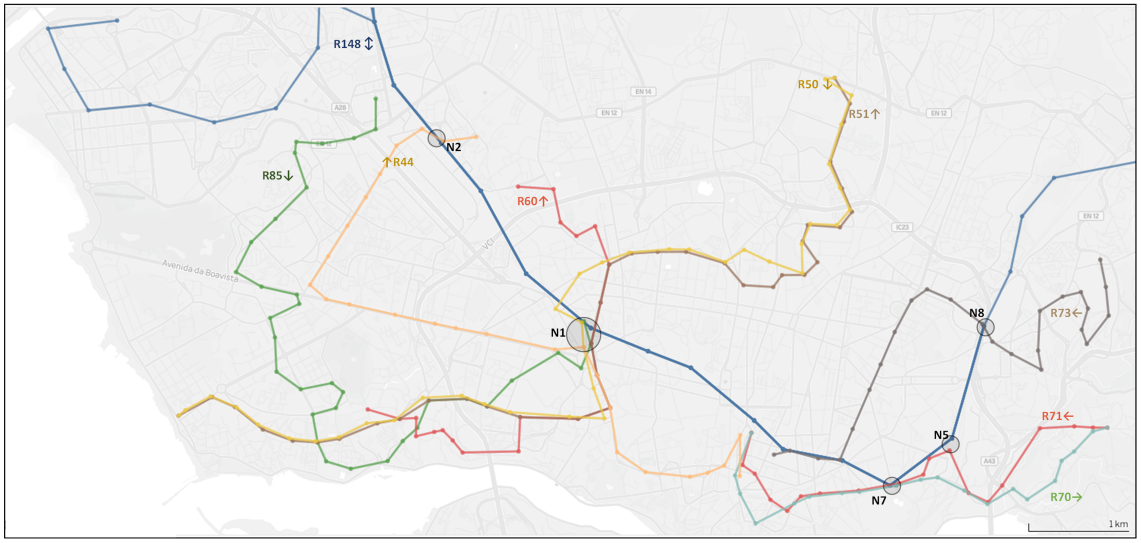


Figure 4.11: Synchronization Network 2 (including transfer-nodes N1, N2, N5, N7, and N8).

The routes integrating the synchronization networks 1, 2, and 3 are: R44 corresponds to route 201 direction *Viso*, R50 to route 204 direction *Foz*, R51 to route 204 direction *São João*, R52 to route 205 direction *Castelo do Queijo*, R60 to route 209 direction *Prelada*, R71 to route 400 direction *Trindade*, R70 to route 400 direction *Azevedo*, R73 to route 401 direction *Bolhão*, R80 to route 504 direction *Casa da Música*, R147 to route 907 direction *Boavista*, R148a to metro routes A, B, C, E, and F as a whole in any direction, and R148b to metro route D in any direction.

Figure 4.13 shows synchronization network 4 which incorporates transfer-node N4 (previously shown in Figure 4.9). The routes included in synchronization network 4 are: R53 corresponds to route 205 direction *Campanhã*, R95 to route 600 direction *Aliados*, and R112 to route 704 direction *Largo da Codiceira*. From the set of transfer-nodes obtained, there were no other transfer-nodes sharing common routes with transfer-node N4. Therefore, the synchronization network 4 is composed of the routes from just one transfer-node.

Similar cases were obtained in synchronization networks 5, 6, and 7, shown in Figures 4.14–

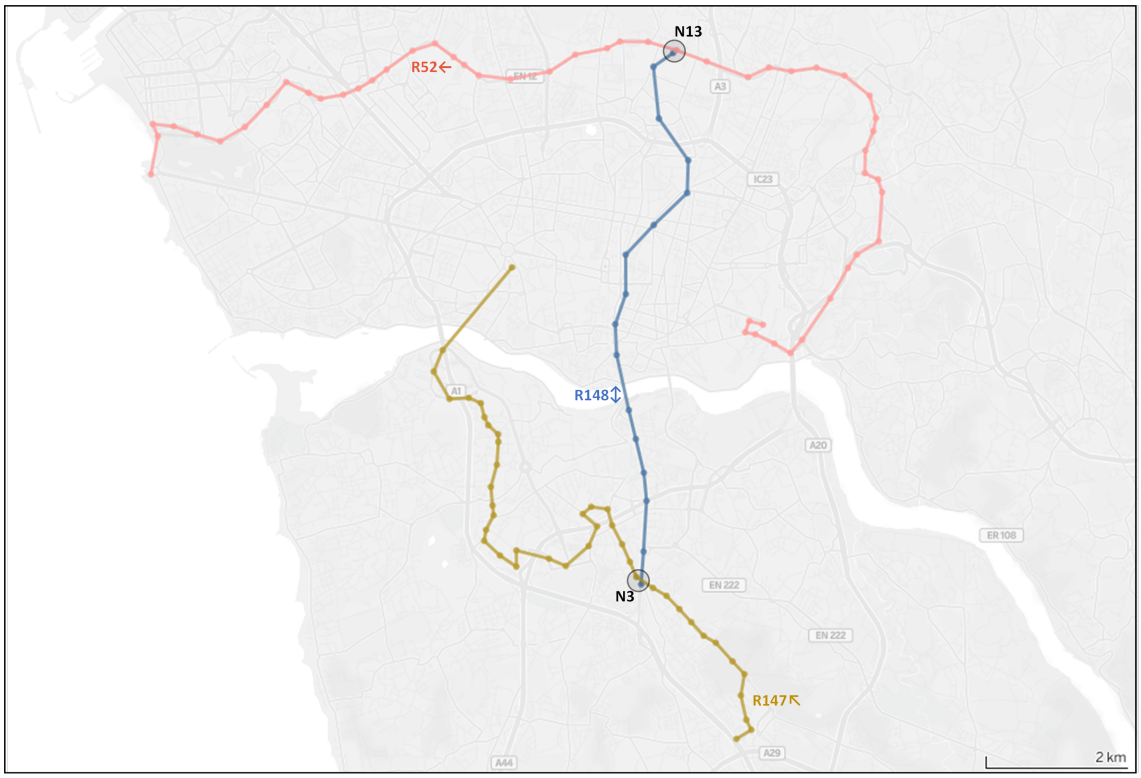


Figure 4.12: Synchronization Network 3 (including transfer-nodes N3 and N13).

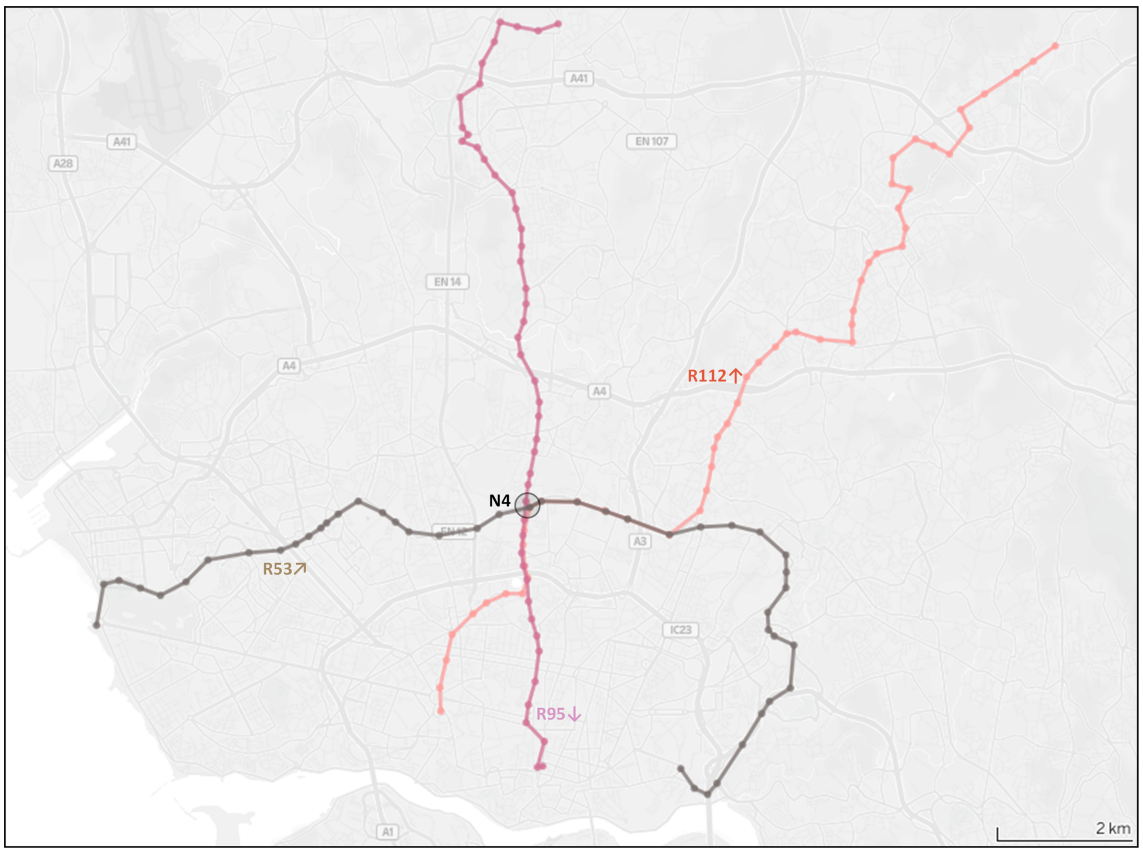


Figure 4.13: Synchronization Network 4 (including transfer-node N4).

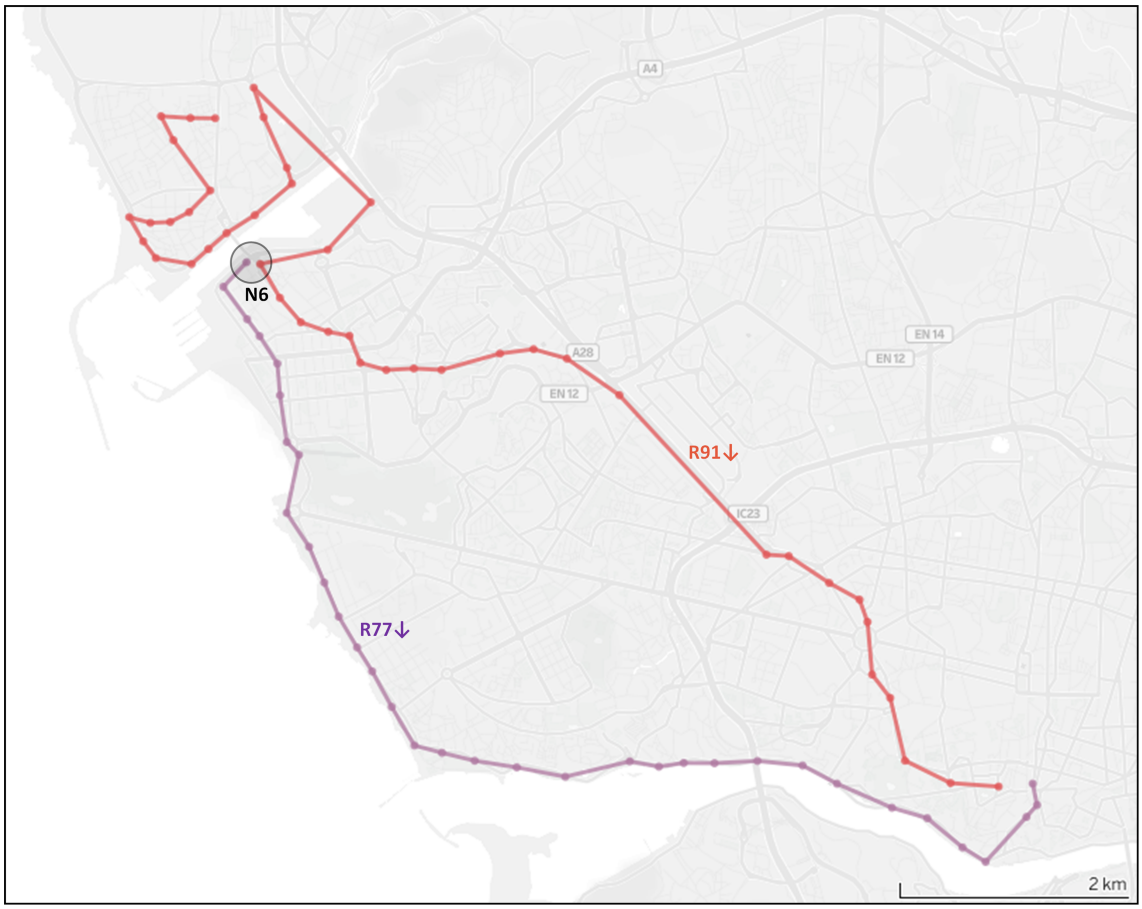


Figure 4.14: Synchronization Network 5 (including transfer-node N6).

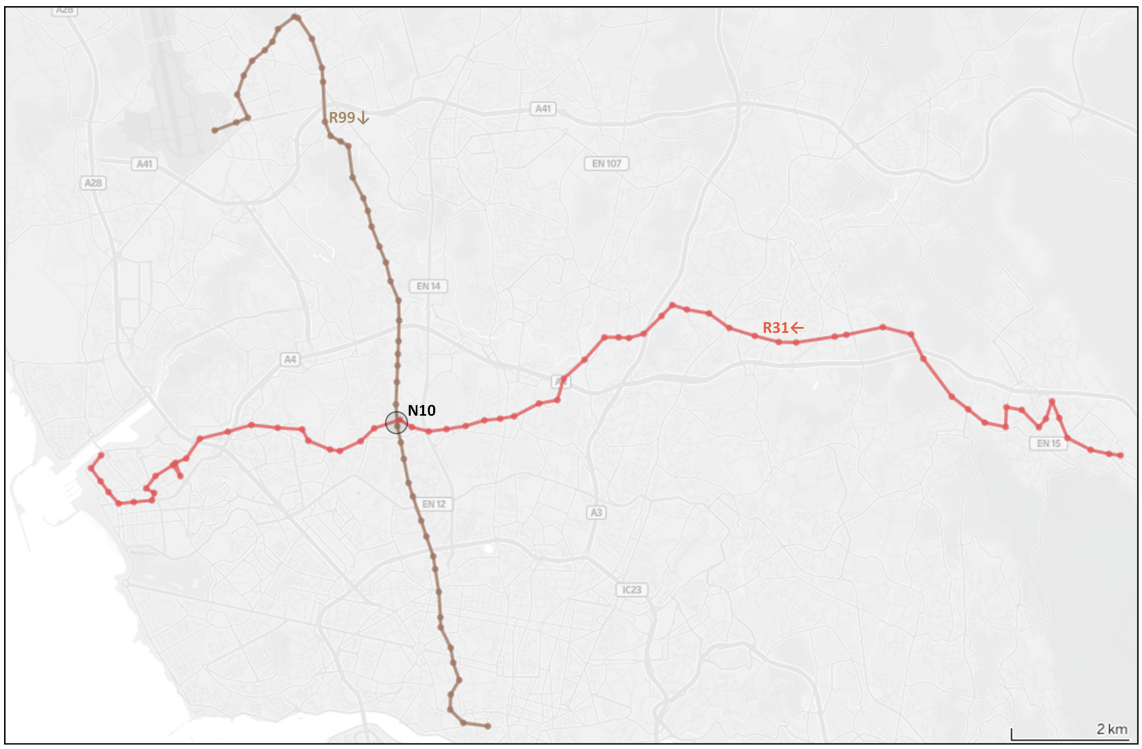


Figure 4.15: Synchronization Network 6 (including transfer-node N10).



Figure 4.16: Synchronization Network 7 (including transfer-node N11).

4.16. Figure 4.14 provides the visualization of synchronization network 5, integrating transfer-node N6, and where R77 corresponds to route 500 direction *São Bento* and R91 to route 507 direction *Cordoaria*.

Figure 4.15 provides the visualization of synchronization network 6, with transfer-node N10, where R31 corresponds to route 61 direction *Mercado Matosinhos* and R99 to route 602 direction *Cordoaria*.

Figure 4.16 provides the visualization of synchronization network 7, with transfer-node N11, where R49 corresponds to route 203 direction *Marquês* and R96 to route 601 direction *Aeroporto*.

4.7 Conclusions

The optimization with Synchronization Timetabling techniques is usually applied to a simplified network of the Public Transport system reflecting its main demand flows. The identification of such a simplified network is not an easy task, especially in Public Transport systems using entry-only AFC, such as the case study of this work, the city of Porto. The main goal of this work was to develop and implement a methodology able to identify synchronization networks in a Public Transport system, suitable for further optimization

with Synchronization Timetabling techniques.

Following this goal, a methodology was developed encompassing two main steps. First identifying transfer-connections candidate for synchronization in the Public Transport system from the set of all possible transfer-connections in the system. Second to determine transfer-nodes and use them to form synchronization networks.

This methodology was applied to the case of Porto, using a sample of 4,000 randomly selected smart cards for 2013. This analysis served as a proof of concept of the methodology. The results obtained are promising and call for the application of this methodology to larger data sets, and to perform statistical analysis regarding the type of passengers (e.g., frequent and occasional passengers), as well as to compare the set of candidate transfer-connections in different UDP, such as peak and off-peak periods of the day.

Identifying the most suitable network to Synchronize (particularly the most relevant transfer-connections) can also aid decision-makers in enhancing the quality of transportation service under uncertainty, even without applying any optimization model. By quantifying the relevance of transfer-connections, decision-makers have a solid basis for deciding on situations where vehicles should wait for the arrival of others during operations (i.e., to support Holding Time Models (HTM)).

For example, when the Feeding-Vehicle arrives earlier than scheduled, and the Receiving-Vehicle is on time, passengers have an extra transfer waiting-time, or in some cases, they might be able to board an earlier run on the Receiving-Route. Another scenario would be when the Feeding-Vehicle arrives later than scheduled, and the Receiving-Vehicle is on time, in which case passengers are likely to miss the transfer and have to wait for the next run on the Receiving-Route (or they might board the Receiving-Vehicle with almost zero transfer waiting-time). Many other transfer scenarios can be studied considering different Feeding-Vehicle arrival-time and Receiving-Vehicle departure-time.

Future research could encompass the sensitivity analysis to understand the effect of changes on the different thresholds adopted. This analysis would provide robustness to the results and conclusions obtained. Also, future research can include the interview with transport specialists in the city of Porto to find out their views on which transfer connections and nodes they consider to have the most significant impact on the system and subsequently incorporate this feedback in the construction of synchronization networks, as well as carry out a comparison with the networks obtained without this input.

5 Synchronizing Public Transportation Networks

This chapter pursues the goal of minimizing passengers' transfer waiting-time through the synchronization of Public Transport networks. To pursue this goal a Mixed Integer Linear Programming (MILP) model was developed. The model returns the timetables of a optimized Public Transport. Timetables are defined with the departure-times of all runs. The objective function maximizes a binary variable stating whether two run-pieces are synchronized or not (i.e., it maximizes the number of synchronized run-pieces). The decision variables are the binary variable on synchronized run-pieces and the departure-times of all run-pieces. Different constraints were included to ensure the feasibility of the resulting timetables, including the minimum and maximum headway, and geographic and temporal feasibility of transfers and runs.

5.1 Introduction

Synchronization Timetabling techniques refer to a set of optimization approaches designed to build Public Transport timetables seeking to improve route connectivity and integration, service quality, attractiveness to passengers, smooth transfer opportunities, and to reduce inconvenient transfer waiting-time and vehicle bunching. The different implementations of synchronization Timetabling techniques published in the literature apply objective functions such as minimizing the sum of transfer waiting-time in the system, minimizing the sum of passengers' wait-time on full-trips, minimizing vehicle bunching at stops or maximizing the number of transfer opportunities at stops. Attaining these goals also has a positive impact on the system's overall reliability.

Timed Transfers is a Synchronization Timetabling technique in which vehicles on two (or more) routes meet simultaneously at focal-points, at regular intervals, to exchange passengers smoothly. The goal is to reduce transfer waiting-time as much as possible by allowing many passengers to transfer simultaneously. The time-window in which vehicles simultaneously meet at a focal-point is called the contact-period.

Timed Transfers follow the same principle as banking of flights at hub airports, in which several flights arrive and depart within short periods (Kemp et al., 1997). Timed Transfers are also known as *pulse scheduling* (Nelson et al., 1981), since, when observing the trajectory of vehicles on the network map, Timed Transfers generates a *pulsing* effect, i.e., several vehicles arrive simultaneously at the focal-point at given intervals. If two (or more) focal-points of the same network *pulse* at the same time, they perform a *simultaneous pulse*. If two or more focal-points of the same network *pulse* alternately in time, they perform a *staggered pulse*.

The regular stream of vehicles arriving simultaneously at each focal-point eases passengers' transferring process. This way, Timed Transfers contribute to network's connectivity and trip planning flexibility, which in turn allows the Public Transport system to serve many Origin-Destination (OD) locations with fewer routes and resources.

Routes synchronized through Timed Transfers have equal headways or exact multiples, conditioning the subsequent definition of the following operating elements: directed-route length, cycle-time, operating-velocity, fleet size, and overall timetable construction. The interrelationship between the headway and these operating elements is presented in Section 2.3.1. In contrast, uncoordinated routes have their operating elements defined independently.

Another important group of Synchronization Timetabling techniques is Transfer Optimization. There are different ways to formulate these problems, depending on whether the system is analyzed from a macro or micro perspective, and depending on the specific aspects targeted for improvement in each system.

Transfer Optimization is less costly to implement than Timed Transfers. Instead of converging trips at focal-points, Transfer Optimization determines the departure-time of each run in order to minimize some objective quantifying overall transfer inconvenience. Usually, the objective functions of Transfer Optimization is to minimize transfer waiting-time. This approach does not require the addition of slack time, can be applied to large networks and does not increase operating costs or inconveniencing for in-vehicle passengers (Bookbinder & Desilets, 1992).

As opposed to other Synchronization Timetabling techniques, Timed Transfers requires the existence of adequate *infrastructure* for holding several vehicles close together simultaneously, which contributes to the increased cost of this approach (in terms of both infrastructure construction and maintenance).

In cases where the existing infrastructure can not accommodate vehicles from all possible routes meeting at a specified focal-point (e.g., a rail station with a limited number of rails), the Timed Transfers technique can be implemented following a concept of *waves*, as reported for example in Clever (1997). The concept of waves is carried out in three steps.

In step 1, all vehicles whose runs end at the focal-point disembark all passengers and wait empty in the vicinity. In step 2, all vehicles having the focal-point as an intermediate stop proceed to exchange passengers at the focal-point. In step 3, all vehicles that waited nearby in step 1 return to the focal-point, proceed with passengers boarding and start the next run. Therefore, these cases include additional costs for the extra time required by waiting vehicles.

The constraint for a *multiplicative relationship* in routes' headway is usually combined with strategies to increase Public Transport attractiveness. This results in the frequent adoption of an *easy to memorize headway* often referred to as clock face headway (for example, 30 minutes). For some routes, this constraint implies a reduction of frequency, translated as a transportation service loss (social cost). For other routes, this constraint implies an increase in frequency, which increases operating costs for the operator (economic cost to operator). Both changes, reducing or increasing frequencies, induce disturbances into the optimum frequency as it was defined in Frequency Setting. Nevertheless, final timetables must comply with headway policies, thus not affecting the transportation service delivered to passengers unacceptably. Overall, the costs associated with the multiplicative relationship of headway are case sensitive, and in some systems they may not even apply.

Sometimes, it is infeasible to force several routes to meet simultaneously at the same focal-point. All operating elements must be accounted for to evaluate the *feasibility of a solution*. For example, one route may be too long to ensure its arrival in time for successful synchronization (a solution could be cutting the *route's length*, which would imply changing the solution obtained at Network Design). Analogously, the path of one route may be too short, so that it would require its vehicles to hold for a very long time for the other routes to meet (in case of a intersecting route), or to increase its terminus time (in case of a terminus route) - thus increasing operating costs. Moreover, all operating elements must be accounted for to check for the feasibility of a solution, including the fleet size.

Applying Timed Transfers also requires attention to running-time uncertainty. In this context, the main strategy to prevent delays from running-time uncertainty is including extra *slack time* at focal-points (i.e., holding-time for intersecting routes, or terminus-time for terminus routes). Slack time allows vehicles to wait for each other, thus absorbing possible delays without disturbing the normal operation to run as planned. However, adding slack time increases operating costs and produces unnecessary delays for in-vehicle passengers. Moreover, this strategy is sensitive to demand variations of each Uniform Demand Period (UDP). For example, if the same schedule is applied for peak periods and off-peak periods (i.e., not accounting for demand variations over the day), and includes enough slack time to absorb uncertainty of peak hours, the operation at off-peak hours will have unnecessary costs from the unused slack time (vehicle idle time).

When a Feeding-Vehicle is late, the following decisions can be adopted for the Receiving-

Vehicle operation: i) The Receiving-Vehicle leaves as planned and passengers on that connection miss their transfer; ii) The Receiving-Vehicle waits for the delayed Feeding-Vehicle, inconveniencing its in-vehicle passengers but allowing all transferring passengers to connect. The rule of hold until the Feeding-Vehicle arrives can not be implemented blindly (a severe delay in the Feeding-Vehicle would imply the Receiving-Vehicle waits indefinitely). A maximum holding time is usually adopted in these cases. The last trip of the day and off-peak periods are traditionally cases where vehicles should wait longer for each other, while first runs of peak periods are seen as cases where vehicles should wait less or not wait at all - due to the difficult recovering due to traffic and congestion; iii) The Receiving-Vehicle receives instructions dynamically, either to hold or to leave. This approach is increasingly used due to the new communication technologies. However, using dynamic control strategies does not replace the need for well-defined planning strategies.

