Spatial Analysis of Shared Bicycle Trip Data

A case study in Rotterdam, the Netherlands

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Preface

This is a report on my graduation assignment written to conclude the Bachelor Civil Engineering at the University of Twente. The assignment was carried out externally under the supervision of "Rotterdamse Electrische Tram" (RET) and the University of Twente between April and June 2022. The project has gained me practical experience of analysing real-life data, reporting the progress and working in the office environment.

First of all, I would like to thank Halmar Kranenburg, my external supervisor, who became a real friend to me over this short yet exciting project period. His endless enthusiasm and support have helped me feel comfortable at the company and keep the research in the right direction.

Secondly, I would like to thank my University supervisors Karst Geurs and Konstantinos Gkiotsalitis for assisting me with finding an assignment, introducing me to the SmartHubs project and providing guidance in writing the report.

Lastly, I would like to thank Kelt Garritsen for sharing his extremely valuable experience in data analysis and usage of ArcGIS software.

Daniil Popov

Enschede, June 2022

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Summary

Local Dutch authorities and transportation companies are actively trying to cut down the car usage in metropolitan areas in order to reduce congestion and promote sustainable transport modes instead. This is being done by increasing the capacity and optimizing the operation of public transit network as well as various alternative modes. Shared mobility is viewed as a service capable of partially solving the first/last mile problem, therefore its integration into the public transit network has been a promising research direction in the recent years.

The primary focus of this report is on processing of a dataset containing origin-destination information collected by a shared bicycle service provider in Rotterdam in September 2021. The goal of the analysis was to extract the trip characteristics, determine the spatial clusters of service demand within the city and relate the usage of shared bicycles to the locations of public transport stations.

The descriptive statistic has shown that the bicycles were primarily being used for short distance trips. The median travel distance was found to be 1.6 km, while the average travel time was just over 20 minutes. Most trips were completed during the day between 11:00 and 20:00 with no characteristic peaks, however a distinctive peak in demand during night time (between 23:00 and 01:00) at the weekends was discovered. The findings were partially inconsistent with related literature, however the observed patterns might have been influenced by the COVID-19 pandemic.

The spatial analysis has demonstrated a high demand for the service in practically all regions of the city center, while on the outskirts “hotspots” could typically be found around various points of interest such as train stations, shopping malls and recreational spaces. It was consequently shown that nearly one third of all trips are not related to any form of public transportation, while the majority of trips that have originated or ended in the proximity of a transit stop serve a complementary role to the public transportation network.

Introduction

Shared Mobility

In the recent years shared mobility services have gained increasing popularity due to their positive influence on the sustainable development of urban infrastructure. As more metropolitan areas are trying to limit the car usage within the cities in order to reduce carbon emissions and free up more public space, public transportation is undergoing significant development. As pointed out by Grosshuesch (2020), one of the side effects of relying on public transportation is the so-called "first/last mile problem": the distance a commuter has to cover from home (or other point of interest) to the public transport station and vice versa. The shared mobility services are specifically oriented at short-distance trips and presumably help to deal with the problem. However, Grosshuesch has also outlined that not all shared mobility models provide an adequate solution to the first/last mile problem, in particular docking bicycle and scooter sharing programs have demonstrated a similar side effect. Free floating bicycle and scooter sharing (FFBS and FFSS), on the other hand, is an attractive alternative solution (Pal & Zhang, 2017). Such sharing scheme is relatively new and so far has only proved to cause small modal shifts. Nevertheless, due to such bicycles and scooters being equipped with GPS technology, several smart management strategies can be developed based on the trip data. Both the shared mobility service providers and the city authorities are interested in integrating these services with the existing transport network. Supply/demand management as well as accessibility of the service is crucial to the model success.

Mobility Hubs

Scientific literature offers different definitions of the term "Mobility Hub". In the context of current research the following definition will be used:

"A mobility hub is a physical location where different shared transport options are offered at permanent, dedicated and well-visible locations and public or collective transport is available at walking distance" (Geurs & Munzel, 2021)

This element of civil infrastructure has the potential to facilitate multi-modal transport usage and optimize the mobility network. A *SmartHubs* project investigates the development of mobility hubs in European cities, including the Hague-Rotterdam area where the project team designs the process of physical and digital integration with public transport.

Problem Statement

Rotterdam is the second largest city in the Netherlands (over 650,000 inhabitants) that is facing major urban challenges associated with mobility transition. As the city's population is expected to increase by 55,000 before 2025, the transportation network is coming under pressure.

The municipality aims to reduce the share of car usage from 42% in 2020 down to 32% by 2030 and down to 28% by 2040 (Municipality of Rotterdam, 2020). In doing so it relies on the public transport network operated by the RET, which transported an average of 480,000 passengers daily in 2019, but due to the COVID-19 pandemic this number has dropped to 260,000. While cars remain a dominant transport mode, the car ownership is declining, especially among younger age groups, and this trend is reinforced by the emergence of various shared mobility services (Municipality of Rotterdam, 2021). The city has encouraged these initiatives by issuing licenses to 8 shared bike and scooter providers in 2020. Moreover, the municipality wants to assure the sharing services are complementing the existing public transportation network by developing mobility hubs. Locations which provide access to multiple travel modes promote the usage of sustainable means of transport by minimizing the transfer time during the modal switch.

The *SmartHubs* project team has developed an "Integration Ladder" model (Figure 1), which describes the typology of mobility hubs and the levels of their integration (Geurs & Munzel, 2021).