The previously mentioned reasons impel operators to use Timed Transfers only at few strategically defined focal-points, usually less than ten (Bookbinder & Desilets, 1992; Desilets & Rousseau, 1992). Noting that Timed Transfers can impact solutions from Network Design and Frequency Setting, it is vital that the choice of the focal-points be made strategically as long-term decisions.

This chapter proposes a synchronization model that seeks the goal of minimizing transfer waiting-time of passengers in a Public Transport system. The model maximizes the number of transfer opportunities by considering a binary decision variable that identifies whether or not two run-pieces are synchronized.

The model can be implemented considering a fixed headway for each directed route, in which case the timetable obtained follows the same principles as a Timed Transfers approach (the timetable becomes periodic over the planning period considered, and is defined by the time of the first run of each directed route and the corresponding headway). The model can also be implemented by allowing the headway between consecutive runs of each directed-route to be uneven, through the definition of thresholds for the minimum and maximum values. The implementation of the model using uneven headways returns timetables following a Transfer Optimization approach.

Additionally, the model considers a time-window between the arrival and departure of vehicles in each transfer-node which is used to classify each transfer opportunity as synchronized or not. If the time-window is set to be zero, the vehicles are considered as synchronized only when they arrive at the same moment at the same transfer-node. Adopting a time-window period increases the model solution space, and returns timetables maximizing the number of transfer opportunities where the arrival of a Feeding-Vehicle and the departure of a Receiving-Route vehicle falls within the defined time-window.

The literature review of Synchronization Timetabling approaches is provided in Section 5.2, including Timed Transfers approaches in Section 5.2.1 and Transfer Optimization

approaches in Section 5.2.2. The majority of formulations proposed in the literature do not cover networks where routes intersect each-other in more than one transfer-node. However this is an often feature in urban Public Transport networks settings. Section 5.3 presents a synchronization model that can be applied to any combination of route intersection, which is the main contribution of this work. Section 5.4 describes the data used to implement and test the model, which considers real-world network design using academic data. The results are in Section 5.5. Finally, Section 5.6 provides final remarks and suggestions for future work.

5.2 Literature Review on Synchronization Timetabling

5.2.1 Timed Transfers

Several cities have been implementing Timed Transfers, even if empirically, since the early 20^{th} century (Kemp et al., 1997). Nelson et al. (1981) reported a survey to 39 Public Transport systems using Timed Transfers in the United States of America (USA) (including Washington - D.C., Portland - Oregon, Albany - New York, Toledo - Ohio, Memphis - Tennessee, among others). The survey by Nelson et al. (1981) provides insights from the perspective of the operators on costs, user satisfaction, ridership, revenue, and other practical considerations. The San Jose Oakland Sacramento corridor, in the USA, is addressed in (Clever, 1997). Petersen (2016) reviewed the application of Timed Transfers in rural areas of Switzerland.

One of the earliest published optimization models addressing Timed Transfers is the work of Salzborn (1980) which includes a deterministic model to synchronize a lineup network, corresponding to a regional bus route stopping at different cities, treated as focal-points. Each focal-point links the regional route with several local routes. This model guides only the regional route timetable, with simplification of several operational constraints. Salzborn (1980) proposes a second Timed Transfers model that synchronizes each focal-point with other local routes, following a uni-focal network setting by fixing the regional route timetable previously obtained.

Ceder and Tal (1999) propose a Timed Transfers Mixed Integer Programming (MIP) model that maximizes the number of simultaneous arrivals at focal-points. This model is a seminal contribution in this area, as it is the basis for many later works. The model accounts with the planning horizon, the set of routes and focal-points composing the network, the minimum and maximum headway allowed for each route, the number of runs to be made by each route, and the deterministic running-time of each route segment. It includes several logic constraints, particularly that all runs must depart within the planning horizon and that headway bounds must be satisfied. The decision variable is a binary value that indicates whether or not each pair of route runs arrives simultaneously

at a focal-point. Other models follow the work by Ceder and Tal (1999).

Chowdhury and Chien (2011) studied Timed Transfers with a mathematical model. The objective function minimizes costs of operators (considering vehicle size and fleet size) and users (considering wait cost and transfer cost). The model seeks to understand the optimal relationship between the following decision variables: vehicle size, headway, and slack time. Constraints included the vehicle capacity. The model was applied using the Powell algorithm to a uni-focal network with several intersecting routes as an example.

Ibarra-Rojas and Rios-Solis (2012) proposed a mathematical model for Timed Transfers using a MIP formulation, applied to a triangular network setting. They also propose multi-start iterated local search algorithms to solve larger multi-focal network settings ranging between three and 40 focal-points. The models maximize the number of simultaneous run arrivals at focal-points (i.e., the number of runs meeting at focal-points with feasible contact periods) and minimizes bunching. Constraints included forcing the first and last runs of each route to depart within the planning period under study, to separate consecutive runs of each route by a minimum and maximum headway, to consider simultaneous run arrivals as feasible if their contact-period range complies with previously defined time-windows.

The approach proposed by Ibarra-Rojas and Rios-Solis (2012) form the basis for other studies that considered variations of some assumptions and constraints. Ibarra-Rojas, López-Irarragorri, et al. (2015) considered each route having a specific UDP, instead of using the same UDP for all routes. They applied a constraint propagation methodology, which allows acknowledging route runs from different UDP in the same timetable (instead of being ignored by merging timetables from different UDP), and returning timetables for the entire day. Fouilhoux et al. (2016) proposed new valid inequalities to reduce the computational effort and allowing feasible solutions for small-sized networks up to 40 focal-points.

Chowdhury and Chien (2019) developed a mathematical model seeking the simultaneous optimization of fare and headway, in a uni-focal network. The model incorporates demand elasticities for fare and travel-time. Timetables are optimized considering constraints on vehicles' capacity and the Least Common Multiple (LCM) headway for the routes intersecting at the focal-point. They consider a fare discount for transfers as a policy to encourage Public Transport ridership.

The most common objective functions include minimizing wait-time on full-trip, transfer wait-time on full-trip, or vehicles' bunching. Improving these features also has a positive effect on the system's reliability.

Heuristic Procedures to address Timed Transfers

Ceder and Tal (2001) proposed two heuristic procedures to address Timed Transfers, aiming to reduce the computational time required for the MILP formulation (addressed in the same work). The first heuristic iteratively selected each node with undefined run departure-times and implemented a set of rules for its definition (a variation of this heuristic is presented in Ceder et al. (2001)). The second heuristic performs re-Timetabling solution by considering possible shifts in the departure-times.

Ting and Schonfeld (2005) apply a heuristic algorithm to optimize headway and slack time in Timed Transfers systems. They considered bi-focal and triangular network settings. The goal was to minimize operating costs. They refer the applicability of Timed Transfers to Low-Frequency routes, as well as the ability of timetables to absorb uncertainty with the introduction of slack time, this way making timetables more reliable.

Cevallos and Zhao (2006) developed a Genetic Algorithm (GA) approach for re-Timetabling. They applied it to a bus system in Broward County Transit, Florida. It uses Automated Fare Collection (AFC) and Global Positioning System (GPS) data. This study accounts for randomness of vehicles' running-time. This study is motivated to reduce overall transfer time in the bus network, with an objective function formulated with a binary variable representing routes' connectivity for each transfer-connection (i.e., not minimizing transfer waiting-time directly). For this reason, this formulation lies within the group of synchronizing pairs of routes.

Z. Liu et al. (2007) formulated Timed Transfers as a particular case of the non-capacity Knapsack Problem using a new synchronization coefficient. The algorithm was implemented using a Nesting Taboo Search heuristic applied to a triangular network setting.

Hassane et al. (2018) proposes the simultaneous optimization of two objectives: maximizing the number of simultaneous run arrivals at focal-points and minimizing deviations of scheduled times due to uncertainty. In addition to the constraints already considered in previous works (e.g., Ceder and Tal (1999)), this study considers the uncertain running-time of each route segment. The problem is solved applying a multi-agent metaheuristic.

Simulation of Timed Transfers

Works addressing Timed Transfers with simulation are mainly directed to the study of operational control (i.e., real-time) strategies to cope with uncertainty impacts, namely delays leading to the loss of planned transfers.

The simulation of scenarios under which Timed Transfers would provide improved service levels was addressed in Abkowitz et al. (1987) for the case of a uni-focal network with two

intersecting routes, and in Chung and Shalaby (2007) for the case of a lineup network. In both studies, the scenarios included unsynchronized transfers, transfers synchronized with Timed Transfers and operated without any real-time control, and transfers synchronized with Timed Transfers and operated with different real-time holding policies to cope with delays.

M. M. Dessouky et al. (1999) simulated a uni-focal network to study a real-time control methodology. The methodology included the tracking of vehicles and dynamically manage delays occurring in the routes under study. The goal was to improve Timed Transfers opportunities, therefore minimizing transfer waiting-time.

Kieu et al. (2017) conducted a simulation approach to study different strategies of Timed Transfers both through timetable planning and operational control. They proposed a multi-agent simulation model incorporating interactions among vehicles, passengers, and the (urban) environment, validated with Automated Vehicle Location (AVL) and AFC data. The timetable planning analysis allowed the estimation of missed transfers probability as well as mean transfer waiting-time. The operation control analysis returned the sensitivity analysis for different real-time holding policies.

5.2.2 Transfer Optimization

An important group of Synchronization Timetabling techniques refers to Transfer Optimization. There are different ways to formulate these problems, depending on whether the system is analyzed from a macro or micro perspective, and depending on the specific aspects in each system intended for improvement.

Transfer Optimization is less costly to implement than Timed Transfers. Instead of converging trips at focal-points, Transfer Optimization determines the departure-time of each run in order to minimize some objective quantifying overall transfer inconvenience. Usually, the objective functions of Transfer Optimization minimize transfer waiting-time. This approach does not require the addition of slack time, can be applied to large networks and does not increase operating costs or inconvenience for in-vehicle passengers (Bookbinder & Desilets, 1992).

Keudel (1988) investigates an interactive tool to minimize transfer waiting-time and the number of situations whose waiting-time exceeds a given time limit. The tool is analyzed in different scenarios by changing fleet size, running-time, and transfer conditions.

Klemt and Stemme (1988) considered a simplified network of three routes intersecting at three transfer-nodes. They propose a Transfer Optimization model based on the Quadratic Assignment Problem (QAP) of Graph Theory for layout-planning (i.e., to find n locations for n machines minimizing the cost of moving materials between machines). The

model minimizes transfer waiting-time for all passengers. The decision variables define the departure-time of each route's run. Constraints require exactly one departure-time for each route (the QAP requires one location for each machine). Several studies followed the Synchronization Timetabling problem formulation by Klemt and Stemme (1988), including Bookbinder and Desilets (1992), Daduna and Voss (1995), Desilets and Rousseau (1992), Domschke (1989), Voss (1992).

Domschke (1989) applied the model of Klemt and Stemme (1988) using heuristics and regret-methods, including Simulated Annealing, Tabu Search and Branch and Bound.

Desilets and Rousseau (1992) developed synchronization software with three possible objective functions. One possibility is to optimize *average reliability* of a transfer-connection, i.e., the transfer waiting-time variability from one day to another due to uncertainty in running-times. In addition to Timetabling, the software allows the identification of extremely unpredictable connections.

Voss (1992) applied heuristic procedures to the problem formulated by Klemt and Stemme (1988) and proposed a variation in which routes overlap each other in some path segments. Voss (1992) also proposes an objective function minimizing the maximal transfer waiting-time, which is intended to avoid extreme transfers' waiting-time. However, such an objective function can result in timetables with a significant number of passengers penalized with long waiting in order to reduce one passenger's waiting by a small amount. Because of this issue, the authors suggest combining both objectives with a weighting factor that dictates the relative importance of each of the components.

Bookbinder and Desilets (1992) developed a combined approach with simulation and optimization. The simulation can account for uncertainty in running-times, whose outputs are further incorporated into the optimization of transfer waiting-time. The variability of running-time is incorporated using time-windows for the arrival of vehicles (instead of a single value intrinsic to deterministic running-times). The model can be applied with several objective functions depending on the goals of the planners, including the possibility to study holding policies at the synchronization nodes through the definition of a waiting function.

Aiming to reduce the computational complexity, Daduna and Voss (1995) applied a regret heuristic together with Simulated Annealing and Tabu Search. Daduna and Voss (1995) considered routes' headway, running-times between transfer-nodes, and transfer walking-time all as known and fixed.

Jansen et al. (2002) minimize overall cost-weighted transfer waiting-time, adopting an objective function similar to Daduna and Voss (1995). The Synchronization Timetabling problem formulation by Jansen et al. (2002) is however distinct from that of Daduna and Voss (1995) in decision variables and constraints. Daduna and Voss (1995) considered the

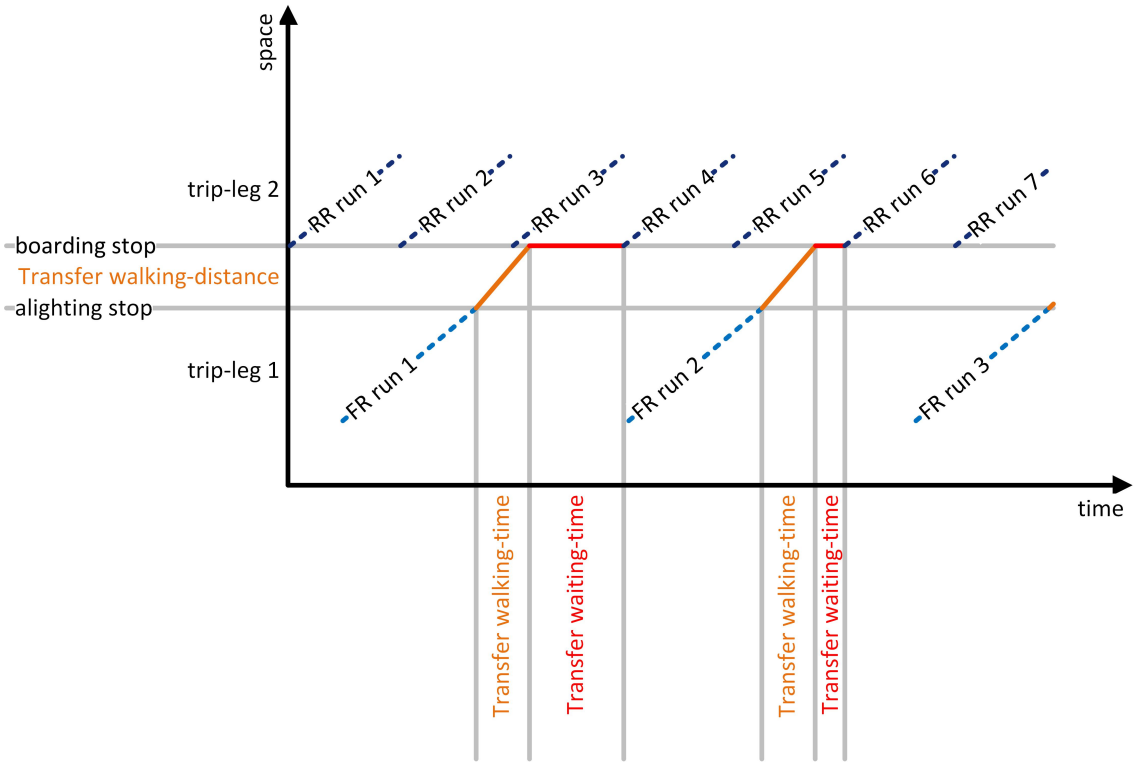


Figure 5.1: Visualization of the assumption that passengers board the first available route run. Related concepts are described in Section 2.3.3.

departure-time of each vehicle as a decision variable (i.e., $x_{ih} = 1$ if the departure-time h is assigned to route i, and zero otherwise). Jansen et al. (2002) considered that passengers always board the next available route run, with an infinite capacity of vehicles, and the decision variable is the existence of a feasible transfer-connection linking two runs between a Feeding-Route and a Receiving-Route. Jansen's model adjusts the departure-times of all vehicles using constraints, such as the departure-time of the first route run.

The principle of passengers' boarding the first available run is illustrated in Figure 5.1. The important idea to retain is that a transferring passenger, once ready at the boarding-stop, will board the first available run of the desired route. The Jansen et al. (2002) model has both waiting-time and number of passengers dependent on the running-time of routes. This rationale conflicts with the assumption *The transfer-flows are not dependent on running-times, path choices of passengers are known and fixed* adopted in earlier works (Bookbinder & Desilets, 1992; Daduna & Voss, 1995; Desilets & Rousseau, 1992; Domschke, 1989; Klemt & Stemme, 1988; Voss, 1992). Therefore, the work of Jansen et al. (2002) brings this new concept of dynamically allocating transfer-flow to timetables under construction during the optimization process.

It is important to note that the concept of *a feasible transfer-connection linking two runs* (Transfer Optimization) is different from the concept of *a time-window allowing passengers to transfer in both directions* (Timed Transfers). The first means that passengers alighting from a specific run of a Feeding-Route are able to board a specific run of a Receiving-

Route. The second considers that passengers from both route runs have enough time to walk and board on the other route.

Fleurent et al., 2004 simultaneously optimize different factors including transfer waiting-time and the relative importance of transfers.

Schroder and Solchenbach, 2006 developed a re-Synchronization Timetabling model to induce small changes in existing timetables by allowing shifts in departure-times. Aiming at improving synchronization, they pursued an approach suitable for coordination among different operators and different modes - in a context where the different operators have already developed their schedules and would not be able to make major changes to them.

Wong et al., 2008 designed a MIP model, using uneven headway, to minimize transfer wait-time on full-trip. Their application to the Hong Kong rail system produced significant improvements over the current timetable. They also added a variation of the model that added random variables to the departure-times of vehicles, representing uncertainty of operations (delays). For future analysis of uncertainty they propose the use of simulation to adjusting running-times, dwell-times, departure-times, and headway for all vehicles (decision variables), with realistic constraints Wong et al., 2008.

Shafahi and Khani, 2010 developed two mathematical models to minimize transfer waiting-time. They propose MIP methods for small and medium sized networks, and GA for large networks. They considered the number of passengers making each transfer-connection as a weighting factor for its relative importance. Overall, the timetables obtained led to a significant reduction in the overall transfer waiting-time. It considers extending dwell-time to improve transfer (decision variable), whose activation implies relaxing the even headway assumption and changes in the cycle-time.

Objective functions used in the literature applying Optimizing Transfers include: i) Minimize transfer waiting-time for all passengers Bookbinder and Desilets, 1992; Cevallos and Zhao, 2006; Chakroborty et al., 1995; Daduna and Voss, 1995; Desilets and Rousseau, 1992; Jansen et al., 2002; Klemt and Stemme, 1988; Voss, 1992; Wong et al., 2008; ii) Minimize the standard deviation in arrival-time of Feeding-Vehicle and Receiving-Vehicle Desilets and Rousseau, 1992; iii) Minimize the number of passengers transferring in extremely unpredictable connections Desilets and Rousseau, 1992; iv) (bi-objective) Minimize wait-time on full-trip for all passengers and Minimize the number of waiting-times exceeding a given time limit Keudel, 1988; v) (bi-objective) Minimize transfer waiting-time for all passengers and Minimize the maximal transfer waiting-time Voss, 1992; vi) Minimize wait-time on full-trip for all passengers Chakroborty et al., 1995; vii) Minimize transfer waiting-time or Minimize wait-time on full-trip Daduna and Voss, 1995; viii) Minimize transfer waiting-time and the relative importance of transfers Fleurent et al., 2004;

Assumptions adopted in the literature applying Optimizing Transfers include: i) Passengers choose the first available departing route run to the desired destination Bruno et al., 2009; Jansen et al., 2002; Shafahi and Khani, 2010; Wong et al., 2008; ii) Passengers prefer not to transfer whenever a direct option is available (choice of fewer transfers path) Wong et al., 2008; iii) Passenger flows are evenly distributed within a short time period (15 min intervals) Wong et al., 2008; iv) Only consider transfer-flows (i.e., flows of on-board passengers are not accounted) Jansen et al., 2002; v) Passenger itineraries are known and fixed, using number of transfers and number of stops of the trip as criteria Wong et al., 2008; vi) Passenger itineraries are known and fixed Daduna and Voss, 1995; vii) Known and fixed transfer walking-time Daduna and Voss, 1995; Jansen et al., 2002; Shafahi and Khani, 2010; Wong et al., 2008; viii) The network is an input Bookbinder and Desilets, 1992; Daduna and Voss, 1995; Jansen et al., 2002; Shafahi and Khani, 2010; ix) Headway is considered even and fixed for each UDP Bookbinder and Desilets, 1992; Daduna and Voss, 1995; Jansen et al., 2002; Shafahi and Khani, 2010; x) Headway is considered uneven for each UDP Wong et al., 2008; xi) Known running-times of vehicles for all network segments Daduna and Voss, 1995; Jansen et al., 2002; Shafahi and Khani, 2010; xii) Known dwell-times of vehicles in each stop Daduna and Voss, 1995; Jansen et al., 2002; Shafahi and Khani, 2010; xiii) Known demand and transfer-flows in each transfer-connection Daduna and Voss, 1995; Shafahi and Khani, 2010; xiv) Infinite vehicle capacity Daduna and Voss, 1995; Wong et al., 2008.

Optimizing transfers at a single node

Chakroborty et al. (1995) applied a GA to optimize transfers at one transfer-node served by three routes. The algorithm minimizes wait-time on full-trip for all passengers in the system. This model considered several constraints, including infinite capacity of vehicles, fixed fleet size, thresholds for minimum and maximum dwell-time, threshold for maximal transfer waiting-time (to prevent extreme waiting-times), and uneven headway limited by a maximum value. The formulation is generalizable for more transfer-nodes.

Bruno et al. (2009) studied the case of one transfer station, using a bi-objective function to minimize transfer waiting-time for passengers and operational costs for operators. The transfer station has a set of arriving routes with deterministic arrival-time and demand. The model returns the departure-time of each route run, considering fleet size, vehicles' capacity and operational cost.

5.3 Synchronization Model

This section presents a Synchronization model which defines timetables for a network under analysis defined by their departure-times in all runs. The model can produce either even or uneven headway timetables for a specified Uniform Demand Period (UDP). Even headway timetables are obtained when the headway is fixed for all runs on each directed-route. Uneven headway timetables are obtained when the headway between consecutive runs on each directed-route is determined by the model.

Accordingly, the model requires as input information the minimum and maximum headway values for each directed-route. When the values for these thresholds is the same, the model returns even headway timetables. When these thresholds are set with different values, the model searches over a wider range of solutions and can produce uneven headway timetables. Note that the headway values required in each directed-route is an output from the Frequency Setting problem.

The input network is defined at the level of transfer-nodes. Accordingly, the input network mesh is composed of transfer-nodes served by the directed-routes supporting transfer-connections suitable for synchronization and the corresponding termini. The stops used at each directed-route in each transfer-node may be shared or not, depending on the infrastructure configuration of each transfer-node.

The main aspect differentiating the synchronization model proposed in this work from the literature is its formulation at the run-piece level instead of the route level. This provides the model with the ability to consider and optimize cases where two directed-routes intersect at more than one transfer-node. Therefore, this model can be applied to any synchronization network setting.

The mathematical formulation of the synchronization model is presented in Equations (5.1), (5.2a), (5.2b) and (5.3a)–(5.3k).

The objective function (Equation (5.1)) maximizes the number of run-pieces synchronized in the system through the sum of the values assumed by the binary decision variable Y_{ij}. The decision variable Y_{ij} is defined in Equation (5.2b) and returns value one when the corresponding pair of run-pieces i and j is synchronized, and zero otherwise.

The decision variable P_i^d is defined in Equation (5.2a) and returns the departure-time of each run-piece i considering the following elements: i) the minimum and maximum headway of the corresponding directed-route, and ii) the start and ending times of the UDP under study (E). Both headway and UDP thresholds are taken as inputs, and defined prior to the application of the model.

Objective Function:

$$\text{maximize: } \sum_{i \in I} \sum_{j \in I} Y_{ij} \tag{5.1}$$

Decision Variables, $\forall i, j \in I$**:**

$$P_i^d \tag{5.2a}$$

$$Y_{ij} = \begin{cases} 1, \text{ if run-piece } i \text{ synchronizes with run-piece } j \\ 0, \text{ otherwise} \end{cases} \tag{5.2b}$$

Constraints, $\forall i, j \in I$:

if $S_i^p = 0$:

$$P_i^d = P_{i-1}^d + T_{i-1}^r + T_i^e \tag{5.3a}$$

if $S_i^p = 1$:

$$P_i^d \leq H_{R_i} \tag{5.3b}$$

if $S_i^p \in 1, .., (J_{R_i} - 1)$:

$$P_{i+A_{R_i}}^d - P_i^d \leq H_{R_i} \tag{5.3c}$$

$$P_{i+A_{R_i}}^d - P_i^d \geq h_{R_i} \tag{5.3d}$$

if $S_i^p = J_{R_i}$:

$$P_i^d \leq E \tag{5.3e}$$

$$P_i^d \geq E - H_{R_i} \tag{5.3f}$$

if $n_i^a \neq n_j^d \vee C_i = C_j$:

$$Y_{ij} = 0 \tag{5.3g}$$

if $n_i^a = n_j^d \wedge C_i \neq C_j$:

$$P_j^d - (P_i^d + T_i^r) \geq w_{n_j^d} - M(1 - Y_{ij}) \tag{5.3h}$$

$$P_j^d - (P_i^d + T_i^r) \leq W_{n_j^d} + M(1 - Y_{ij}) \tag{5.3i}$$

Domain:

$$P_i^d, T_i^r, T_i^e, H_{R_i}, h_{R_i}, E \geq 0 \tag{5.3j}$$

$$Y_{ij} \in \{0, 1\} \tag{5.3k}$$

Where:

- Y_{ij} - boolean returning one when run-pieces i and j are synchronized, and zero otherwise (decision variable)
- P_i^d - the departure-time of run-piece i (decision variable)
- I - set of run-pieces of the entire system
- S_i^p - the position of a run-piece i in its run (0: the run-piece does not start a run, 1: the run-piece starts the first run of its directed-route, 2: the run-piece starts the second run of its directed-route, etc.)
- T_i^r - the running-time of run-piece i (in minutes)
- T_n^e - the dwell-time at transfer-node n (in minutes)
- H_r - maximum headway between consecutive runs in directed-route r
- h_r - minimum headway between consecutive runs in directed-route r
- R_i - the directed-route of run-piece i
- A_r - the number of run-pieces that the directed-route r has
- J_r - the number of runs of the directed-route r has
- E - planning period (in minutes)
- n_i^d - the transfer-node of departure of run-piece i
- n_i^a - the transfer-node of arrival of run-piece i
- C_i - the route of run-piece i
- w_n - transfer walking-time at transfer-node n
- W_n - maximum transfer waiting-time at transfer-node n (i.e., threshold to activate Y_{ij})
- M - Big number

Equation (5.3a) calculates the departure-time of all run-pieces which do not start a run (i.e., when $S_i^p = 0$) as the departure-time of the previous run-piece of that run plus the running-time of previous run-piece plus the dwell-time of the current run-piece.

The constraint shown in Equation (5.3b) applies only to run-pieces starting the first run of each directed-route. It forces the first run-piece of each directed-route to depart after the beginning of the planning period E, and within the maximum headway allowed for that directed-route.

The constraints in Equation (5.3c) and Equation (5.3d) apply to all run-pieces starting runs, except for the last run of each directed-route. They satisfy the constraints on minimum and maximum headways.

Equation (5.3e) and Equation (5.3f) force the last run of each directed-route to depart before the end of period E and after $E - H_{R_i}$.

A pair of run-pieces i and j is synchronized when the following requirements are met:

- i and j have *transfer-node compatibility*: the destination of run-piece i is at the same transfer-node as the origin of run-piece j (i.e., that $n_i^a = n_j^d$);
- i and j have *route compatibility*: run-pieces i and j belong to different routes, assuming passengers will not transfer within the same route regardless of direction (i.e., that $C_i \neq C_j$);
- i and j have *time compatibility*: the difference between arrival-time of run-piece i and departure-time of run-piece j is within $[w_{n_d^j}; W_{n_d^j}]$.

Both requirements *transfer-node compatibility* and *route compatibility* are ensured in the conditional statements *if* $n_i^a \neq n_j^d \vee C_i = C_j$ and *if* $n_i^a = n_j^d \wedge C_i \neq C_j$, associated with the activation of the Y_{ij}, as shown in Equations (5.3g)–(5.3i).

The *time compatibility* requirement is defined in Equations (5.3h) and (5.3i). Accordingly, Y_{ij} is activated if, in addition to meeting the two previous requirements, the transfer waiting-time between run-pieces i and j is within $[w_{n_d^j}; W_{n_d^j}]$. Note that w_n and W_n are set for each transfer-node.

5.4 Data

The application presented in this section uses the synchronization network 2 defined in Figure 4.11. However, it was not possible to obtain frequency data for these routes in 2013 for this study, nor the expected running-times and dwell-times. Therefore, in this section the synchronization network 2 is considered from an academic perspective, using artificial data with the goal of testing the synchronization model.

Figure 5.2 shows the simplified synchronization network 2, where termini are represented with filled circles and transfer-nodes are represented with unfilled circles. This network includes a total of 10 directed-routes, 5 transfer-nodes, and 15 termini. The application to this network will allow estimating the departure-time of each run-piece from each terminus and from each transfer-node.

As shown in Figure 5.2, the network has 19 segments linking termini and transfer-nodes. Note that routes R51 and R50 are represented by the same segments but treated separately, and similarly for routes R1481 and R1482. Therefore, there are a total of 27 segments considered, each of which will have four runs, totaling 108 run-pieces.

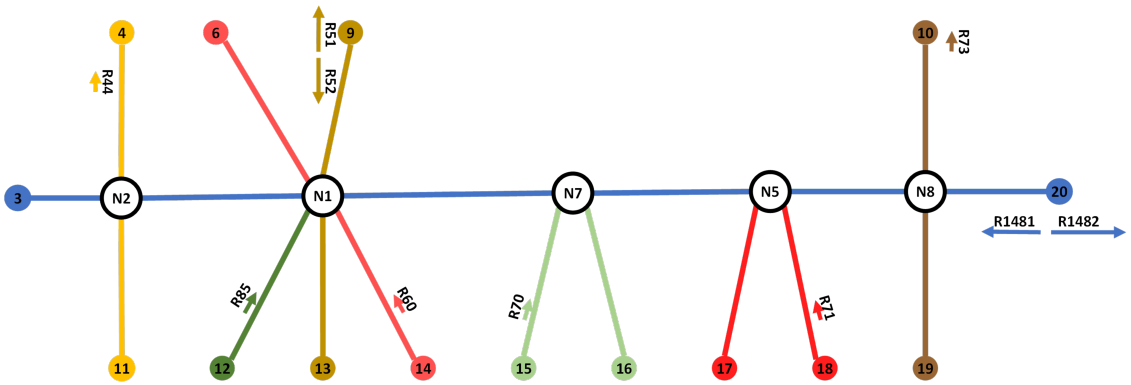


Figure 5.2: Simplified schematic of the synchronization network 2. Termini are represented with filled circles and transfer-nodes are represented with unfilled circles.

The running-time of run-pieces was defined to vary between 4 and 11 minutes. Dwell-time was set as one minute at all transfer-nodes. Headway was allowed to vary between 10 and 14 minutes (corresponding to h_r and H_r) between consecutive runs on each directed-route. The maximum transfer waiting-time to classify two run-pieces as synchronized was 3 minutes.

5.5 Results

This section presents the results obtained from the implementation of the synchronization model defined in Section 5.3. The synchronization model was implemented using the IBM ILOG CPLEX Optimization Studio (Version 12.10.0.0), in a Intel(R) Core(TM) i7 processor.

The model was tested with a range of the different parameters. In cases where the headway was set as fixed (by attributing equal values to the headway upper and lower limits in each directed route - h_r and H_r), the processing time to convergence to an optimal solution was always less than one minute.

However, a significant increase in the computational time was observed when the model could choose the best headway from a range of values (due to the increase in the solution space). For the problem presented in this section, where the headway was allowed to vary (and therefore resulting an uneven headway timetable), the time required for the model to converge to the optimal solution was 5349 seconds (i.e., 89 minutes).

The threshold corresponding to the maximum transfer waiting-time at each transfer-node to determine if run-pieces are synchronized (i.e., the value of W_n in Equation (5.3i)) was set to three minutes for all transfer-nodes.

Figures 5.3–5.7 show, for each node (TN1 - TN8), the time each vehicle is stopped for passenger boarding and alighting (i.e., dwell-time) with black rectangles. The route on

which each vehicle operates is shown on the y-axis. The time horizon is shown on the x-axis.

Figures 5.3–5.7 highlight the synchronization opportunities at each transfer-node. Since each figure shows vehicles stopped at the same transfer-node, the *transfer-node compatibility* requirement is satisfied for all possible transfers. Furthermore, since for each vehicle, the route is identified on the y-axis, and the arrival and departure time on the x-axis, the cases where *route compatibility* and *time compatibility* are satisfied can easily be visualized.

In these figures, the maximum transfer waiting-time is represented with blue arrows, showing a time-window of possible synchronized transfers regarding other vehicles intersecting the same transfer-node. Moreover, these figures include lightly shadow areas showing when run-pieces are synchronized.

There were a total of 108 run-pieces, corresponding to four runs on each directed-route. From the $11,664$ run-piece pairs in the system (i.e., 108^2), the number of synchronized run-piece pairs was 672.

The planning period was set as 60 minutes, which means that the last run of each directed-route must start within 60 minutes. All runs are complete, meaning that once a run is started, all corresponding run-pieces are finished.

Accordingly, in Figures 5.3–5.7, the run-pieces with a departure-time after minute 60 relate to runs starting prior to minute 60. For example in Figure 5.3 there are two run-pieces starting after minute 60, belonging to directed-routes 1481 and 1482.

Finally, Figure 5.8 shows an overview of the timetables obtained with the model. It provides the visualization of the departure-times of the 108 run-pieces obtained. The y-axis includes the run-piece identification number, and the x-axis the corresponding departure-time.

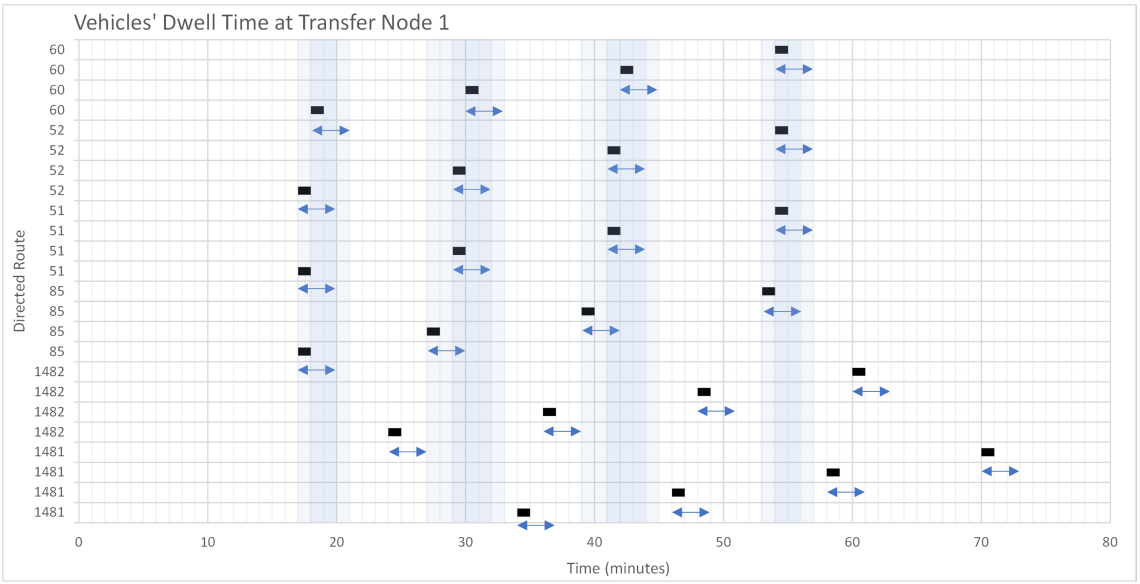


Figure 5.3: Visualization of dwell-time of vehicles at transfer-node TN1.

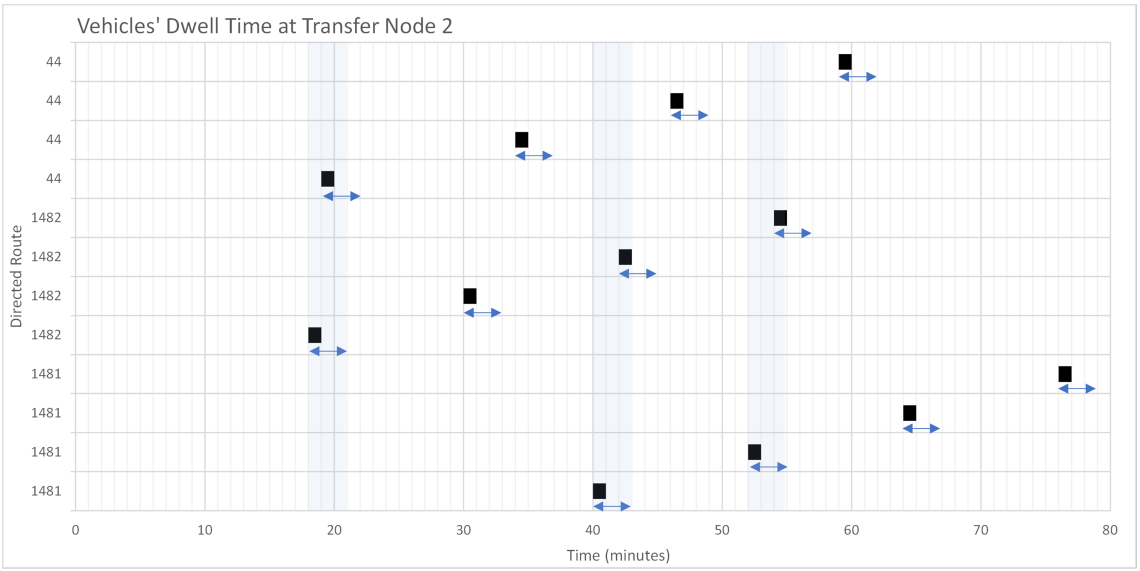


Figure 5.4: Visualization of dwell-time of vehicles at transfer-node TN2.

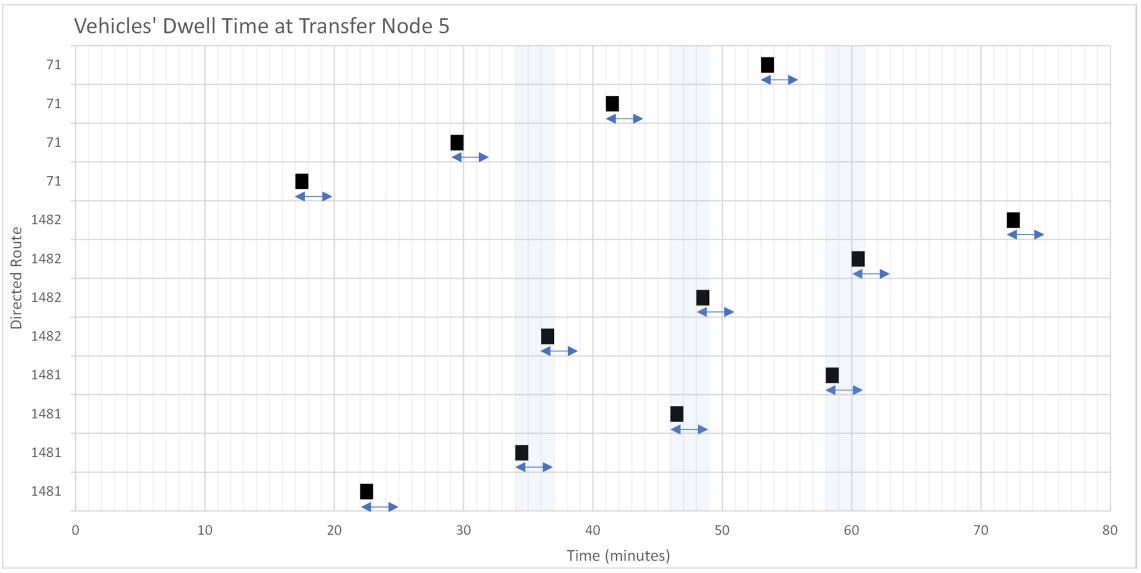


Figure 5.5: Visualization of dwell-time of vehicles at transfer-node TN5.

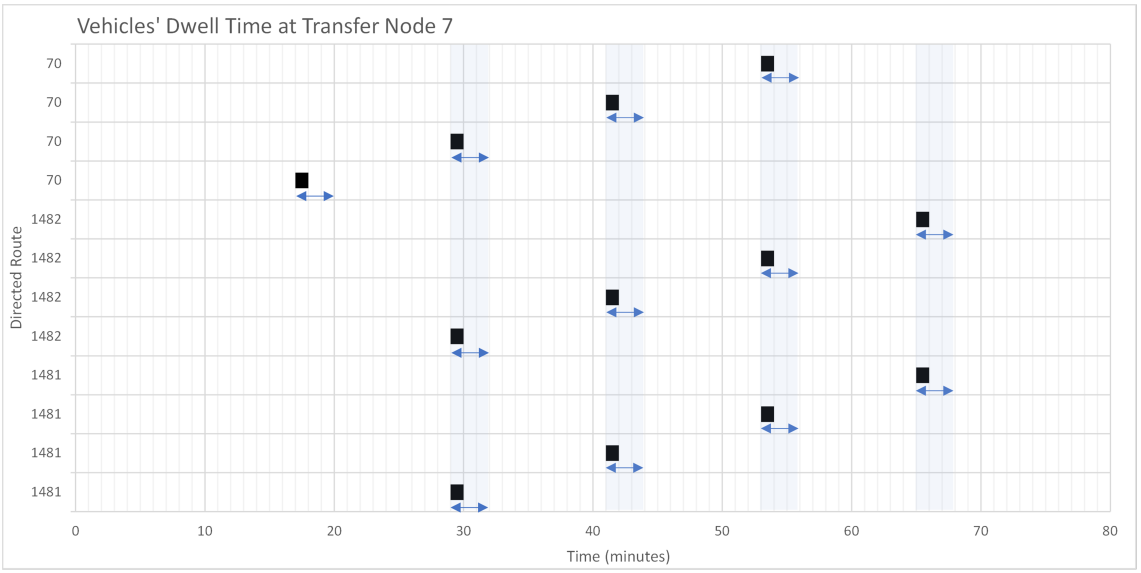


Figure 5.6: Visualization of dwell-time of vehicles at transfer-node TN7.

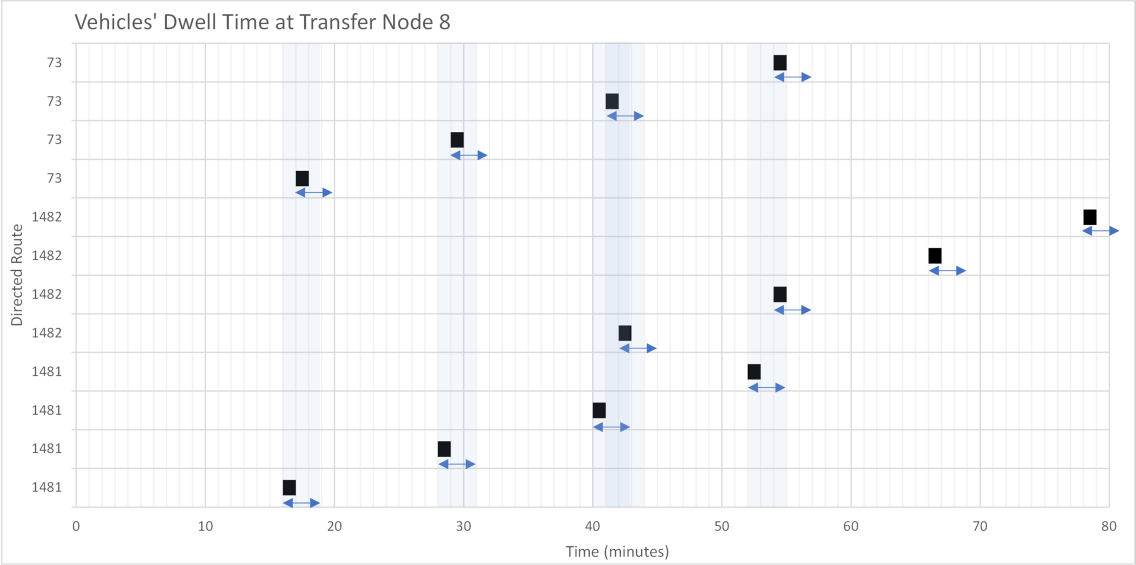


Figure 5.7: Visualization of dwell-time of vehicles at transfer-node TN8.

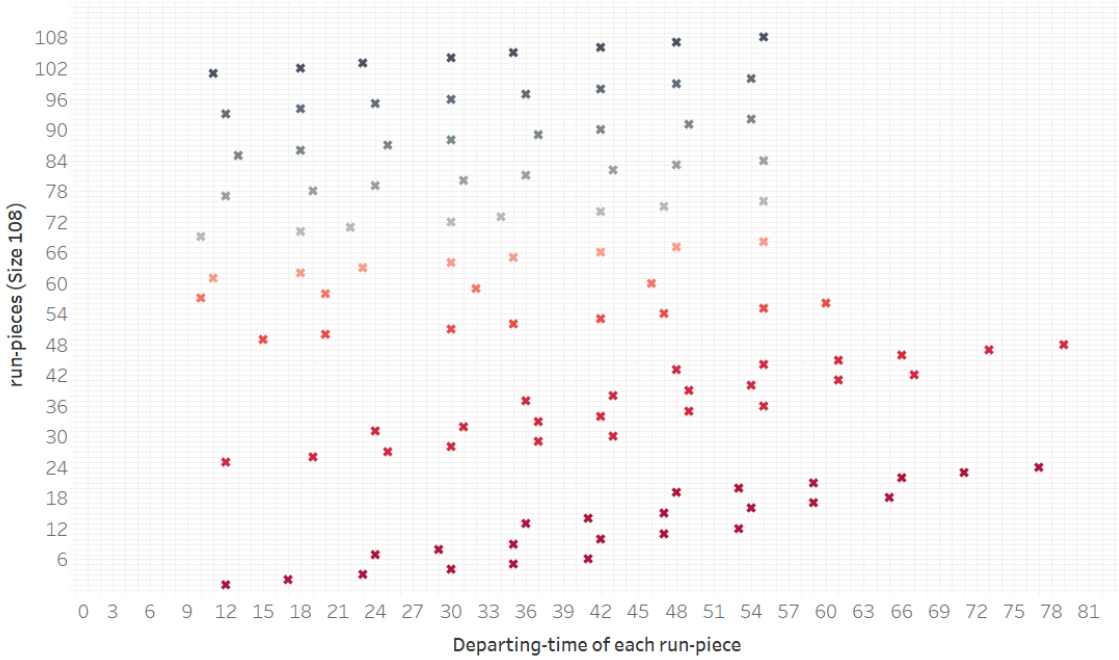


Figure 5.8: Visualization of departure-times of all run-pieces in the network.

5.6 Final remarks

This chapter proposes a synchronization model to minimize transfer waiting-time of passengers in a Public Transport system. The model maximizes the number of transfer opportunities by considering a binary decision variable that identifies when two run-pieces are synchronized or not. The model gives equal weight to the synchronization of all pairs of run-pieces. Therefore, all transfer-connections in the network were given the same importance. It would be interesting to explore in the future the incorporation in the model of different weights able to favor the synchronization of more important transfer-connections.

The model can be implemented with a fixed headway for each directed-route, in which case the timetable obtained follows the same principles as a Timed Transfers approach (the timetable becomes periodic over the planning period considered, and is defined by the time of the first run of each directed route and the corresponding headway).

The model can also be implemented allowing the headway between consecutive runs of each directed-route to be uneven, through the definition of thresholds for the corresponding minimum and maximum values. The implementation of the model using uneven headway returns timetables following a Transfer Optimization approach.

Additionally, the model considers a time-window between the arrival and departure of vehicles at each transfer-node which is used to classify each transfer opportunity being synchronized or not. If the time-window is set to be zero, the vehicles are considered as synchronized only when they arrive at the same transfer-node at the same moment. Adopting a time-window period increases the model solution space, and returns timetables maximizing the number of transfer opportunities whose arrival of a Feeding-Vehicle and the departure of a Receiving-Route is within the defined time-window.

The time-window is defined for each transfer-node, which means that the model allows defining specific time-windows for each transfer-node (defined by the value of transfer walking-time and maximum transfer waiting-time at each transfer-node). Future work could include time-windows specific of the transfer-connection, mostly regarding the transfer walking-time component which is not always the same for all transfer-connections at each transfer-node. Future work could also include adding a vehicle capacity constraint.

A frequent Timetabling assumption is to consider running-time as deterministic and fixed. This assumption is also included in the work described in this chapter. However real running-times are frequently subject to unforeseen delays. This is a variable for which uncertainty could be accounted in at the planning stage. This is another aspect that could be the subject of future research, not only in the estimation of uncertainty, but also in the proposal of strategies that can reduce it.

The model was applied using artificial data. The application considered a synchronization

network obtained in the previous chapter. The formulation allowed uneven headways with a time-window of 3 minutes to consider transfer opportunities as synchronized. The results are promising and demonstrate the applicability of the model. Future work should include applying the model to a case study considering real data on the various operational elements of the system.

6 Robustness in Public Transport Timetables

This chapter proposes an optimization model to improve the robustness of Public Transport timetables. Robustness represents the ability of timetables to absorb deviations from the plan and prevent their propagation during operations. The model developed proposes an optimal assignment of arrival times and distribution of slack time among Time Control Point (TCP)s of a Public Transport route to minimize delays and earliness from the plan. The model was applied to the case of a bus route operating in Porto. This required the use of data collected through Global Positioning System (GPS) devices installed in vehicles, informing its location during their daily operation. The robustness of timetables was evaluated through the quantification of delays and earliness of bus shifts from the plan. The performance measures used to assess robustness are: Average Delay (AD), Relative Average Delay (ADr), Proportion of Delays (PD), Relative Proportion of Delays (PDr), Average Earliness (AE), Relative Average Earliness (AEr), Proportion of Earliness (PE), and Relative Proportion of Earliness (PEr). The results showed that the timetables obtained with the model were able to minimize delays and earliness in all shifts when compared with the original timetable.

6.1 Introduction

Daily Public Transport operations are highly exposed to uncertainty arriving from unforeseen events, such as traffic congestion, accidents, weather conditions, mechanical failures, roadblocks, road works, strikes, or unexpected demand peaks (Amberg et al., 2011; Farahani et al., 2013; Naumann et al., 2011; van Oudheusden & Zhu, 1995). Uncertainty in Public Transport operations may lead to the occurrence and propagation of deviations from the plan (either delays or earliness) and even disruptions of the service, which negatively impact the transportation service quality and often trigger expensive recovery actions (Amberg et al., 2011; Naumann et al., 2011; Veelenturf et al., 2012).

Delays can be classified into two categories: primary delays and secondary delays. A

primary delay cannot be prevented and may induce the late arrival of a run-piece that departed on time (Naumann et al., 2011). A secondary delay occurs when an already delayed run-piece leads to a delayed start of the next run-piece. The transmission of delays is called delay propagation (Amberg et al., 2011; Naumann et al., 2011).

Earliness can occur for several reasons, such as reduced demand or reduced traffic. The driver cannot compensate for earliness in all cases. It is often impossible for the Public Transport vehicle to stop or travel at lower speeds than planned. For vehicles running on rails, such as the metro, the travel speed directly interferes with other vehicles' operation on the same (or connected) trails. For vehicles running on streets, such as buses, many stops do not have space to accommodate parking even for a short time, at the risk of generating undesired traffic not only on that street but in the road network in general. Moreover, slowing down the running speed may lead to unwanted congestion on the road network.

The negative impacts resulting from deviations from the plan are felt mostly by passengers and operators. Negative impacts felt by passengers include: a) dissatisfaction from loss in the service quality; b) increased waiting-time; c) transfers become more difficult, due to the possibility of missing connections and the consequent increase in transfer waiting-time; d) for some passengers, waiting-time unpredictability is worse than the waiting-time magnitude, causing frustration and preventing travel planning; e) unique aspects associated with the circumstances of each passenger.

Negative impacts felt by operators include: a) need for additional costs from corrective actions; b) deterioration of the Public Transport service and operating efficiency; c) increased deviations from the plan through propagation: if a vehicle runs behind schedule, it will typically pick up more passengers and be even further delayed at following stops; if a vehicle runs earlier than planned, it will have fewer than expected passengers at the following stops, leading to increased earliness; d) deviations from the plan occurring on one route will impact the Public Transport system, both along the same route and over other routes.

Public Transport operators seek strategies to mitigate these impacts (Xuan et al., 2011). During Public Transport planning, the development of strategies for improving timetables' robustness is a valuable approach to this problem. Public Transport timetables are typically built with little slack time, envisaging the minimization of cost (Amberg et al., 2011). Timetables with improved robustness better absorb deviations from the plann and their propagation. Therefore, implementing robust timetables improves the quality of the transportation service delivered to passengers, leading to more reliable service.

Improving the robustness of timetables is achieved through the optimization of slack times at each TCP so as to allow absorbing delays during operations. This process can be understood as a re-Timetabling task, as it changes the magnitude of slack time to allocate

in previously defined timetables.

In Public Transport planning, the improvement of timetable robustness can mitigate the impacts mentioned above. Moreover, when timetables are unable to absorb deviations from the plan, Public Transport operators may apply corrective actions during operations, such as dynamic re-planning techniques (M. Dessouky et al., 2003; Ehrgott & Ryan, 2002; Fu et al., 2003; Huisman et al., 2004; Kramkowski et al., 2009).

This chapter aims to contribute to the mitigation of negative impacts arising from uncertainty in Public Transport through optimization techniques at the planning stage. It explores the quantification and improvement of Public Transport timetables' robustness.

Robustness refers to the ability of timetables to absorb deviations from the plan throughout daily operations, both delays and earliness, and preventing their propagation. Section 6.2 provides a literature review on the topic of Public Transport robustness.

Two research questions are pursued: i) how to assess the robustness of Public Transport timetables?, and ii) how to improve the robustness of Public Transport timetables at the planning stage?

The first research question was explored by defining eight measures to quantify the robustness of Public Transport timetables: AD, ADr, PD, PDr, AE, AEr, PE, and PEr, as discussed in Section 6.3.

The second research question was explored through the development of an optimization model seeking the minimization of deviations from the plan, both delays and earliness, detailed in Section 6.4. The decision variables are the set of slack times to be allocated between each pair of adjacent TCPs. The model includes constraints on the total slack time of the optimized timetable to be no greater than the timetable in use by the operator, implying the two timetables have comparable operational costs.

Deviations are the difference between planned and observed times for each run. The management of slack times can provide timetables with buffers able to absorb primary delays' propagation, therefore mitigating secondary delays (Carey, 1999; Kramkowski et al., 2009).

The model was applied to a real-world case study concerning a bus route operating in Porto, described in Section 6.5. The route studied operates with five coordinated shifts and with uneven headway. The data-set used in this case study was obtained through GPS devices installed in all buses. The model was implemented using the CPLEX solver. Real-world data was used to define the range of uncertainty.

The timetables obtained by the optimization model were evaluated using the robustness measures mentioned above and compared with the timetable in use by the operator, as

shown in 6.6. This allowed evaluating the relative performance of the timetables proposed by the optimization model developed in this work. Main conclusions are summarized in 6.7.

6.2 Literature Review on Public Transport Robustness

The literature is not consistent on the definition of robustness in Public Transport systems (Amberg et al., 2011; Roy, 2010; Salido et al., 2008). There is a panoply of approaches designed to address specific cases, leading to a diversity of robustness definitions and measures. While studies with bus applications are still scarce, the literature devoted to railway systems is more advanced (Amberg et al., 2011; Kramkowski et al., 2009; Naumann et al., 2011; Y. Yan et al., 2012).

Y. Yan et al. (2012) quantifies the robustness of a timetable as the average deviation (in time units) between observations and the timetable under assessment. Accordingly, timetables are more robust when they return smaller deviations from the plan. Moreover, Y. Yan et al., 2012 proposes an optimization model returning the distribution of slack times that minimizes time deviations, including delays, earliness, and overall variability from the schedule.

Price of Robustness (PoR) was proposed in Liebchen et al. (2007) to measure robustness through the trade-off between an optimal and a robust solution. This trade-off is quantified through the ratio between the cost of a robust solution and its non-robust counterpart. The cost of each solution is calculated by the objective function adopted in each problem. Values of PoR<1 indicate that the new solution is more robust than the current schedule and PoR>1 indicates that the new solution is less robust than the current one. Values of PoR$=1$ indicate that the two solutions are identical in terms of robustness.

Salido et al. (2008) proposes a Robustness Index for railway schedules. For a system of several stops and vehicles, four components are considered at each stopping point of each vehicle: (1) the slack time, (2) the flow of passengers, (3) the distance between stops, and (4) the number of vehicles that may be disrupted by an unforeseen event occurring in each vehicle. The index is the ratio between the number of delays absorbed by the schedule and the total number of locations assessed (i.e., number of vehicles multiplied by the number of stops). A delay is 'absorbed' when it complies with a criterion.

Amberg et al. (2011) propose the measure Delay-tolerance to quantify the propagation of delays through the schedule. This measure is calculated in two steps: first it quantifies the time (in seconds) that each planned trip starts behind schedule. Next, it calculates the expected secondary delays through the schedule. Therefore, this measure quantifies the impact of delay propagation occurring from a specific unforeseen event, considering delay

propagation through the schedule until it is absorbed by slack times or until the working day ends.

The Total Slack Time is the sum of all slack time included within a robust solution, and is proposed as a robustness measure in the study of Salido et al. (2008). This measure considers a solution to be more robust when it encompasses a higher amount of slack time. This measure can be a good indicator on the robustness of a schedule, but it can also lead the user to misleading conclusions, since the amount of slack allocated within a schedule is only beneficial when it is effectively divided over the several points.

The robustness of a Public Transport timetable can be defined as its ability to absorb secondary delays, considering penalties every time a primary delay causes the late start of the next run-piece (i.e., when the slack time can not compensate for a delay). Naumann et al., 2011 applied this concept through simulation of disruption scenarios designed with stochastic programming and pursuing the minimization of total costs (i.e., planned costs plus the costs caused by disruptions). The study concluded that robust Timetabling significantly reduces the total expected costs (plan and disruption costs) when compared with the minimization of planned costs or with the simple addition of fixed slack time between run-pieces. This approach can be infeasible in large-scale problems.

In railways, robustness has been described as the *ability to resist to imprecision* (Tormos et al., 2008, p. 1), and a railway timetable is considered *robust* if it is able to absorb disruptions or to reduce their repercussion effects (Tormos et al., 2008, p. 1). Slack time is normally used to improve the robustness of timetables, allowing them to compensate for small disruptions or to reduce the impacts of large disruptions. Endowing a timetable with robustness implies an additional cost concerning the planned operation. The study by Cacchiani and Toth (2012) compared the timetables in their nominal and robust approaches (for trains). The nominal approach is focused on *efficiency* (i.e., to minimize the schedule costs or to minimize the total passenger travel time), whilst the robust approach minimizes delay propagation. Robust and nominal models pursue contrary goals, i.e. efficiency vs avoiding delays; therefore, the solutions obtained with each approach are distinct.

Kramkowski et al. (2009) considers that improving the robustness in vehicle schedules will only benefit the absorption of secondary delays. Accordingly, an improved schedule will not prevent primary delays, as they will continue to occur unexpectedly and will be propagated until slack time absorb them or the working day ends. Kramkowski et al. (2009) quantifies robustness as the expected length of secondary delays (i.e., the average length of delays). This measure is calculated as zero when runs start on time, and the authors do not consider the case of earliness.

Another definition proposed by Kramkowski et al., 2009 considers that Public Transport timetables are robust when they are able to reduce the propagation of the effects

of unforeseen events. Kramkowski et al., 2009 pursued this concept with a measure for delay-tolerance in bus timetables (including planned costs and costs of delays), to obtain timetables with optimized distribution of slack times, improving the absorption of disruptions and preventing delay propagation. Similarly, Amberg et al., 2011 applied this concept to the Vehicle Scheduling-Driver Scheduling integrated stages, building a Public Transport timetable with increased delay-tolerance by redistributing its slack time and minimizing its costs.

An associated concept is the *recoverable robustness*, when Public Transport timetables are recoverable to a limited extent in all likely scenarios, proposed by Liebchen et al., 2009.

The literature on slack time optimization is often related to the literature on Holding Time Models (HTM). This is because the slack times determined at the planning stage will be the safety bubble during operations. Slack times are defined at TCPs, the same spots at which HTM can be applied. HTM make decisions in real-time for vehicles that are early (either deciding to hold or dispatch a vehicle), but they are more limited for vehicles that are late. It is more difficult to compensate for delays in real-time.

Finally, it is important to clarify the differences between alternative robust optimization techniques, all of which can be used to address problems whose information is uncertain to some extent. This is the case with bus daily operations that are often unable to comply with the planned schedule. Strictly Robust Optimization returns the best feasible solution for any realization of uncertainty within a convex set (Ben-Tal & Nemirovski, 2002; Soyster, 1973). The formulation of strictly robust concepts for Public Transport timetables is discussed in Goerigk et al. (2011). A Strictly Robust Optimization model is deterministic, set-based and solved through traditional optimization concepts and algorithms (Bertsimas et al., 2011). Moreover, uncertainty does not follow a specific probabilistic distribution, from where Strictly Robust Optimization diverges from Stochastic Optimization (Bertsimas et al., 2011). However, strictly robust solutions are often considered too conservative, as they imply a great loss of optimality in order to guarantee robustness (Goerigk et al., 2011). As an alternative to Strictly Robust Optimization, Fischetti and Monaci (2009) proposed the approach of Light Robustness Optimization, whose solutions comply with an established quality level whilst maximizing robustness (Goerigk et al., 2011). Models of Light Robustness are solved with heuristic methods, which require the initial specification of parameters such as *robustness goal* and *maximum objective function deterioration* (Fischetti & Monaci, 2009).

Many studies addressing robustness in Public Transport systems provide their own definitions and measures of robustness. Consequently, the scientific community lacks on an agreed definition of robustness, as well as appropriate indicators to assess it.

Other concepts that are close to robustness in Public Transport systems include: From the perspective of passengers: i) reliability, a transportation service is reliable when passengers

can count on it, when passengers can trust that trips are going to be performed as planned and on time. From the perspective of operators: i) flexibility, the ability to readjust upon the occurrence of disturbances, usually with dynamic re-scheduling (during operations);

6.3 Defining and Measuring Robustness

In this work, robustness is defined as the ability of Public Transport timetables to absorb deviations from the plan (both delays and earliness) and to prevent their propagation through the daily operations. This section proposes the performance measures to assess the robustness of Public Transport timetables. It comprises a set of eight indicators detailed in Equations (6.1)–(6.8).

Four indicators quantify delays: AD, ADr, PD, and PDr. Another four indicators quantify earliness: AE, AEr, PE, and PEr. Moreover, the indicators ADr, AEr, PDr and PEr give relative performance measures comparing two timetables, where the subscript r highlights their relative nature.

Average Delay (AD)

$$AD = \frac{1}{M \cdot K} \sum_{m=1}^{M} \sum_{k=1}^{K} |SD_{mk}|, \quad \text{if} \quad SD_{mk} < 0 \tag{6.1}$$

Where:

- $M \in \mathbb{Z}$: number of TCPs;
- $K \in \mathbb{Z}$: number of days in the sample (i.e., observations);
- SD_{mk}: is the Schedule Deviation at TCP_m on day k (in time units).

Average Earliness (AE)

$$AE = \frac{1}{M \cdot K} \sum_{m=1}^{M} \sum_{k=1}^{K} |SD_{mk}|, \quad \text{if} \quad SD_{mk} > 0 \tag{6.2}$$

Where:

- $M \in \mathbb{Z}$: number of TCPs covered by the route;
- $K \in \mathbb{Z}$: number of days in the sample (i.e., observations);
- SD_{mk}: is the Schedule Deviation at TCP_m on day k (in time units).

The indicator AD in Equation (6.1) is the average delay time per TCP. The indicator AE in Equation (6.2) is the average earliness time per TCP. These indicators are calculated considering the sequence of TCPs covered by the route over the course of a day. The

average is calculated from a set of real observations, each observation being for one day.

Proportion of Delays (PD)

$$PD = 100 \cdot \frac{\sum_{m=1}^{M}\sum_{k=1}^{K} D_{mk}}{M \cdot K} \quad , \quad \begin{cases} D_{mk} = 1 & \text{if} \quad SD_{mk} < -\epsilon, \quad \epsilon \geq 0 \\ D_{mk} = 0 & \text{if} \quad SD_{mk} \geq -\epsilon, \quad \epsilon \geq 0 \end{cases} \tag{6.3}$$

Where:

- $M \in \mathbb{Z}$: number of TCPs;
- $K \in \mathbb{Z}$: number of days in the sample (i.e., observations);
- D_{mk}: is a binary variable identifying a delay at TCP_m on day k, considering the threshold ϵ;
- SD_{mk}: is the Schedule Deviation at TCP_m on day k (in time units).
- ϵ: tolerance threshold defining the amount of time from which a delay or earliness should be accounted (e.g., $\epsilon = 1$ min), $\epsilon \geq 0$;

Proportion of Earliness (PE)

$$PE = 100 \cdot \frac{\sum_{m=1}^{M}\sum_{k=1}^{K} A_{mk}}{M \cdot K} \quad , \quad \begin{cases} A_{mk} = 1 & \text{if} \quad SD_{mk} > \epsilon, \quad \epsilon \geq 0 \\ A_{mk} = 0 & \text{if} \quad SD_{mk} \leq \epsilon, \quad \epsilon \geq 0 \end{cases} \tag{6.4}$$

Where:

- $M \in \mathbb{Z}$: number of TCPs;
- $K \in \mathbb{Z}$: number of days in the sample (i.e., observations);
- A_{mk}: is a binary variable identifying earliness at TCP_m on day k, considering the threshold ϵ;
- SD_{mk}: is the Schedule Deviation at TCP_m on day k (in time units).
- ϵ: tolerance threshold defining the amount of time from which a delay or earliness should be accounted (e.g., $\epsilon = 1$ min), $\epsilon \geq 0$;

The indicators PD and PE represent the proportion of delays and the proportion of earliness per TCP, respectively. The measure PD is the proportion of delays observed in the TCP of the bus line during the period studied, which is computed in 6.3. The transportation service is considered delayed when a vehicle arrives at a TCP later than planned exceeding a tolerance threshold (ϵ) specified by the analyst or decision maker. This measure represents the probability that a passenger arriving on time at a TCP will have to wait longer than the time threshold specified.

Relative Average Delay (ADr)

$$AD_r = 100 \cdot \frac{AD_R}{AD_N} \tag{6.5}$$

Where:

• R: refers to a timetable whose robustness will be compared to another timetable taken as a reference;

• N: refers to the timetable taken as a reference for the comparison of robustness.

Relative Average Earliness (AEr)

$$AE_r = 100 \cdot \frac{AE_R}{AE_N} \tag{6.6}$$

Where:

• R: refers to a timetable whose robustness will be compared to another timetable taken as a reference;

• N: refers to the timetable taken as a reference for the comparison of robustness.

Relative Proportion of Delays (PDr)

$$PD_r = 100 \cdot \frac{PD_R}{PD_N} \tag{6.7}$$

Where:

• R: refers to a timetable whose robustness will be compared to another timetable taken as a reference;

• N: refers to the timetable taken as a reference for the comparison of robustness.

Relative Proportion of Earliness (PEr)

$$PE_r = 100 \cdot \frac{PE_R}{PE_N} \tag{6.8}$$

Where:

• R: refers to a timetable whose robustness will be compared to another timetable taken as a reference;

• N: refers to the timetable taken as a reference for the comparison of robustness.

Similarly, the measure PE represents the proportion of early arrivals at the TCP of the bus line. According to 6.4, a vehicle's run is considered as early when its arrival at the TCP occurs before planned in the timetable, by a deviation greater than the tolerance threshold ϵ.

Relative measures ADr, AEr, PDr and PEr are appropriate to compare the robustness of two timetables. In this study, the indicators associated with the timetable obtained using the optimization model (identified with an R, representing a Robust timetable) are compared with the timetable currently in use by the Public Transport operator (identified with an N, representing the Nominal timetable). When these measures have values lower than one, it means that the new timetable performs better than the reference timetable.

6.4 Optimization Model to Improve the Robustness of Public Transport Timetables

This section presents an optimization model aiming to improve the robustness of an existing Public Transport timetable. This model is an adapted formulation of the model proposed in Yan and Chen, 2002. The model can be applied to a Public Transport route serving multiple stops, some of which are monitored by the Public Transport operator, called TCPs.

The optimization model considers the entire set of sequential TCPs to be covered during a daily shift. The timetable is optimized by minimizing its deviation from a set of real observations ($k = 1, \cdots, K$). The decision variables of the optimization model shown in 6.9 are the values of slack time (stored in vector $\boldsymbol{\tau}$) to be allocated between two adjacent TCPs in the timetable under construction.

This model can be converted by standard techniques into an equivalent Mixed Integer Linear Programming (MILP) model (Garfinkel & Nemhauser, 1972). The objective function quantifies, for all TCPs, the deviations of a set of real observations from a given timetable under assessment. The objective function penalizes early arrivals at each TCP with weight γ_1 and late arrivals with weight γ_2.

This model has several features that differentiate it from the approach proposed by Yan and Chen, 2002. It involves the optimization of non-cyclic vehicle schedules adopting a daily perspective. The component of the objective function associated with the minimization of the absolute value of deviations, included in Yan and Chen, 2002, was removed from our formulation as the quantification of deviation variability was considered to have a high degree of redundancy with the other two components of the objective function. This term would also greatly increase the computational complexity of the optimization model (changing from quadratic complexity to cubic complexity).

Minimize:

$$F(\boldsymbol{\tau}, \gamma_1, \gamma_2) = \frac{1}{K} \sum_{m=1}^{M} \sum_{k=1}^{K} \gamma_1 \cdot \max(0, SD_{mk}) + \gamma_2 \cdot \max(-SD_{mk}, 0) \tag{6.9a}$$

Subject to:

$$SD_{1k} = 0 \quad , \forall k \tag{6.9b}$$

$$SD_{m+1,k} = E(T_{m,m+1}) + \tau_{m,m+1} - T_{(m,m+1),k} + (1 - \beta_{m,m+1}) \cdot SD_{mk} \tag{6.9c}$$

$$E(T_{m,m+1}) + \tau_{m,m+1} \geq N_{m,m+1} \tag{6.9d}$$

$$\sum_{m=1}^{M} (E(T_{m,m+1}) + \tau_{m,m+1}) = \Psi \tag{6.9e}$$

Where:

• $M \in \mathbb{Z}$: number of TCPs;

• $K \in \mathbb{Z}$: number of days in the sample (i.e., observations);

• $\gamma_1 \in \mathbb{R}$: weight for early arrivals, $\gamma_1 \in [0, 1]$;

• $\gamma_2 \in \mathbb{R}$: weight for late arrivals, $\gamma_2 \in [0, 1]$;

• $\Psi \in \mathbb{R}$: total time of daily trip (in time units);

• $\boldsymbol{\tau} = [\tau_{m,m+1}] \in \mathbb{R}^{M-1}$: vector storing the slack time to allocate in each run-piece of consecutive TCPs (decision variables, in time units);

• $\boldsymbol{\beta} = [\beta_{m,m+1}] \in \mathbb{R}^{M-1}$: vector storing the Adjustment Factor of Driver for each run-piece (input data, in percentage);

• $\mathbf{E}(\mathbf{T}) = [E(T_{m,m+1})] \in \mathbb{R}^{M-1}$: vector storing the expected running-time for each run-piece (in time units);

• $\mathbf{N} = [N_{m,m+1}] \in \mathbb{R}^{M-1}$: vector storing the minimum running-time a vehicle needs to perform each run-piece (input data, in time units);

• $\mathbf{T} = [T_{(m,m+1),k}] \in \mathbb{R}^{(M-1)\text{x}K}$: array storing the running-time in each run-piece $[m, m+1]$ at each real observation k (input data, in time units);

• $\mathbf{SD} = [SD_{mk}] \in \mathbb{R}^{M\text{x}K}$: array containing in each position the Schedule Deviation at TCP_m under observation k (in time units); $SD_{mk} < 0$ indicates a delay, $SD_{mk} > 0$ indicates earliness and $SD_{mk} = 0$ indicates perfect compliance with the plan.

The total time of the daily trips (Ψ) is not allowed to change, in order to ensure that the original timetable and the new one returned by the optimization model have similar operational costs. Furthermore, a minimum running-time was imposed between adjacent TCPs, to ensure the feasibility of the proposed timetable.

Constraint 6.9b means that the system starts on time at the first TCP, for all observations ($SD_{1,k} = 0$). Constraint 6.9c defines each value of Schedule Deviation (SD_m, k) as the cumulative deviation from schedule for observation k at TCP_m (considering all preceding TCPs). This constraint quantifies delays and earliness in each TCP for each observation with respect to the planned schedule and accounts for deviation recovery through the behavior of drivers. When deviations from schedule occur, the model considers that drivers will adapt the average velocity (always complying with regulation) to attempt to recover from the delay. This is included in the model through vector $\boldsymbol{\beta}$, which stores a recovery percentage for each run-piece composing the daily path. A value of $\beta_{m,m+1} = 0$ means the driver cannot recover from deviations between TCP_m and TCP_{m+1}, and a value of $\beta_{m,m+1} = 1$ means the driver would recover completely from the deviation during that run-piece. $SD_{m,k}$ is defined as the difference between the expected time ($E(T)_{m,m+1} + \tau_{m,m+1}$) and the real time ($T_{(m,m+1),k}$), plus the accumulated SD from the previous moment ($SD_{m,k}$) multiplied by the percentage of recovery from drivers ($1 - \beta_{m,m+1}$). Values of $SD_{m,k} < 0$ indicate the vehicle is behind schedule, $SD_{m,k} > 0$ indicate that the vehicle is ahead of schedule, and $SD_{m,k} = 0$ indicate that the vehicle is on time.

Values composing the vector $\boldsymbol{E(T)}$ correspond to the current schedule. The values comprising array $\boldsymbol{T}$ concern the real observations, which include the arrival-time retrieved at each TCP in each day. The vector $\boldsymbol{\tau}$ stores the slack time assigned to each TCP which optimizes the problem (decision variables).

Constraint 6.9d ensures that the arrival-time at each TCP is always greater than, or equal to, the arrival-time of its preceding TCP plus the minimum running-time ($N_{m,m+1}$). Note that the value of $N_{m,m+1}$ is strictly positive. The slack time assigned to a specified TCP can assume a positive or negative value, provided that its joint duration with the corresponding expected time $E(T)_{m,m+1} + \tau_{m,m+1}$ complies with the minimum time necessary to travel between the two adjacent TCPs ($N_{m,m+1}$).

Constraint 6.9e allows the user to define the total schedule time through the definition of parameter Ψ. In our empirical study this parameter was set to be equal to the total running-time of the daily trips in the original timetable.

6.5 Application to Porto

The model was applied to the real world case of bus route 206 operating in Porto. Figure 6.2 shows the map with the path of route 206, including the location of the six TCPs used by the bus company: TCP1 *Campanha*, TCP2 *Campo 24 de Agosto*, TCP3 *Marques*, TCP4 *Carvalhido*, TCP5 *Viso* and TCP6 *Br. Sto. Eugenio*. The total distance between TCP1 and TCP6 (one-way) is 11.1km, and it includes a total of 37 bus stops.

On work days, the operation of bus route 206 is organized into five shifts, designed to satisfy the demand of passengers as shown in Figure 6.1, following an uneven headway approach. Figure 6.1 also shows that the run-piece between TCP5 and TCP6 is served less frequently than the other run-pieces: in every four runs on route 206, only one serves TCP6.

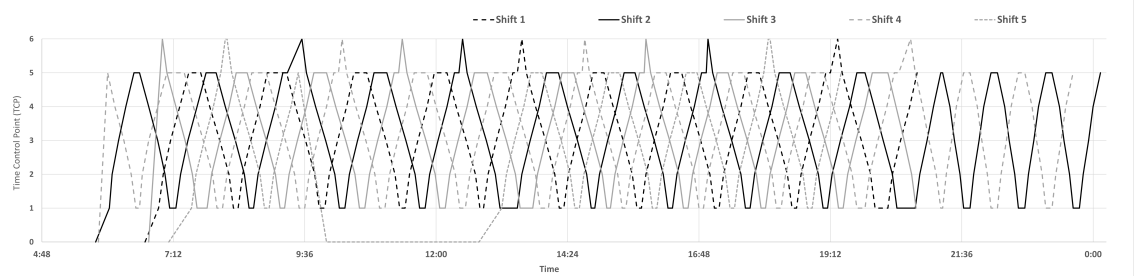


Figure 6.1: Current schedule for route 206 including the five shifts on work days.



Figure 6.2: Map of route 206 with six TCPs.

Table 6.1 summarizes each shift, including the start, end and length of daily trips, along with the corresponding daily slack time, total number of TCPs composing the daily path of each shift (i.e., M). Table 6.1 also includes the number of positions under assessment for each daily shift, calculated as the number of days in the sample (K) multiplied by the number of TCPs (M).

Table 6.1: Information on schedules currently operating in all shifts.

Shift	Daily Start	Daily End	Total daily length (ϕ)	Daily slack time	M	$K \cdot M$
1	TCP1 (06h56)	TCP5 (20h47)	13h51=831 min	166 min.	99	1287
2	TCP1 (06h02)	TCP5 (00h08)	18h06=1086 min	211 min.	141	1833
3	TCP6 (07h00)	TCP1 (20h46)	13h46=826 min	161 min.	100	1300
4	TCP5 (06h00)	TCP5 (23h38)	17h38=1058 min	207 min.	137	1781
5	TCP1 (07h32)	TCP5 (19h24)	11h52=712 min	232 min.	67	871

The data used in this case study was collected by the Optimização e Planeamento de Transportes, S.A. (OPT) company using a script, with data from the GPS devices installed on all buses operating in Porto. For each vehicle, the script automatically recorded the following information every 5 minutes: the vehicle identification code, the time of the record, and the estimated arrival time to the next TCP. The script recorded three weeks of operation of route 206, resulting in a set of 13 working day observations (excluding holidays, Saturdays and Sundays).

Figure 6.3 shows the daily observations (each gray line corresponding to one working day) alongside the current schedule (black line) for each of the five shifts under study. In general, the shifts are able to follow the plan reasonably well during the first half of the day. The trips observed between 14h00 and 21h00 are systematically late. The last trip of shift 1 is an exception, as it always ends earlier than scheduled. Shift 3 has the most irregular pattern, including severe deviations from schedule throughout the day. Buses of all shifts typically incur into small deviations to the plan in TCP5, and often arrive delayed to TCP6.

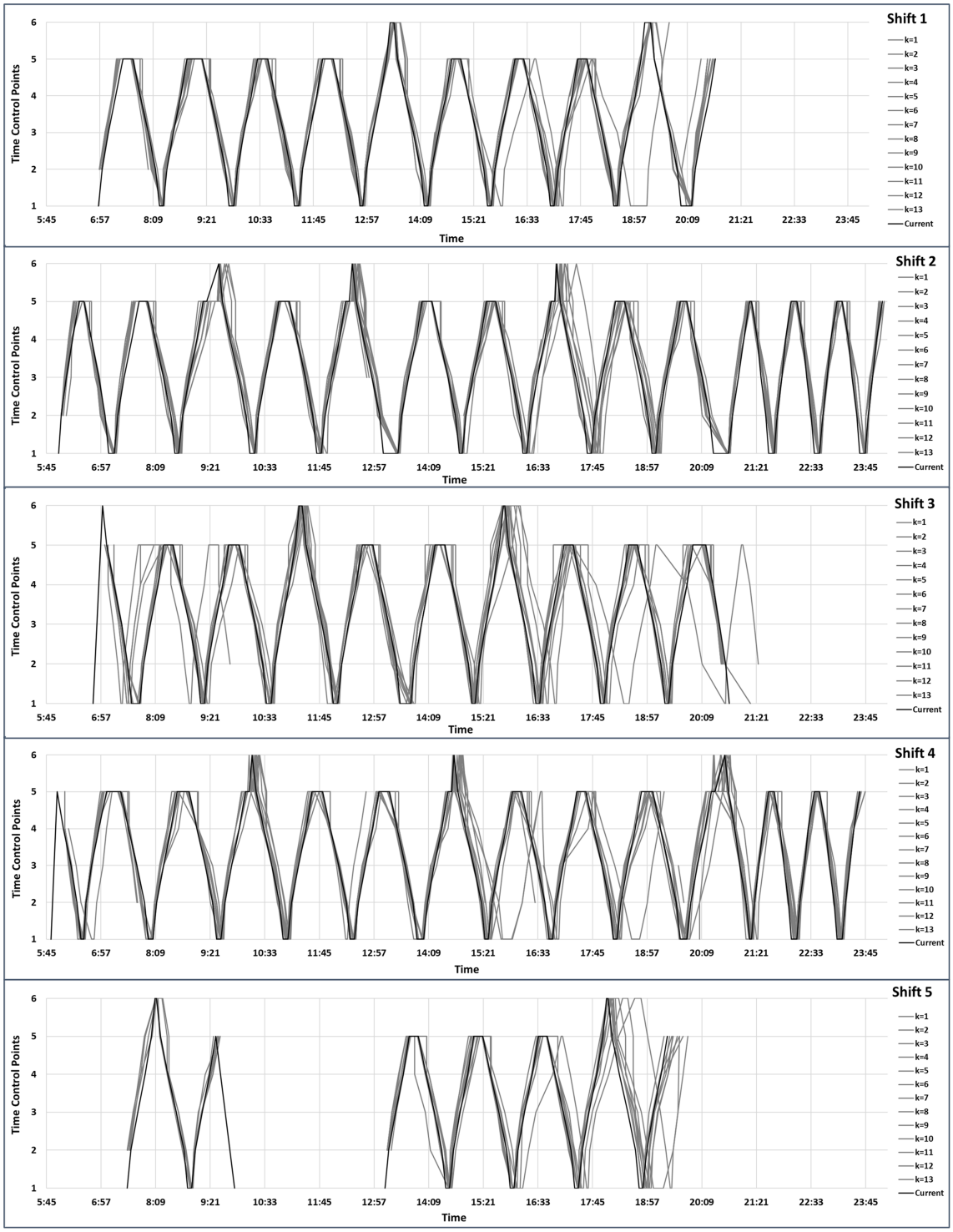


Figure 6.3: Current schedule and the set of real observations of route 206 for shifts 1, 2, 3, 4, and 5.

6.6 Results and Discussion

This section presents the results obtained with the optimization model implemented using IBM ILOG CPLEX Optimization Studio, version 12.6, for the case analyzed.

The optimization model has the freedom to reallocate slack time, preserving the total running-time of each shift in the current timetable, defined by Ψ (i.e., the total running-time of each shift). This constraint allows a fair comparison between the current timetable and the timetables obtained by the optimization model, as both have the same total duration of daily trips, implying similar operational costs. All trips used a β value of zero, meaning that efforts of drivers to minimize deviations from schedule are not included. Thus, it is assumed that drivers have similar behavior on all trips between given TCPs.

The model optimizes the robustness of each shift separately. Different viewpoints regarding the relative importance of delays and earliness can be adopted changing the values of parameters γ_1 and γ_2. This study considered three scenarios: a neutral perspective with equal weighting of $\gamma_1 = \gamma_2 = 1$ was labeled as $R[1;1]$; the full minimization of delays with $\gamma_1 = 0$ and $\gamma_2 = 1$ was labeled as $R[0;1]$; and the exclusive minimization of earliness with $\gamma_1 = 1$ and $\gamma_2 = 0$ was labeled as $R[1;0]$.

Figure 6.4 provides a visualization of the current timetable (black line) and the timetables obtained with the optimization model for scenarios $R[1;1]$ (blue line), $R[0;1]$ (gray line), and $R[1;0]$ (blue dashed line) for each of the five shifts on route 206.

Whilst in the current timetable the slack time is incorporated exclusively in path inversion TCPs (i.e., TCP_1, TCP_5 or TCP_6), the timetables returned by the optimization model provide the optimal re-distribution of the slack time considering all TCPs over the daily path.

The measures defined in Section 6.3 were used to assess the robustness of the different timetables obtained with the optimization model. Table 6.2 summarizes the results obtained (AD, AE, ADr, and AEr) for each scenario (i.e., $R[1;1]$, $R[1;0]$, and $R[0;1]$) and for each shift, plus the average values over all shifts.

In shift 1, the value of AD indicates that the current timetable operates with an average delay of 1.32 minutes per TCP, while the timetables obtained with the optimization model for the three scenarios would result in an average delay of about 0.90 minutes per TCP, representing a reduction in the average delay time of about 0.43 minutes per TCP.

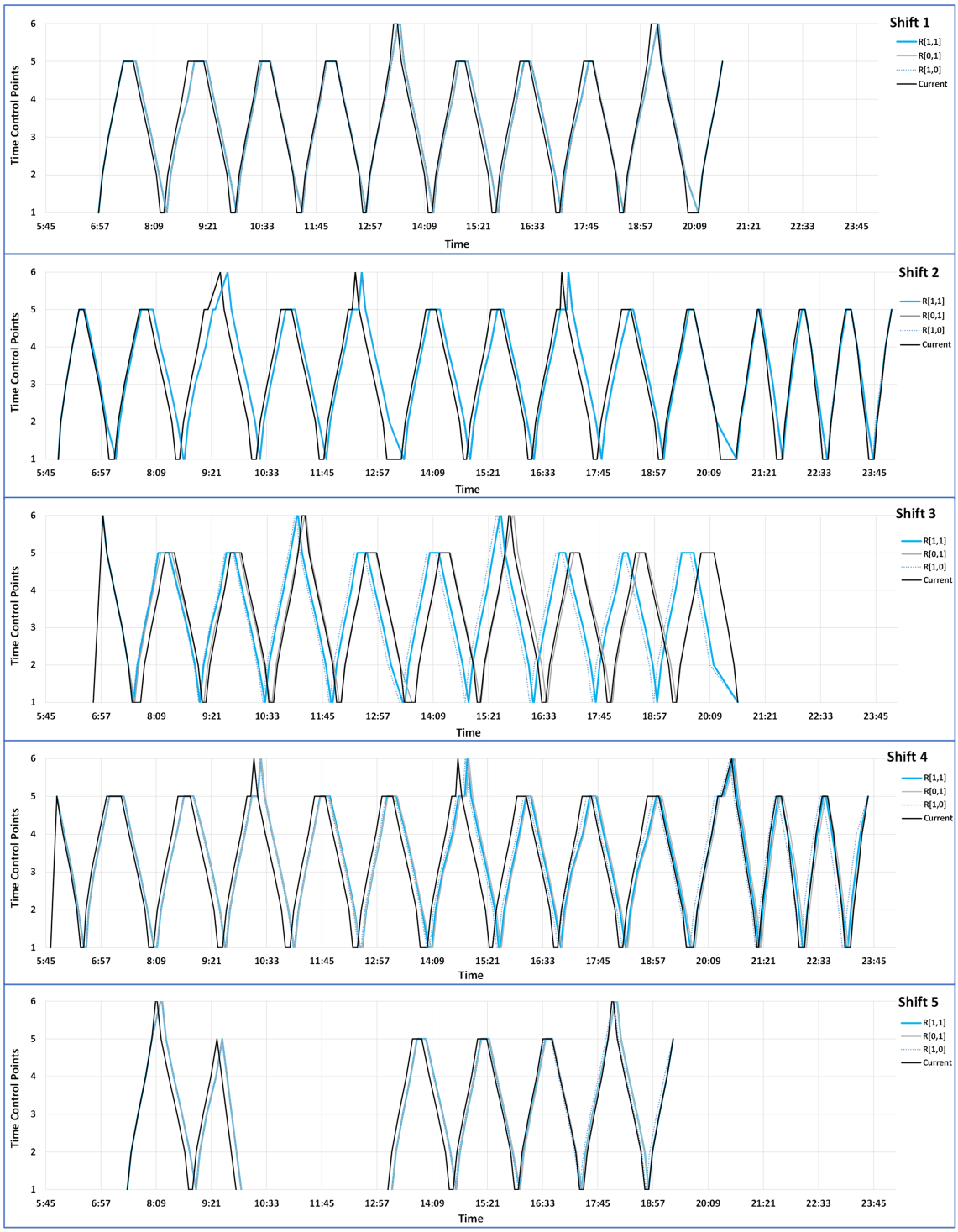


Figure 6.4: Visualization of the current timetable and the timetables obtained in scenarios $R[1;1]$, $R[0;1]$, and $R[1;0]$ for route 206.

Table 6.2: Comparing AD, AE, ADr, and AEr of the current timetable and timetables obtained in scenarios $R[1;1]$, $R[0;1]$, and $R[1;0]$, for all shifts on route 206.

Scenario	AD(min.)	AE(min.)	ADr	AEr
Shift 1				
N	1.32	1.67	–	–
$R[1;1]$	0.90	1.25	0.68	0.75
$R[0;1]$	0.90	1.25	0.68	0.75
$R[1;0]$	0.90	1.25	0.68	0.75
Shift 2				
N	1.08	1.26	–	–
$R[1;1]$	0.74	0.96	0.69	0.76
$R[0;1]$	0.74	0.97	0.68	0.77
$R[1;0]$	0.75	0.96	0.70	0.76
Shift 3				
N	1.53	1.68	–	–
$R[1;1]$	1.52	1.14	0.99	0.68
$R[0;1]$	1.21	1.36	0.79	0.81
$R[1;0]$	1.57	1.10	1.03	0.66
Shift 4				
N	1.07	1.17	–	–
$R[1;1]$	0.84	1.00	0.78	0.85
$R[0;1]$	0.82	1.01	0.77	0.86
$R[1;0]$	0.87	0.96	0.81	0.82
Shift 5				
N	2.65	1.29	–	–
$R[1;1]$	1.10	1.14	0.42	0.89
$R[0;1]$	1.10	1.14	0.41	0.89
$R[1;0]$	1.14	1.13	0.43	0.88
Average of all shifts				
N	1.53	1.41	–	–
$R[1;1]$	1.02	1.10	0.71	0.79
$R[0;1]$	0.95	1.15	0.67	0.82
$R[1;0]$	1.05	1.08	0.73	0.77

For shift 1, the AE value indicates an average earliness of 1.67 minutes per TCP for the current timetable, while the timetables obtained in the three scenarios have lower values of about 1.25 minutes per TCP, representing a reduction on the average earliness time per TCP of about 0.42 minutes. The corresponding relative measures (ADr and AEr respectively) return values lower than one, indicating that the new timetable would be preferred to the current timetable regarding both the occurrence of delays and earliness.

The current timetable has different patterns regarding the occurrence of delays and earliness in the different shifts. In shift 5 the average length of delays is considerably longer than the length of earliness (AD of 2.65 and AE of 1.29), whilst the reverse is true for the other shifts. The greatest improvements in terms of delays occurred for shift 5, whereas for shift 3 the improvements are less significant. Regarding earliness, the improvement pattern is more homogeneous among the shifts, although shifts 1, 2 and 3 have slightly better results for the indicator AEr than shifts 4 and 5.

Considering the average of all shifts, we can observe that the average delay and earliness for the current timetable is around 1.5 minutes per TCP (i.e., AD of 1.53 and AE of 1.41). In the optimized timetables, the length of deviations from the plan could be reduced to values around one minute, which represents an overall improvement in relation to the current timetable, with an overall reduction between 67% and 73% of the length of delays of the current timetable and an overall reduction between 79% and 82% of the length of earliness of the current timetable, depending on the scenario considered.

The analysis of the three scenarios with different priorities for the reductions of delays or earliness (R[1;1], R[1;0], R[0;1]) revealed that the performance of the timetables obtained is not very sensitive to the specification of parameters γ_1 and γ_2.

Tables 6.3 and 6.4 summarize the results obtained regarding PD, PE, PDr, and PEr of the current timetable and timetables obtained with $\epsilon = 0, 1, 3, 6$ in scenarios $R[1;1]$, $R[0;1]$, and $R[1;0]$, for all shifts on route 206, plus the average values over all shifts. These results include different values for the tolerance threshold ϵ, varying between 0 and 6 minutes, allowing a broad depiction of the sensitivity of the performance measures to changes in the threshold used for the evaluation of deviations from the plan.

For a tolerance threshold of $\epsilon = 3$ minutes and considering the average of all shifts, we see that in the current timetable a bus is delayed in 16.69% of all cases, while in the timetables obtained with the optimization model, buses would be delayed between 9.64% and 10.85% of all cases, depending on the scenario. The analysis for the occurrence of earliness shows that in the current timetable a bus is early in 20.15% of all cases, while with the timetables obtained with the model this proportion is reduced to values between 12.49% and 13.64%, depending on the scenario. Values of indicators PDr and PEr are always lower than one, indicating an improvement on the proportion of deviations for all scenarios.

Table 6.3: Comparing PD, PE, PDr, and PEr of the current timetable and timetables obtained with $\epsilon = 0$ and $\epsilon = 1$ in scenarios $R[1;1]$, $R[0;1]$, and $R[1;0]$, for all shifts on route 206.

	$\epsilon = 0$ **min.**				$\epsilon = 1$ **min.**			
Scenario	PD(%)	PE(%)	PDr	PEr	PD(%)	PE(%)	PDr	PEr
Shift 1								
N	38.31	60.30	–	–	29.60	48.64	–	–
$R[1;1]$	39.32	57.19	1.03	0.95	26.81	40.79	0.91	0.84
$R[0;1]$	39.01	58.20	1.02	0.97	27.12	40.95	0.92	0.84
$R[1;0]$	39.78	57.26	1.04	0.95	26.88	40.79	0.91	0.84
Shift 2								
N	28.75	39.83	–	–	23.13	33.88	–	–
$R[1;1]$	27.50	39.99	0.96	1.00	19.69	30.61	0.85	0.90
$R[0;1]$	27.99	39.55	0.97	0.99	19.59	30.61	0.85	0.90
$R[1;0]$	27.28	40.21	0.95	1.01	19.75	30.50	0.85	0.90
Shift 3								
N	40.62	56.38	–	–	31.92	46.31	–	–
$R[1;1]$	46.85	48.46	1.15	0.86	35.31	35.62	1.11	0.77
$R[0;1]$	48.62	46.85	1.20	0.83	27.54	40.46	0.86	0.87
$R[1;0]$	40.15	55.62	0.99	0.99	37.00	34.62	1.16	0.75
Shift 4								
N	31.33	39.92	–	–	24.20	31.95	–	–
$R[1;1]$	27.85	42.11	0.89	1.05	18.98	29.98	0.78	0.94
$R[0;1]$	28.75	41.27	0.92	1.03	18.70	30.38	0.77	0.95
$R[1;0]$	27.51	42.67	0.88	1.07	19.93	28.80	0.82	0.90
Shift 5								
N	47.99	48.79	–	–	39.72	39.61	–	–
$R[1;1]$	41.91	53.85	0.87	1.10	30.31	39.38	0.76	0.99
$R[0;1]$	43.17	52.81	0.90	1.08	30.08	39.61	0.76	1.00
$R[1;0]$	42.14	53.73	0.88	1.10	31.46	39.27	0.79	0.99
Average of all shifts								
N	37.40	49.04	–	–	29.71	40.08	–	–
$R[1;1]$	36.69	48.32	0.98	0.99	26.22	35.28	0.88	0.89
$R[0;1]$	37.51	47.74	1.00	0.98	27.00	34.80	0.91	0.88
$R[1;0]$	35.37	49.90	0.95	1.02	24.61	36.40	0.83	0.91

Table 6.4: Comparing PD, PE, PDr, and PEr of the current timetable and timetables obtained with $\epsilon = 3$ and $\epsilon = 6$ in scenarios $R[1;1]$, $R[0;1]$, and $R[1;0]$, for all shifts on route 206.

	$\epsilon = 3$ **min.**				$\epsilon = 6$ **min.**			
Scenario	PD(%)	PE(%)	PDr	PEr	PD(%)	PE(%)	PDr	PEr
Shift 1								
N	17.79	24.01	–	–	5.67	3.81	–	–
$R[1;1]$	8.70	15.00	0.49	0.62	2.49	1.32	0.44	0.35
$R[0;1]$	8.55	14.84	0.48	0.62	2.33	1.24	0.41	0.33
$R[1;0]$	8.70	14.76	0.49	0.61	2.49	1.32	0.44	0.35
Shift 2								
N	12.98	18.44	–	–	5.46	3.93	–	–
$R[1;1]$	7.69	11.89	0.59	0.64	2.62	1.47	0.48	0.37
$R[0;1]$	7.69	11.95	0.59	0.65	2.56	1.53	0.47	0.39
$R[1;0]$	7.75	11.84	0.60	0.64	2.62	1.47	0.48	0.37
Shift 3								
N	17.00	23.77	–	–	6.85	4.69	–	–
$R[1;1]$	16.08	13.00	0.95	0.55	6.46	2.77	0.94	0.59
$R[0;1]$	12.08	16.46	0.71	0.69	5.46	3.23	0.80	0.69
$R[1;0]$	16.46	12.31	0.97	0.52	6.85	2.69	1.00	0.57
Shift 4								
N	13.53	16.40	–	–	5.00	2.70	–	–
$R[1;1]$	8.70	12.75	0.64	0.78	3.71	1.85	0.74	0.69
$R[0;1]$	8.53	13.03	0.63	0.79	3.59	1.85	0.72	0.69
$R[1;0]$	8.93	12.30	0.66	0.75	3.71	1.74	0.74	0.64
Shift 5								
N	22.16	18.14	–	–	10.79	1.72	–	–
$R[1;1]$	11.60	11.94	0.52	0.66	3.21	1.26	0.30	0.73
$R[0;1]$	11.37	11.94	0.51	0.66	3.21	1.26	0.30	0.73
$R[1;0]$	12.40	11.25	0.56	0.62	3.21	1.26	0.30	0.73
Average of all shifts								
N	16.69	20.15	–	–	6.75	3.37	–	–
$R[1;1]$	10.55	12.92	0.64	0.65	3.70	1.73	0.58	0.55
$R[0;1]$	9.64	13.64	0.59	0.68	3.43	1.82	0.54	0.56
$R[1;0]$	10.85	12.49	0.65	0.63	3.78	1.70	0.59	0.53

Regarding the indicators evaluating the proportion of delayed (i.e., PD) or earliness (i.e., PE) arrivals of vehicles to the TCPs, we can see that the optimized timetables are particularly good in terms of avoiding extreme values of delays and earliness. As the threshold of delays and earliness increases, the performance of the optimized timetables in terms of the proportion of delays and earliness improves significantly. For example, considering a tolerance value of $\epsilon = 3$ minutes in the scenario $R[1;1]$ giving equal importance to delays and earliness, the new timetables reduce the probability of delays and earliness to around 65% of the values for the current timetable. Regarding the individual shifts, the greatest improvements to these indicators are for shifts 1, 2 and 5.

6.7 Conclusions

The main objective of this work was to endow Public Transport timetables the ability to absorb uncertainty through their adjustment to historical data from real trips collected by Information and Communication Technologies (ICT). This involves the use of optimization techniques for the robust planning of Public Transport timetables. This study proposed an approach to enhance existing timetables based on a mathematical programming model applicable to Public Transport routes. The model uses real observations to learn the best distribution of slack time to be incorporated in each TCP included in the daily path.

A set of measures was proposed and applied to quantify the robustness of Public Transport timetables. The assessment of delays was quantified with the AD and the PD at each TCP. These measures were complemented with relative measures ADr and PDr allowing comparisons with a reference timetable. The assessment of earliness was conducted using analogous measures: AE, PE, and the relative measures AEr and PEr, involving direct comparisons with a reference timetable.

The validity of the optimization model was demonstrated with its application to a real-world case study, concerning a bus route operating in Porto, with five daily shifts. The timetables obtained with the model were able to minimize delays and earliness in all shifts when compared with the corresponding original timetable. For the cases analyzed in this work, the timetables obtained with different values of the parameters γ_1 and γ_2, reflecting the priorities assigned to improvements in delays or earliness, were similar. This demonstrates that this model does not need extensive experimentation for the calibration of the parameters.

The development of models and measures for the improvement of robustness of Public Transport timetables is relevant to support managers in their effort to enhance urban transportation systems. The optimization model developed in this paper can contribute to improve existing timetables based on the data made available by ICT regarding the actual daily trips. This type of quantitative modeling approach, involving mathematical

programming, can help translate the vast amounts of data currently collected by transportation companies into valuable information allowing the continuous improvement of mobility services provided to citizens.

Even though the development of HTM integrates the operations control stage, the improvement of timetables able to account with running time variability, can help the establishment of effective holding policies at the planning stage.

Finally, future work could include incorporating the lessons learned in this chapter to improved synchronization Timetabling techniques, particularly regarding the assessment of timetables' robustness and the research for methods able to mitigate uncertainty in the timetables produced.

7 Conclusions

The starting point of the research presented in this thesis was the literature review on Public Transport planning, which is presented in Chapter 2. This literature review discussed the interconnections between the different Public Transport planning stages (i.e., Network Design, Frequency Setting, Timetabling, Vehicle Scheduling, Driver Scheduling, and Driver Rostering) and their associated problems. This literature review also explored Network Design, Frequency Setting, and Timetabling planning stages. Understanding these stages was essential to appreciating key factors linked to the central planning stage explored in this thesis, Timetabling.

The second part of Chapter 2 included a review of terminology used in this work, which was consistently applied in the thesis. The need to create this terminology section, and the Glossary, arises from a lack of consistency in the terms used in the literature in this area. The systematization of the terminology used in the thesis proved valuable for its construction, and hopefully, it will also make it easier to read.

The work presented in this thesis applied data from Intelligent Transportation System (ITS), namely Automated Fare Collection (AFC) systems and Global Positioning System (GPS). In light of the increasing availability and quality of these technological means and the data extracted from them, exploring optimization methods capable of taking advantage of these new data sources is an important contribution of this thesis.

Chapter 3 followed a two-step methodology to estimate OD flows from entry-only AFC data. The first step applies the Trip Chaining Method (TCM) to estimate the alighting-stops of each AFC record, while the second step identifies transfers.

The main assumptions adopted to implement the TCM were: (1) the majority of passengers will start the next trip-leg at or near the alighting-stop of their previous trip-leg; (2) the majority of passengers end the last trip-leg of the day at or near the boarding-stop of the first trip-leg of the day; (3) by default, passengers travel within the Public Transport system; (4) passengers travel outside the Public Transport system when there is a single trip-leg on a day; (5) passengers travel outside the Public Transport system when the walking-distance between consecutive trip-legs exceeds a specified threshold; (6) when an alighting-stop cannot be inferred, the corresponding trip-leg is discarded; (7) passengers

can only alight in the sequence of downstream stops on the directed-route boarded; and (8) the alighting-time is not inferred;

The assumptions adopted to identify transfers were: (1) passengers do not walk more than a specified distance to transfer; (2) passengers do not wait more than a specified time to transfer; (3) a transfer occurs between consecutive trip-legs; (4) a transfer occurs between trip-legs on the same smart card; (5) passengers do not transfer to the same route; (6) when passengers travel out of the Public Transport system, the next trip-leg starts a new full-trip.

The methodology to estimate OD flows was applied to the case of Porto. The results included, for the data analyzed, the estimation of the OD flows and the construction and visualization of the corresponding OD matrices. The analysis of these results considered three segmentation analyzes: (1) the segmentation of trips by workdays, Sundays and holidays, and Saturdays; (2) the segmentation of trips by regular service days and reduced service days; (3) the segmentation of trips by frequent passengers and by occasional passengers.

Synchronization techniques focus on the optimization of transfers by minimizing transfer waiting-time and reducing bunching. The reduction of transfer waiting-time, especially at transfer-connections of greatest demand, has a significant impact on the overall quality of the service provided by the Public Transport system, regarding efficiency of operations and flexibility of traveling. Transfer waiting-time can also be achieved by increasing the frequency of strategic routes at the Frequency Setting planning stage, which is associated with an increase in operation costs. Moreover, the best solutions obtained with Synchronization Timetabling techniques may prove to be sub-optimal at Vehicle Scheduling and Driver Scheduling stages of Public Transport planning. This can be overcome by integrating Synchronization Timetabling with the following planning stages, or through the iterative solution of these planning stages until an acceptable equilibrium is found.

Chapter 4 proposes a methodology to determine Public Transport networks whose Synchronization would most benefit a Public Transport system. The methodology starts by identifying transfer-connections candidate to synchronization in the Public Transport system according to a set of assumptions. The assumptions include (1) a transfer-connection is a candidate for synchronization when so identified by experts, considering social, historical, and service quality aspects; (2) when two directed-routes have an overlapping path segment, favor the selection of transfer-connections at their merging and splitting transfer-nodes; (3) a transfer-connection must be within a specified transfer walking-distance; (4) select transfer-connections whose constituent directed-routes are Low-Frequency; (5) select the transfer-connections with the highest demand (i.e., with high transfer-flows).

When proposed by experts, a transfer-connection is immediately classified as a candidate. For the remaining cases, a transfer-connection is a candidate only if it satisfies all the

criteria (i.e., network positioning, transfer walking-distance, Low-Frequency, and number of passengers). Of these criteria, the last one to be applied is the number of passengers, thus identifying the transfer-connections with the highest demand and consequent impact from synchronization. The transfer-connections identified as suitable for synchronization are then used to define aggregate transfer-nodes, whose common routes compose a network candidate for synchronization.

The methodology to identify synchronization networks was applied to the case of Porto using a small data set of transfers (obtained from the application of Chapter 3's methodology). The results serve as a proof of concept. The implementation of this methodology to larger data sets seems promising, including information on frequency and expert's opinion, which was not possible in this particular implementation.

The methodology proposed in Chapter 4 can also aid decision-makers in enhancing the quality of transportation service under scenarios of uncertainty, even without applying any optimization model. The quantification of transfer-connections importance is information that could be used by decision-makers for example, to decide if vehicles should wait for the arrival of a feeder route vehicle during operations (e.g., to support Holding Time Models (HTM)).

Synchronization Timetabling techniques refer to a set of optimization approaches designed to build Public Transport timetables seeking the goal of minimizing passengers' transfer waiting-time and vehicles' bunching. Chapter 5 proposes a synchronization Timetabling model seeking to minimize passengers' transfer waiting-time in Public Transport systems. The synchronization model maximizes the number of synchronized transfer opportunities. The model is formulated at the level of run-pieces, which allows its application to synchronization networks in which routes intersect each other more than once, which is a differentiating aspect of this model when compared to similar studies in the literature.

The synchronization Timetabling model includes a binary decision variable that identifies when the two run-pieces are synchronized or not. All pairs of run-pieces are given the same weight regarding synchronization. The model can be implemented considering a fixed headway for each directed route, or by allowing uneven headways, through the definition of minimum and maximum headways. Additionally, the model considers a time-window between the arrival and departing of vehicles at each transfer-node which is used to classify each transfer opportunity as synchronized or not. The time-window can be set to zero (i.e., vehicles must arrive at the same transfer-node at the same moment to be synchronized) or any positive value.

Chapter 6 proposes an optimization model to enhance the robustness of Public Transport timetables by mitigating the impact of unforeseen events occurring in operations of Public Transport systems. The model performs a re-Timetabling of existing timetables, considering the operation of each route independently. Therefore, this model can be applied

to routes that are already synchronized provided that the arrival time at synchronized transfer nodes is kept unchanged. The model can also be applied to routes that are not selected to be synchronized.

The re-Timetabling model seeks to reallocate slack time, preserving the total running-time of each shift from the current timetable. This constraint allows a fair comparison between the current timetable and the timetables obtained by the optimization model, as both have the same total duration of daily trips, implying similar operational costs. Each shift is optimized separately.

The re-Timetabling model optimizes timetables by minimizing the deviation of a set of real observations from the plan. It considers the possibility of attributing different viewpoints regarding the relative importance of delays and anticipations in the optimization process, by changing the corresponding weighting parameters. Different values were implemented for these weights and the results were compared.

Another contribution of Chapter 6 was the proposal of a set of quantitative measures to evaluate the robustness of timetables, which were used to assess the robustness of the different timetables obtained with the implementation of the optimization model for the case study of a bus route operating in Porto.

Future areas of research could include investigating ways to integrate the problems explored in this thesis with operational control, promoting the participation of the various stakeholders, and involving the use of new technologies.

Both the methodology for identifying synchronization networks and the proposed synchronization model should be tested with more data and on other transportation systems. Furthermore it would be very important to include the participation of experts and other stakeholders in the future development and application of these tools.

Another relevant research topic would be to study synchronization approaches for systems where some routes operate at medium and irregular frequencies.

Other future work could focus on assessing the impacts that changes in slack times may bring to operations, both positive and negative, to understand how these approaches could benefit transportation systems.

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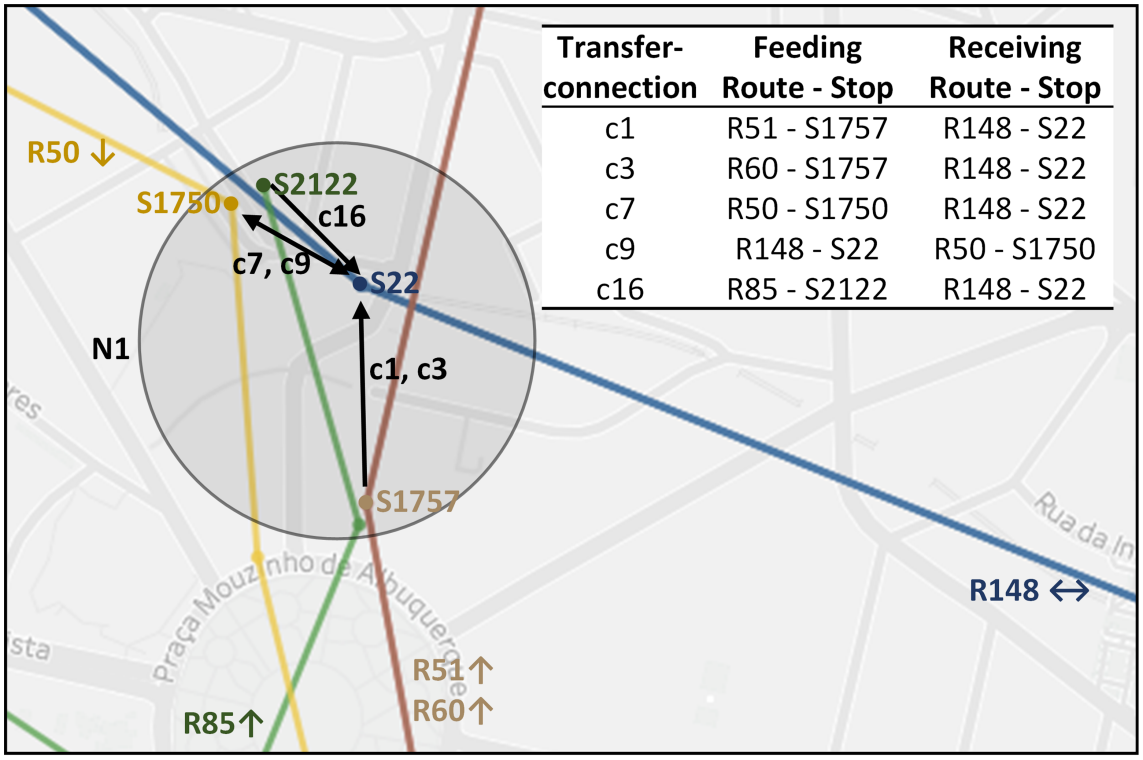
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A Transfer Nodes



Transfer-connection	Feeding Route - Stop	Receiving Route - Stop
c1	R51 - S1757	R148 - S22
c3	R60 - S1757	R148 - S22
c7	R50 - S1750	R148 - S22
c9	R148 - S22	R50 - S1750
c16	R85 - S2122	R148 - S22

Figure A.1: Transfer-node 1, visualization with detail of transfer-connections 1, 3, 7, 9, and 16. R50 corresponds to route 204 direction *Foz*, R51 to route 204 direction *São João*, R60 to route 209 direction *Prelada*, R80 to route 504 direction *Casa da Música*, and R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

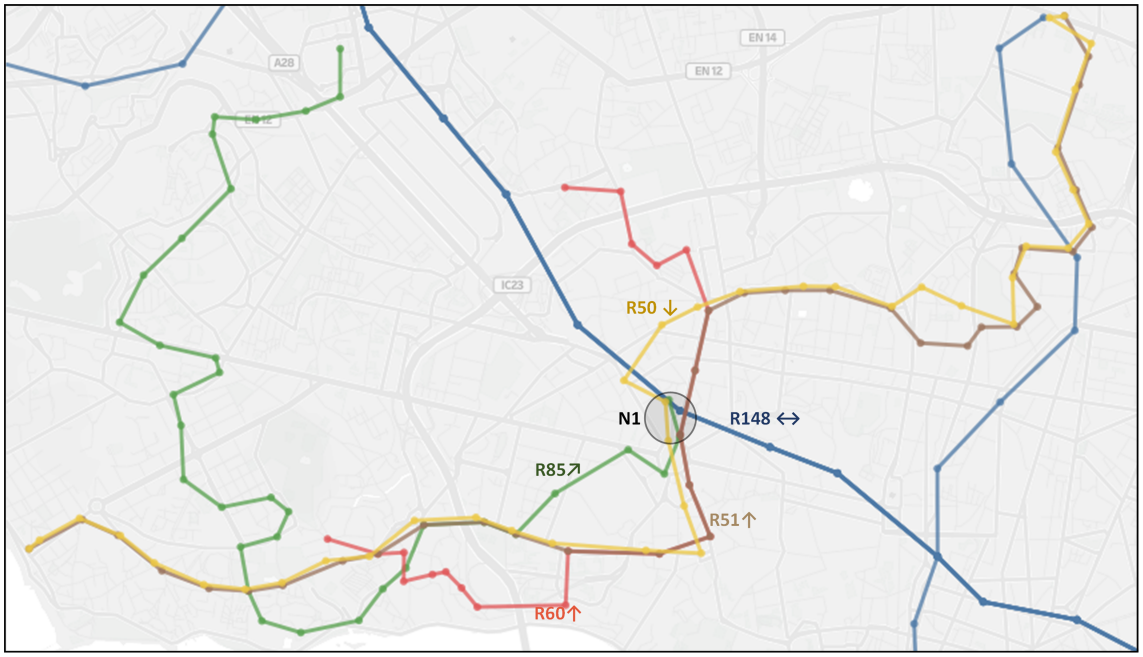


Figure A.2: Transfer-node 1, perspective view of routes. R50 corresponds to route 204 direction *Foz*, R51 to route 204 direction *São João*, R60 to route 209 direction *Prelada*, R80 to route 504 direction *Casa da Música*, and R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

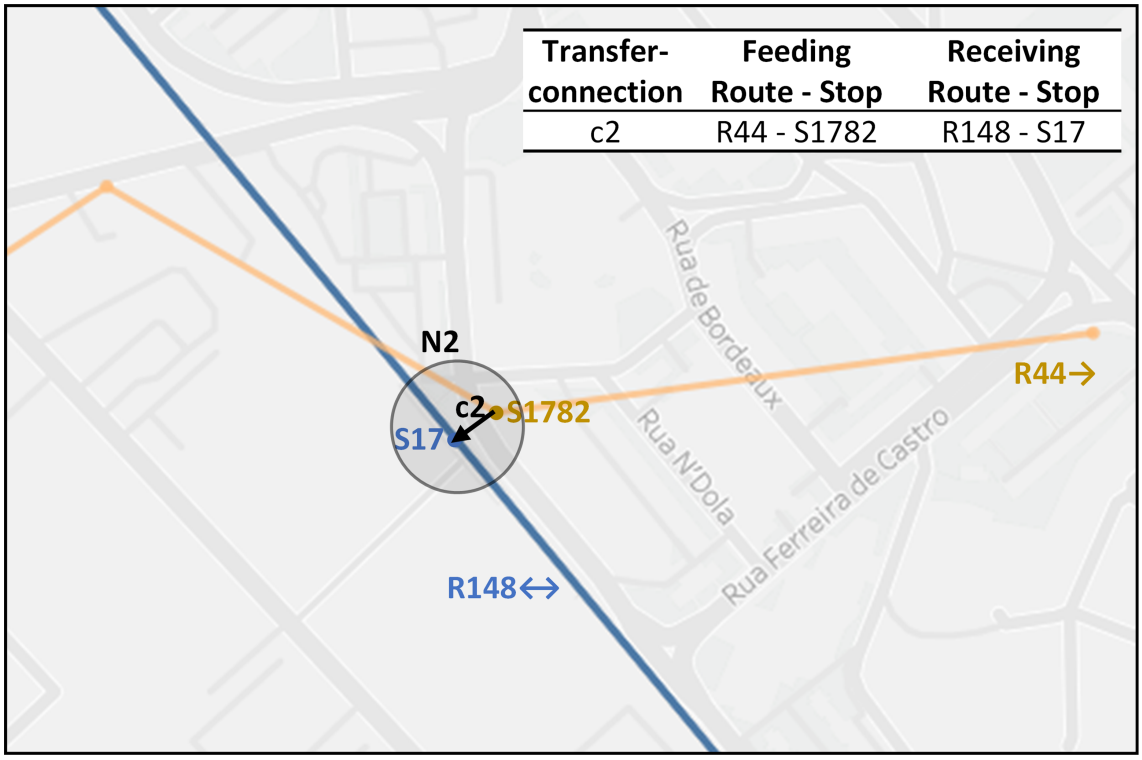


Figure A.3: Transfer-node 2, visualization with detail of transfer-connection 2. R44 corresponds to route 201 direction *Viso*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

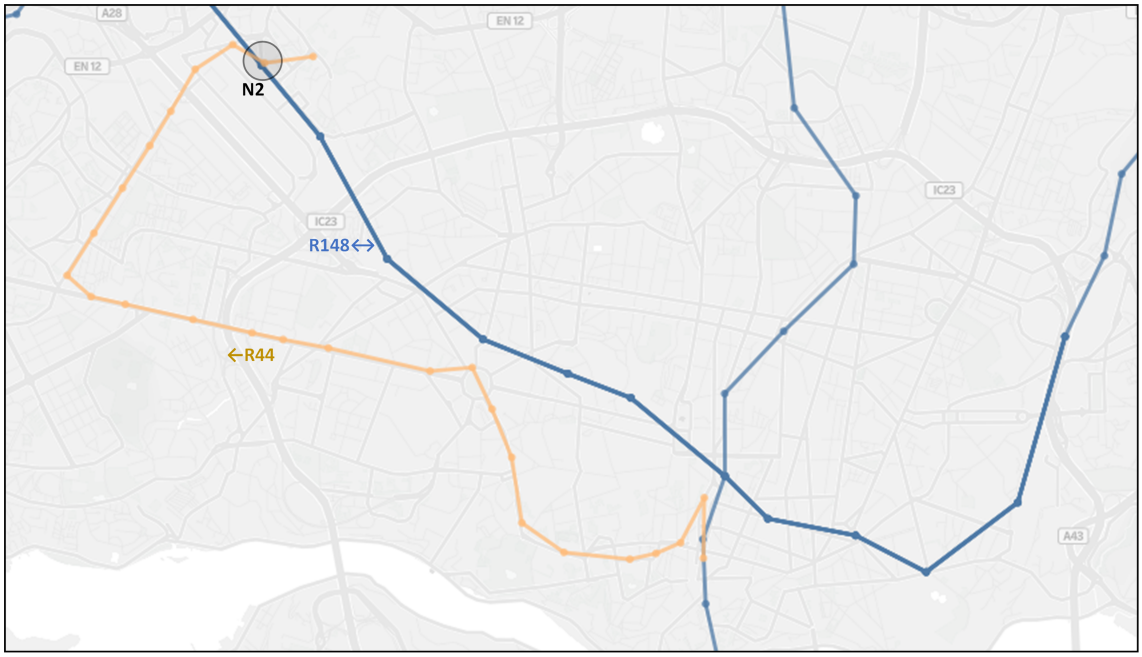


Figure A.4: Transfer-node 2, perspective view of routes. R44 corresponds to route 201 direction *Viso*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

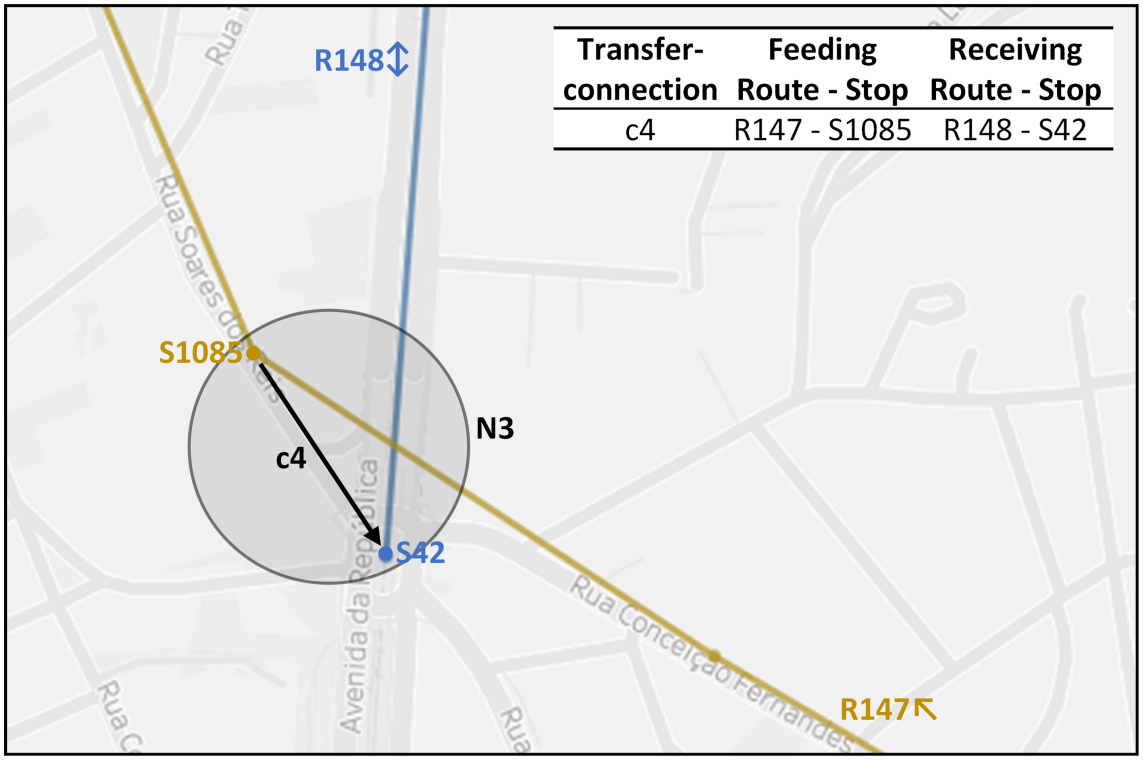


Figure A.5: Transfer-node 3, visualization with detail of transfer-connection 4. R147 corresponds to route 907 direction *Boavista*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

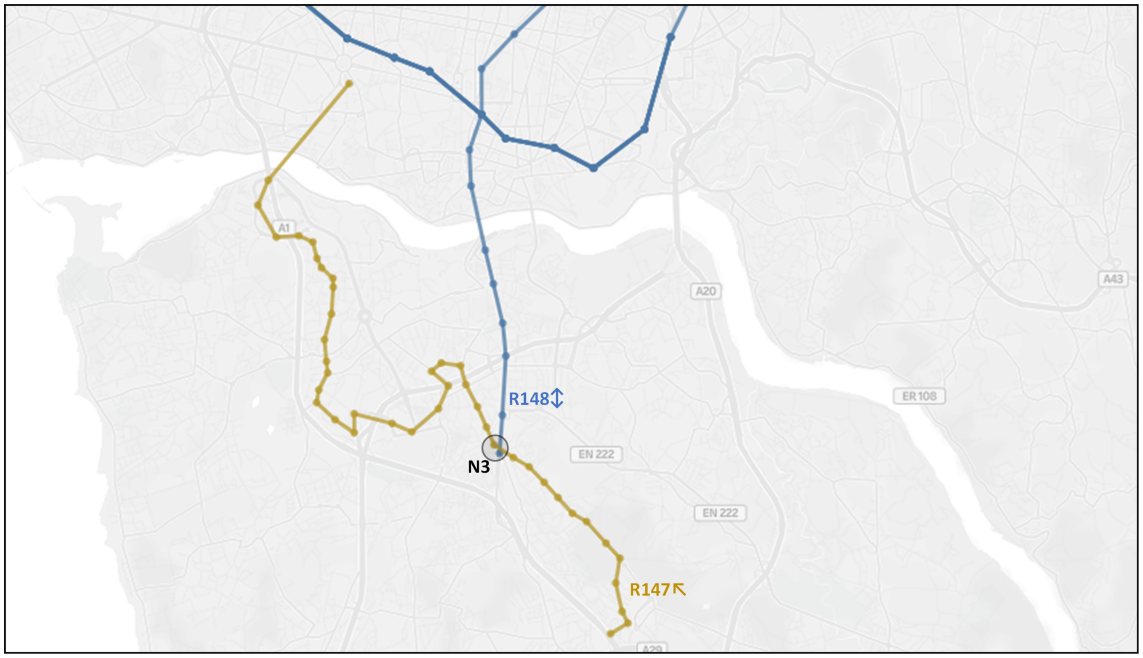


Figure A.6: Transfer-node 3, perspective view of routes. R147 corresponds to route 907 direction *Boavista*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

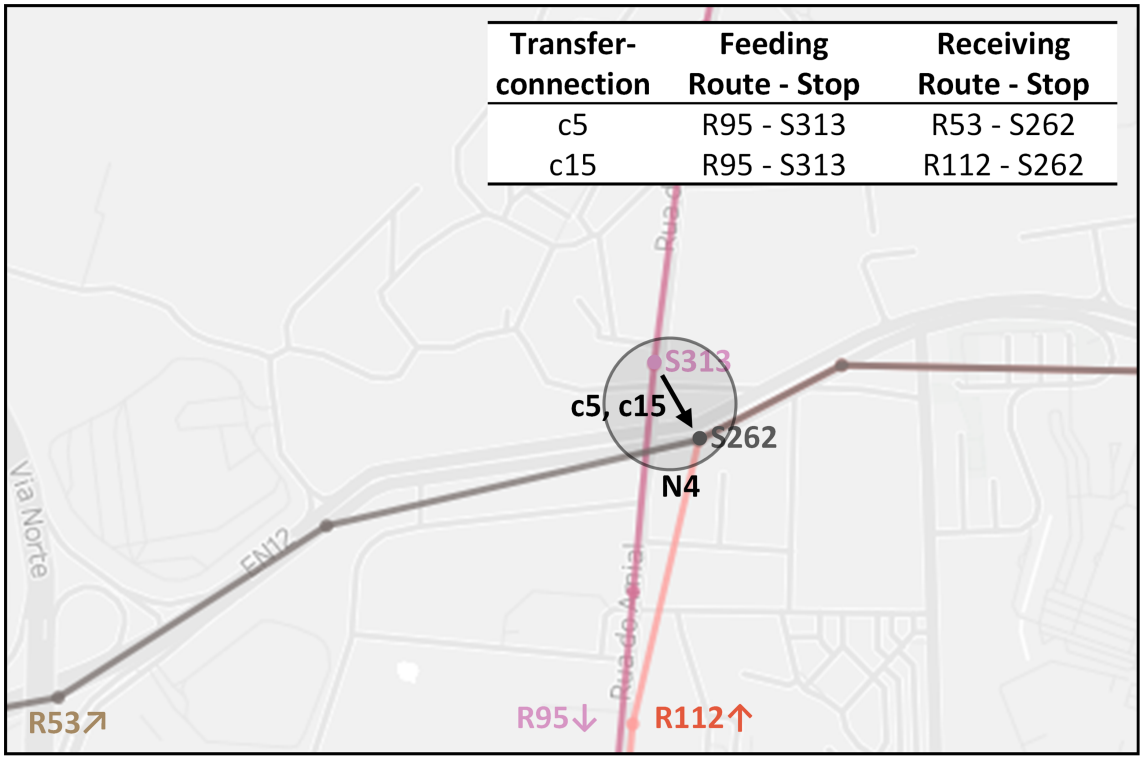


Figure A.7: Transfer-node 4, visualization with detail of transfer-connections 5 and 15. R95 corresponds to route 600 direction *Aliados*, R53 to route 205 direction *Campanhã*, R112 to route 704 direction *Largo da Codiceira*.

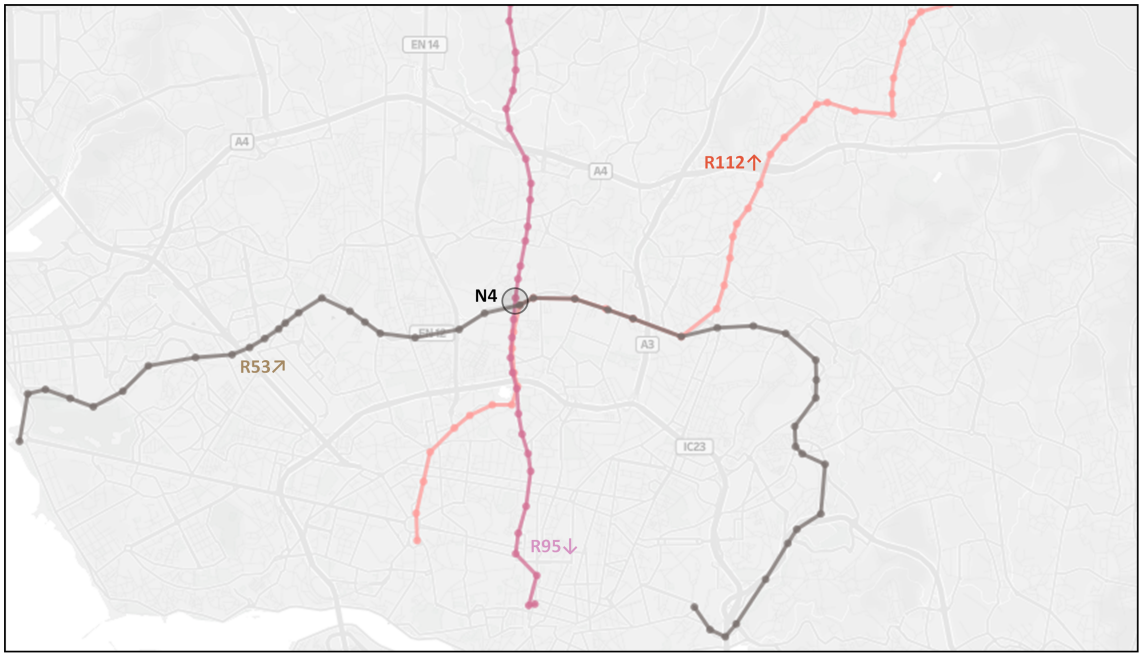


Figure A.8: Transfer-node 4, perspective view of routes. R95 corresponds to route 600 direction *Aliados*, R53 to route 205 direction *Campanhã*, R112 to route 704 direction *Largo da Codiceira*.

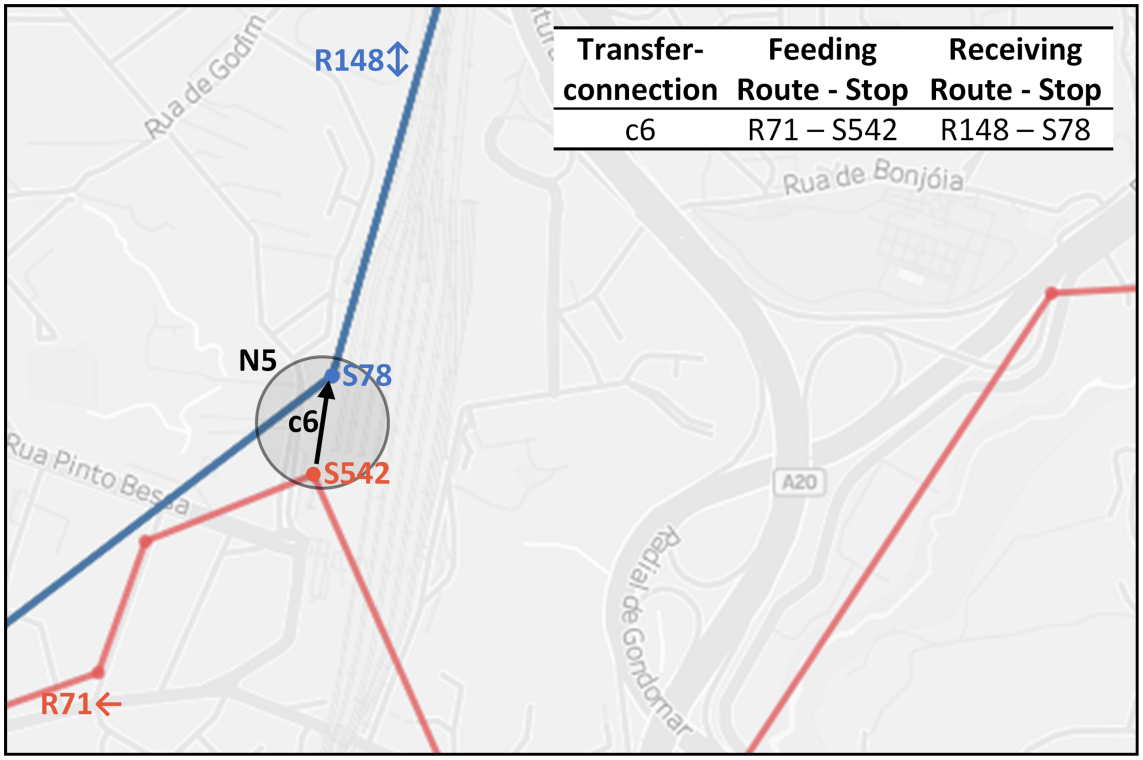


Figure A.9: Transfer-node 5, visualization with detail of transfer-connection 6. R71 corresponds to route 400 direction *Trindade*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

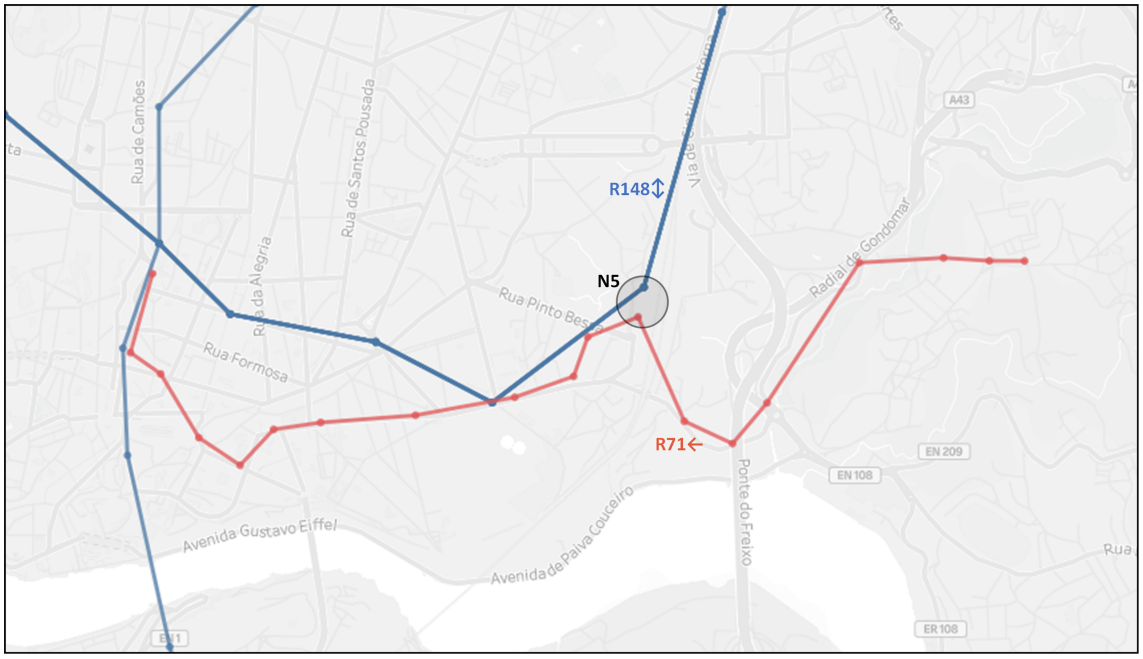


Figure A.10: Transfer-node 5, perspective view of routes. R71 corresponds to route 400 direction *Trindade*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

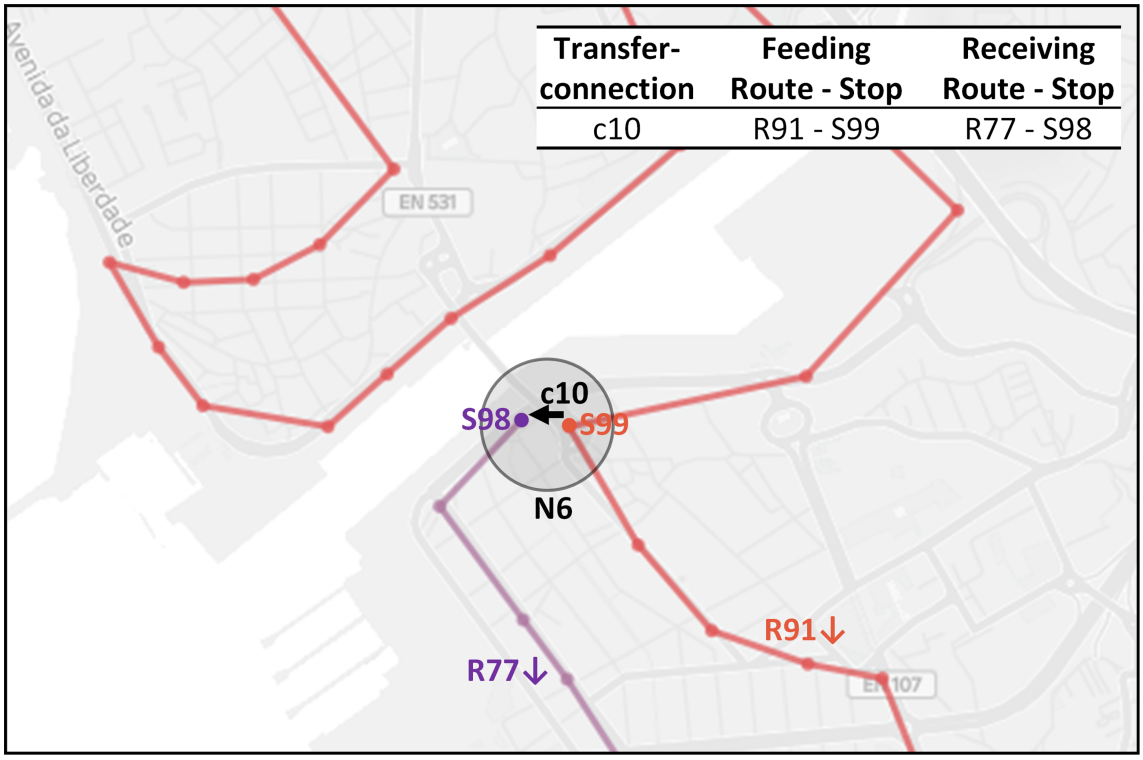


Figure A.11: Transfer-node 6, visualization with detail of transfer-connection 10. R91 corresponds to route 507 direction *Cordoaria*, R77 to route 500 direction *São Bento*.

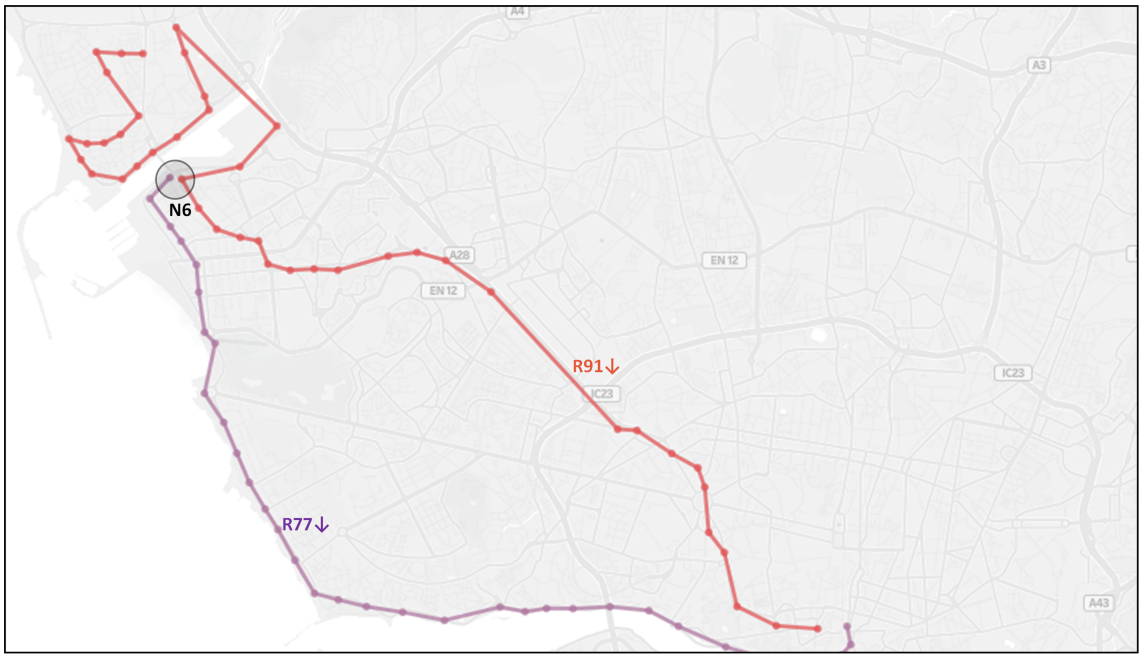


Figure A.12: Transfer-node 6, perspective view of routes. R91 corresponds to route 507 direction *Cordoaria*, R77 to route 500 direction *São Bento*.

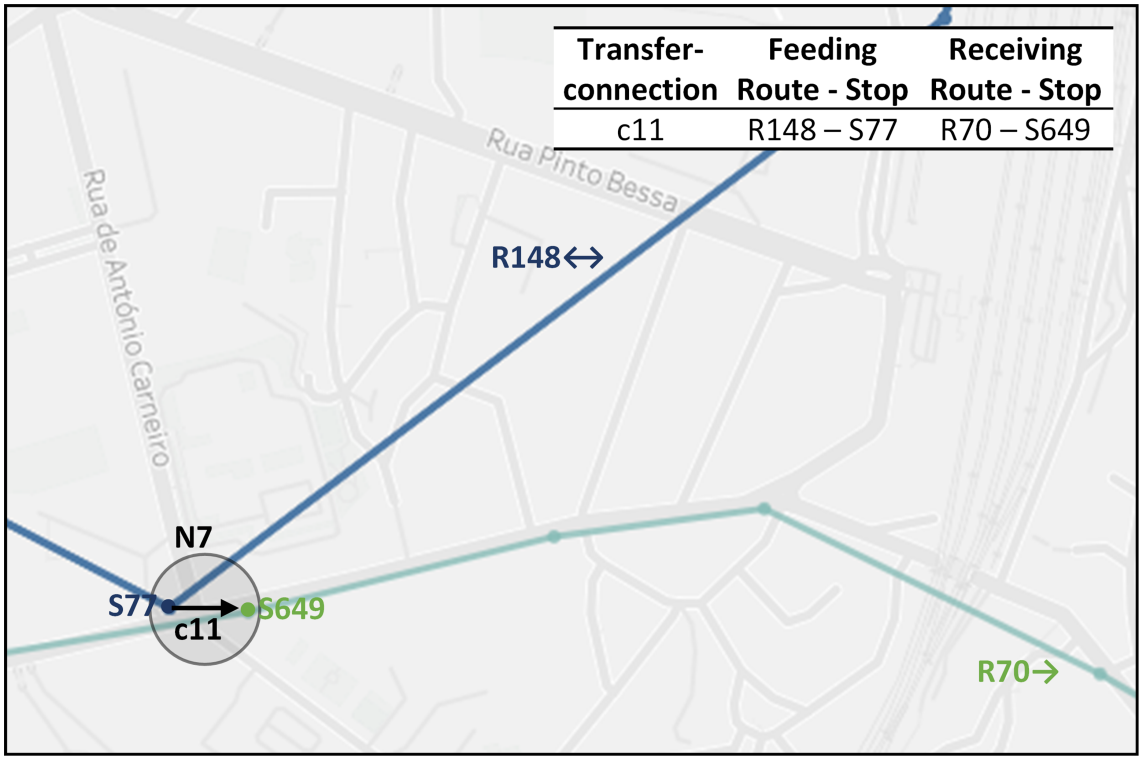


Figure A.13: Transfer-node 7, visualization with detail of transfer-connection 11. R148 corresponds to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction, R70 to route 400 direction *Azevedo*.

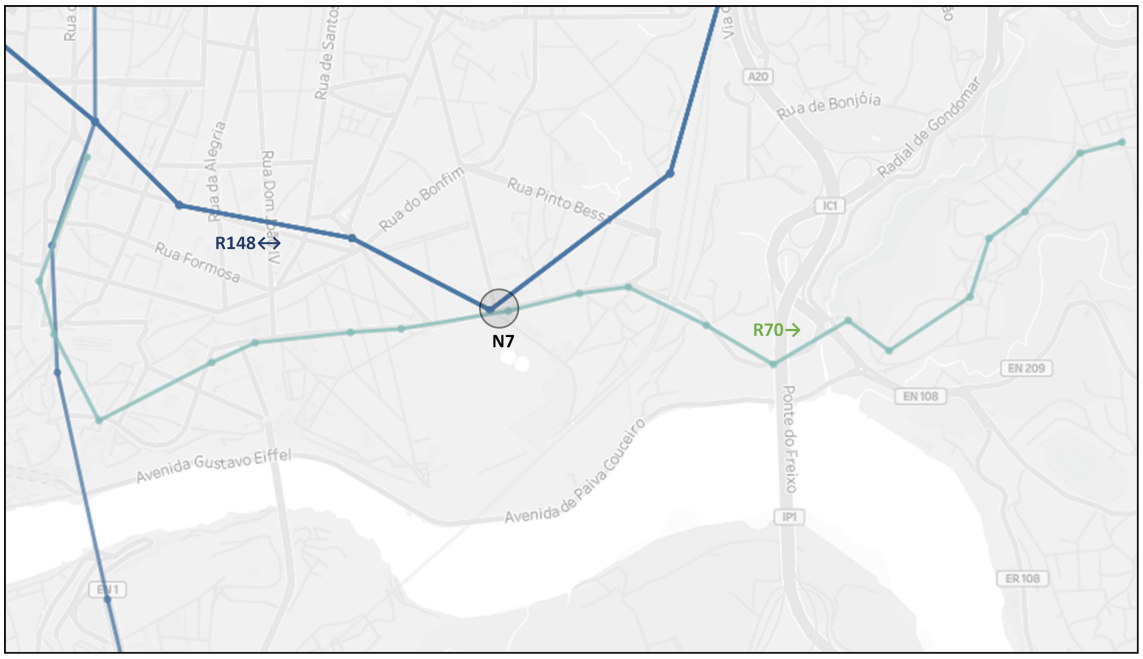


Figure A.14: Transfer-node 7, perspective view of routes. R148 corresponds to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction, R70 to route 400 direction *Azevedo*.

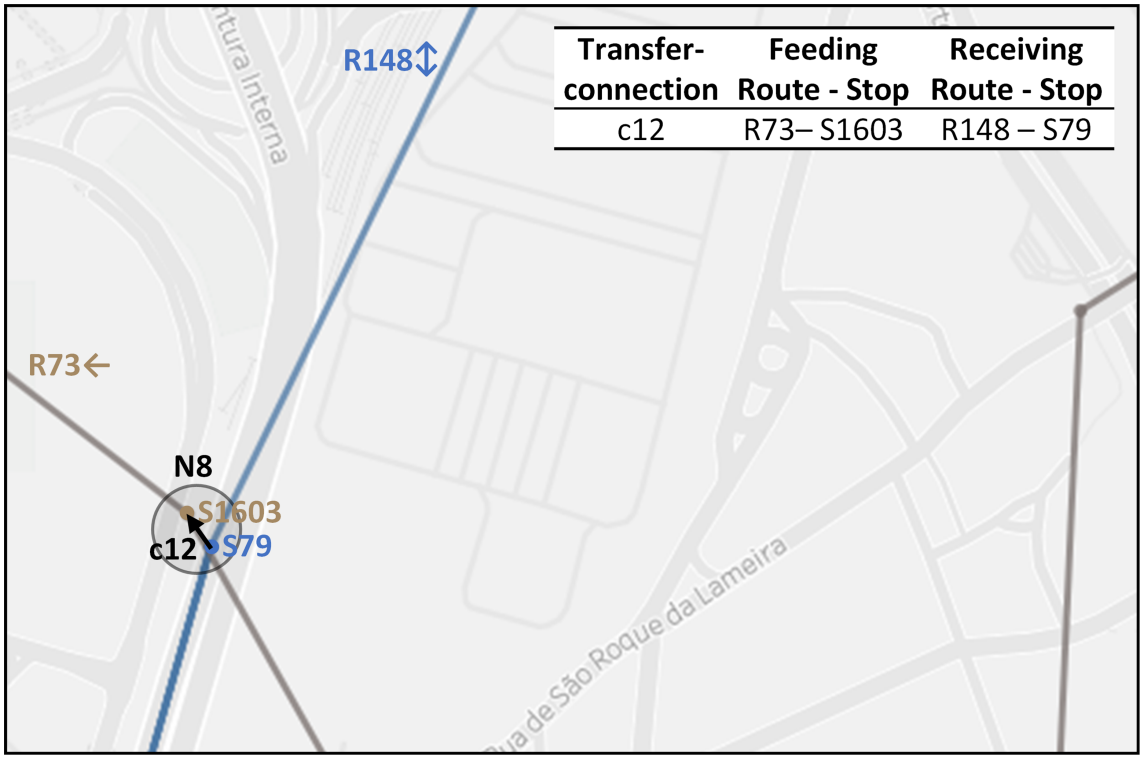


Figure A.15: Transfer-node 8, visualization with detail of transfer-connection 12. R73 corresponds to route 401 direction *Bolhão*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

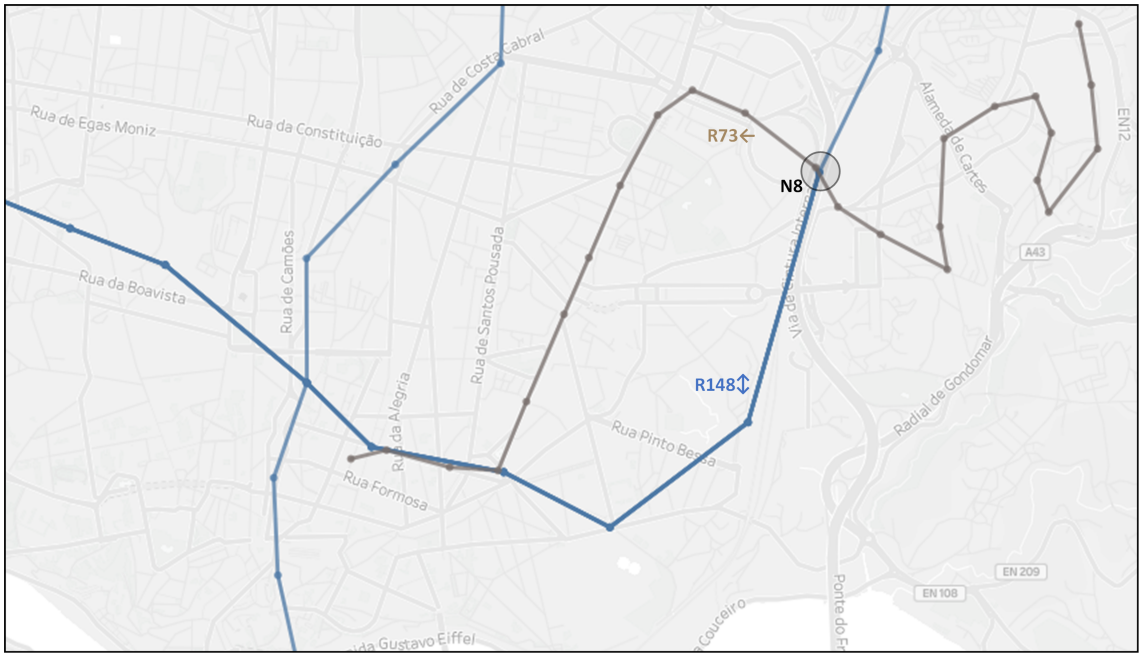


Figure A.16: Transfer-node 8, perspective view of routes. R73 corresponds to route 401 direction *Bolhão*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

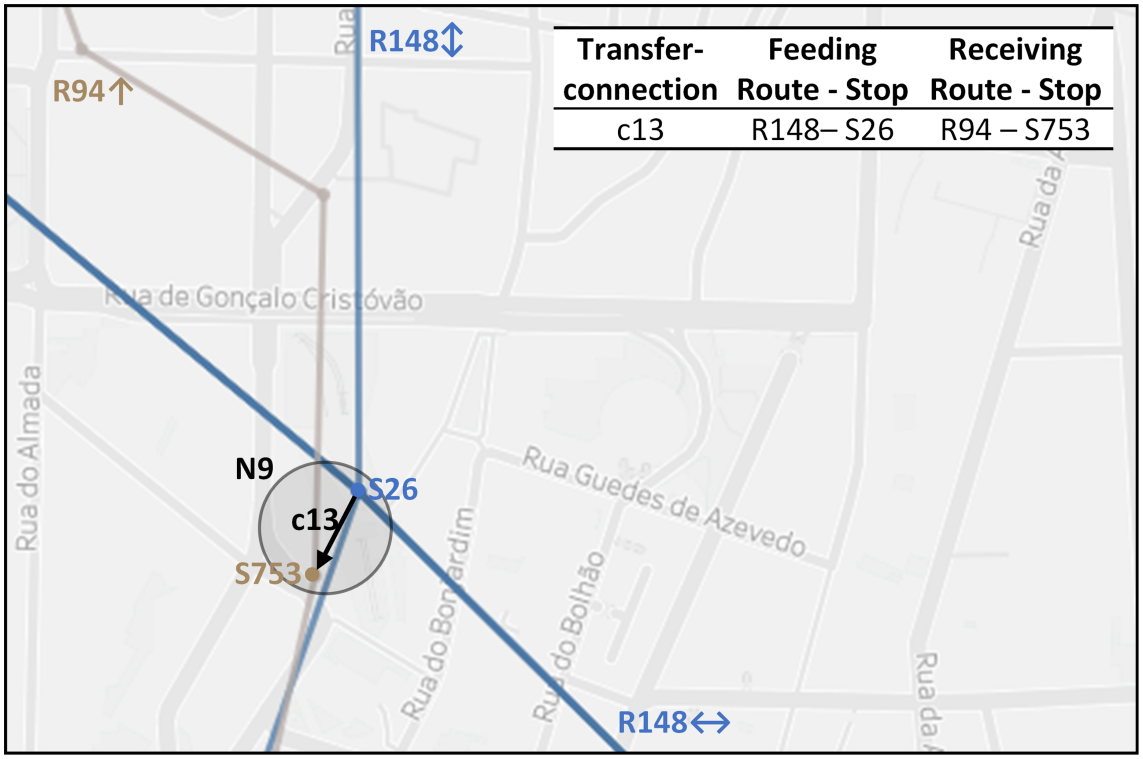


Figure A.17: Transfer-node 9, visualization with detail of transfer-connection 13. R148 corresponds to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction, R94 to route 600 direction *Barca*.

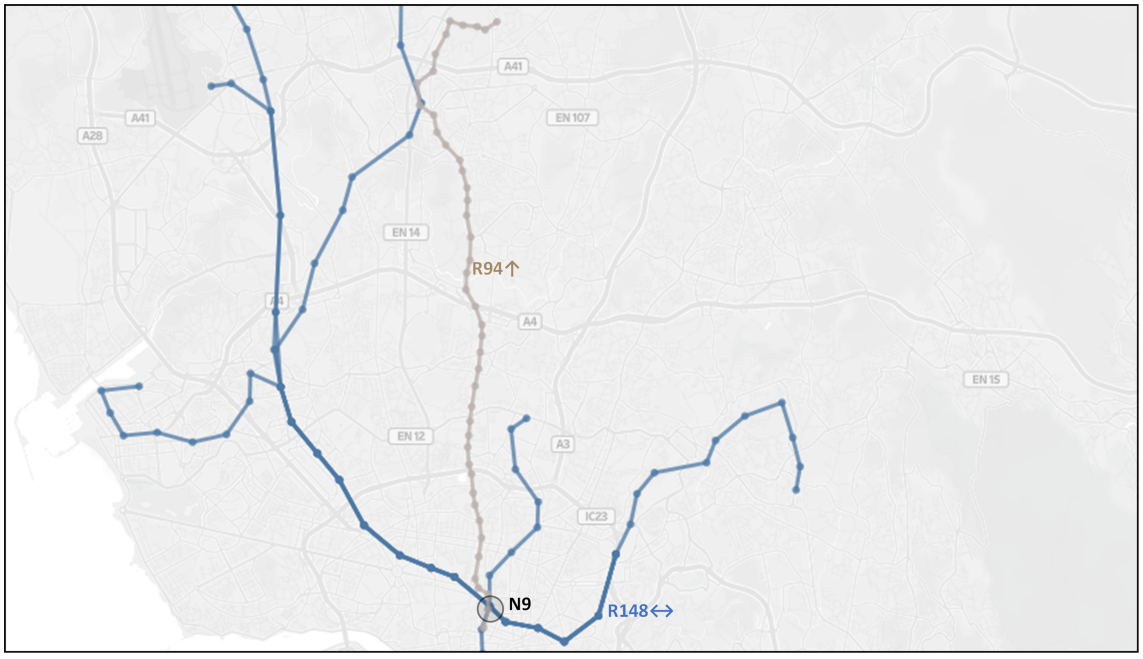


Figure A.18: Transfer-node 9, perspective view of routes. R148 corresponds to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction, R94 to route 600 direction *Barca*.

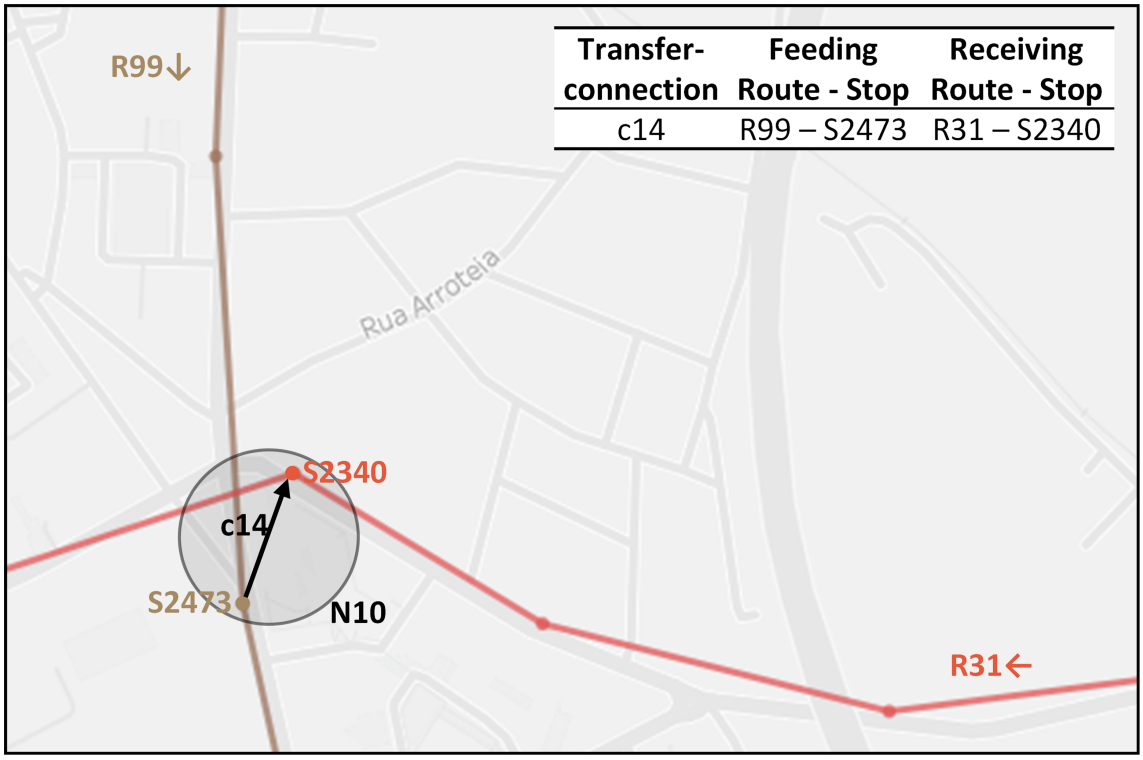


Figure A.19: Transfer-node 10, visualization with detail of transfer-connection 14. R99 corresponds to route 602 direction *Cordoaria*, R31 to route 61 direction *Mercado Matosinhos*.

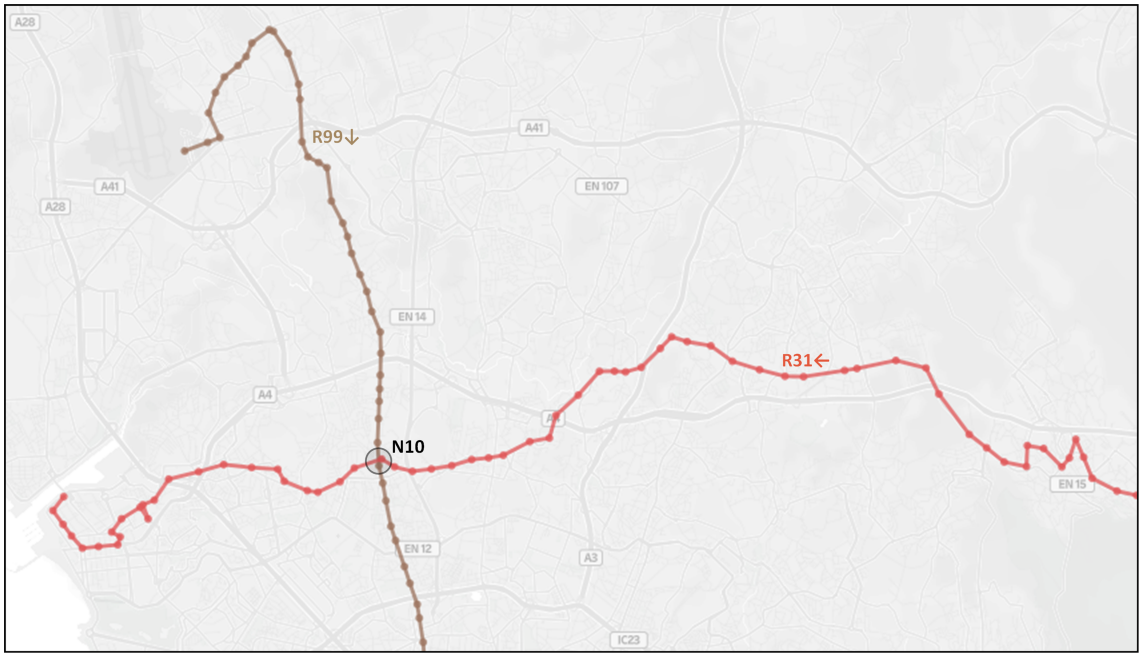


Figure A.20: Transfer-node 10, perspective view of routes. R99 corresponds to route 602 direction *Cordoaria*, R31 to route 61 direction *Mercado Matosinhos*.

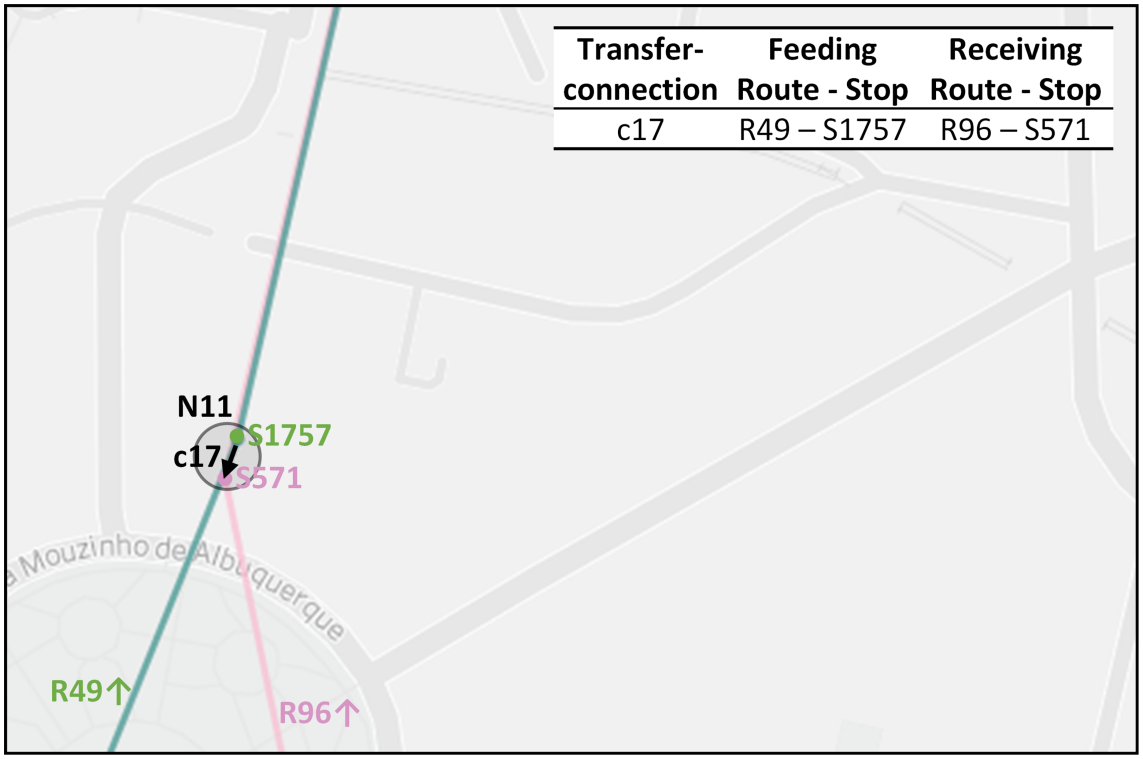


Figure A.21: Transfer-node 11, visualization with detail of transfer-connection 17. R49 corresponds to route 203 direction *Marquês*, R96 to route 601 direction *Aeroporto*.

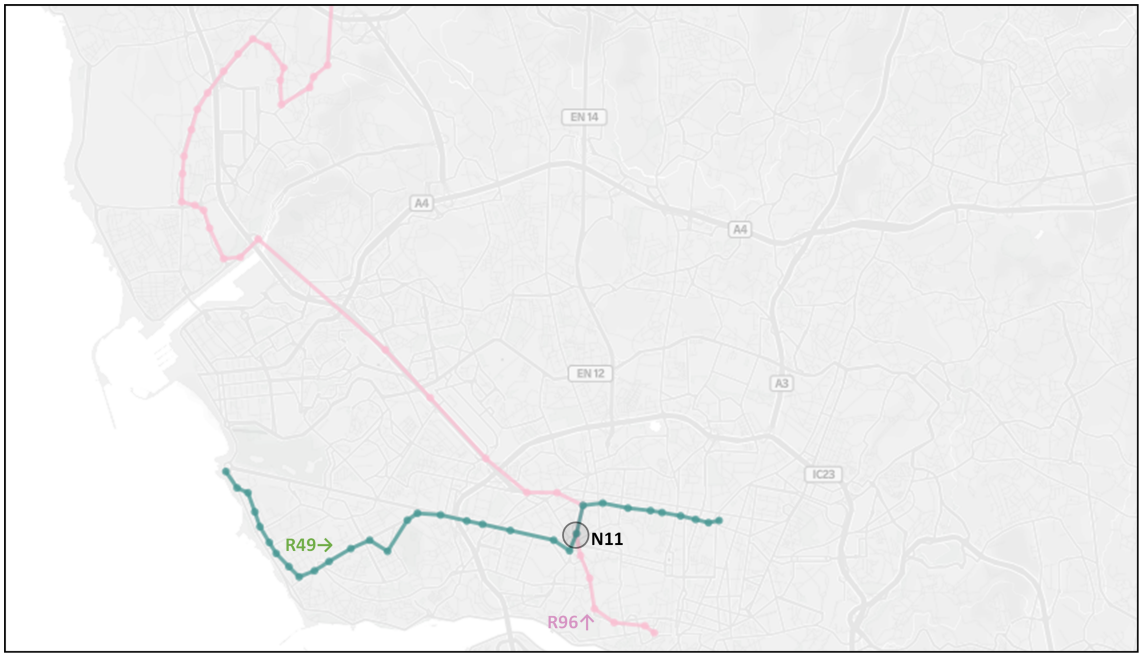


Figure A.22: Transfer-node 11, perspective view of routes. R49 corresponds to route 203 direction *Marquês*, R96 to route 601 direction *Aeroporto*.

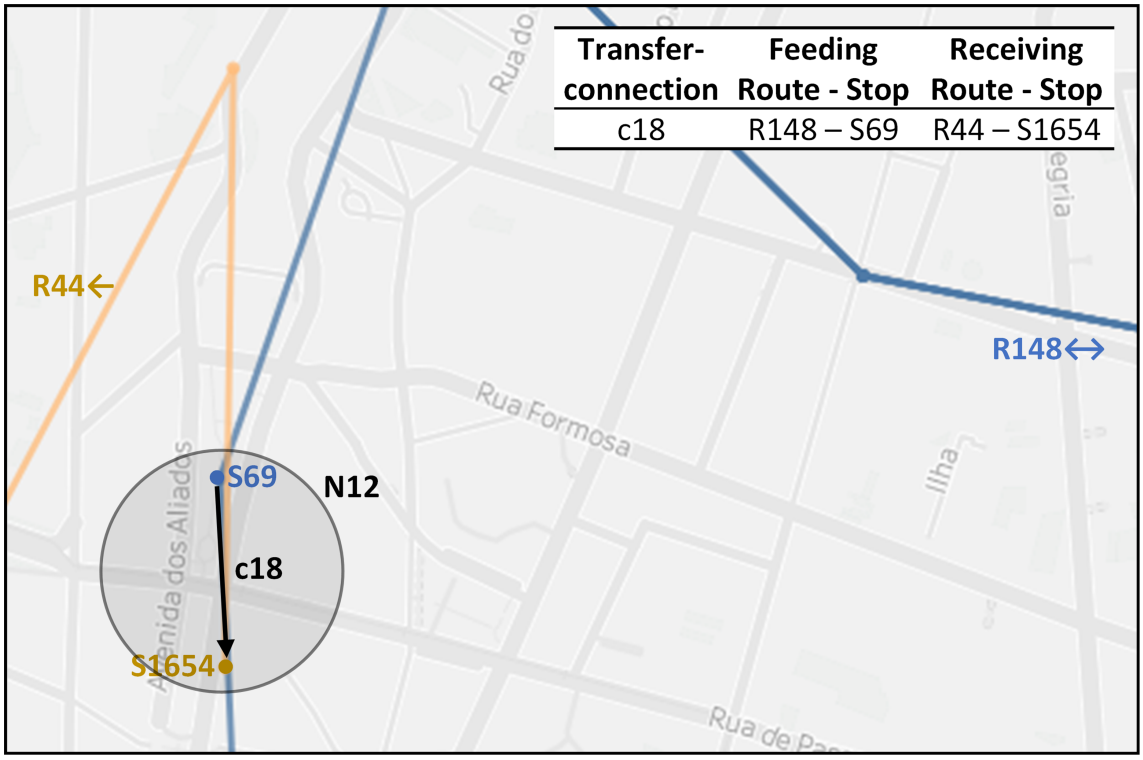


Figure A.23: Transfer-node 12, visualization with detail of transfer-connection 18. R148 corresponds to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction, R44 to route 201 direction *Viso*.



Figure A.24: Transfer-node 12, perspective view of routes. R148 corresponds to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction, R44 to route 201 direction *Viso*.

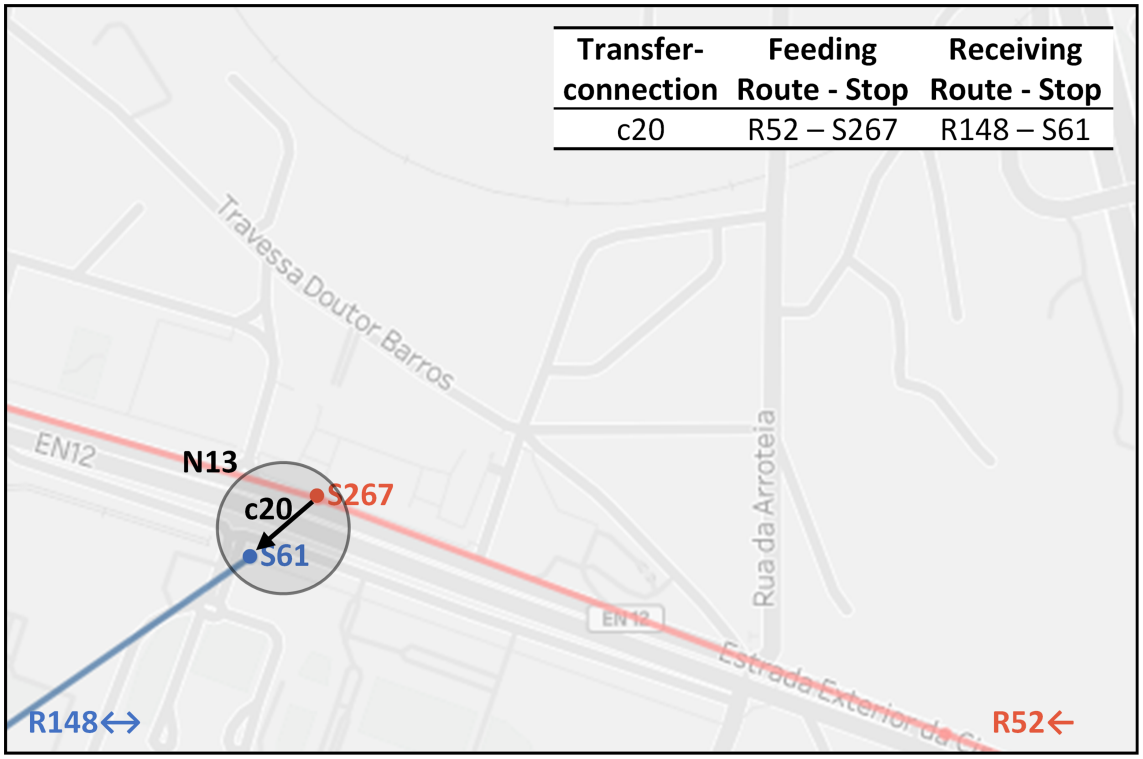


Figure A.25: Transfer-node 13, visualization with detail of transfer-connection 20. R52 corresponds to route 205 direction *Castelo do Queijo*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.

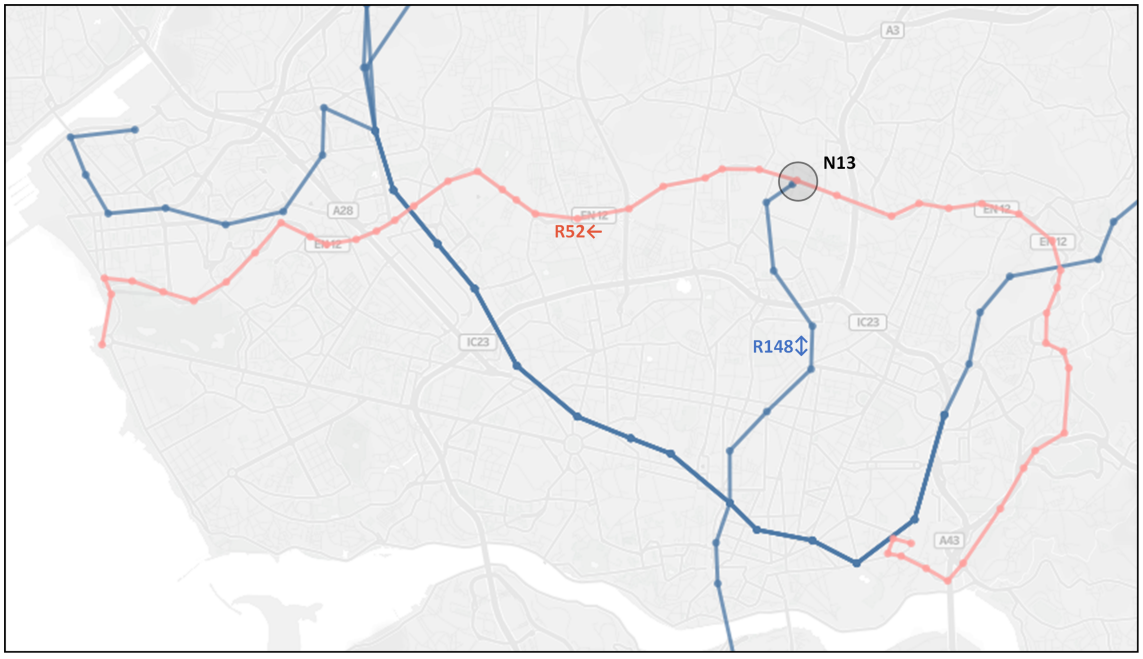


Figure A.26: Transfer-node 13, perspective view of routes. R52 corresponds to route 205 direction *Castelo do Queijo*, R148 to all metro routes as a whole (i.e., A, B, C, D, E, and F) in any direction.