	Physical integration	Digital integration	Democratic integration
4	Conflict free and place making	Integration of societal goals and policies, and consideration of universal design principles	Social learning
3	Visibility and branding	Integration of service offers and consideration of universal design principles	Integration of different knowledge
2	Wayfinding and consideration of universal design principles	Integration of booking and payment and consideration of universal design principles	Deliberative engagement of stakeholders, including (vulnerable) user groups
1	Acceptable walking distance to shared and public transport, minimum inclusive design standards	Digital integration of information	Appropriate representation of stakeholder interests, no or limited attention for vulnerable user groups
0	No physical integration	No digital integration	No stakeholder involvement and consideration of (vulnerable) user needs

Figure 1 - Integration Ladder (Geurs & Munzel., 2021)

The current research is related to the physical integration of mobility hubs, in particular identification of potential hub locations and assessment of the shared bicycles' role in the general transport network.

Literature Review

Bicycle sharing programs have first appeared in the 1960s in Amsterdam under the name "Witte Fietsenplan". The initiative has gained attention initially, but was short lived. It was in the 1990s that next generations of bicycle sharing have spread to other European cities. Eventually, huge success of sharing programs in Europe has generated enormous interest in such concept throughout the world. Today shared mobility is thought to be the most effective solution to the first/last mile problem (Torabi et al., 2022). Similar findings were made in China, where shared bicycles attract travellers from different generations and occupations and promote the usage of public transport (Fan et al., 2019; Zuo et al., 2020). It was found that shared bicycles account for 46% of first/last mile trips, followed by walking and private bicycles. In the US the so-called "Mobility on Demand" services typically feature car sharing rather than bike or scooter sharing, however the importance of physical and digital integration of such services into the existing public transit network is recognized (Patel et al., 2022).

The papers related to shared mobility typically have two research directions: factors influencing commuters' mode choice and evaluation of impacts of shared mobility on urban accessibility. Among the most distinctive predictors of mode choice are travel costs, time savings (associated with usage of shared transports), density of PT stops, availability of cycling lanes and weather. Several studies have found that travel costs are of highest importance in influencing passengers' attitude towards a certain transport mode. Therefore, new (short-distance) transport modes need to be price-wise competitive and require support from the authorities to get them fully functional (Torabi et al., 2022; Geurs & Puello, 2015).

Policy-influenced	Non policy-influenced
Physical infrastructure	-Hilliness
-Urban form (trip distance, density, mixture of functions)	-Weather / Climate (wind, rain, temperature)
-Cycling infrastructure	-Seasons
-Design of infrastructure (continuity, number of stops, cyclist priority, etc.)	-Gender
-Bicycle parking	-Age
-Bicycle sharing system	-Income
Non-physical context	-Employment status
-Social norms	-Household structure
-Costs (of both cycling and its alternatives)	
-Safety (both perceived and actual)	
-Giving cyclists protection in law	
-Education (training cyclists, informing car-users, etc.)	
Individual characteristics	
-Bicycle and car ownership	
-Frequency of physical activity	
-Level of education	
-Attitudes	
-Deeply held environmental beliefs	
-Habits	
-Identity	

Figure 2 - Overview of factors related to bicycle use (Liu et al., 2012)

A wide range of studies explored the relations between shared mobility and public transit as well as other POIs. A case study in Nanjing, China has revealed that generation and attraction of trips is positively influenced by presence of employment locations, entertainment centres, educational facilities and public transit stations, while parks, sport and medical facilities demonstrate a negative influence (Zhao et al., 2021). Bicycle sharing is considered to be complementary to train with bicycle-train combination being a competitive alternative to motorized transport modes (Kager et al., 2016). Although, there are fundamental differences between different PT and bicycle sharing stations in terms of trips they attract, therefore more research is needed to understand the role of sharing services in urban transportation (Hyland et al., 2018). In general, cycling is an attractive transport mode for short-distance trips facing a probable substitution by walking when a trip is within a 800 m. distance. With an increase of trip distance shared bicycles lose their competitiveness to public transit services and other (motorized) modes (Wu et al., 2019). The findings related to bicycle trip characteristics are fairly consistent across different studies showing a clear preference for short commutes, however the popularity of the service depends on the study region, characteristics of the built environment and availability of alternative means of transportation. As more micro-mobility modes emerge, they may cannibalize each other's share, compete with existing modes and influence commuters' behaviour in an unpredictable manner (Liao & Correira, 2019). Such a research gap calls for further exploration of interrelations between shared bicycles and other public transit modes (tram, bus, metro).

Research Goal and Questions

The research aims to provide the PT operator in Rotterdam and the *SmartHubs* project with information on current travel patterns of shared bicycles. The goal is formulated as follows:

To analyze the current use of free-floating shared bicycles and determine the spatial correlation between trip origins/destinations and locations of PT stations.

Three research questions were formulated. The first question concerns the recognition of patterns in shared bicycle usage. The second question is focused on integration of shared bicycles with the mobility hubs. Lastly, the third question aims to establish a relation between shared bicycle and public transport usage.

1. What are the spatiotemporal characteristics of free-floating shared bicycle usage?

2. Are origins and destinations of shared bicycle trips correlated with the locations of potential mobility hubs?

3. Are shared bicycles competing or complementing existing public transit modes (bus, tram, train, metro)?

Answering these questions will allow further inquiry into how higher levels of physical and digital integration can increase the usage of mobility hubs.

Reading Guide

The chapter "Methodology" describes the set-up of the analysis. This chapter provides information on the processed dataset, outlines the methods used to answer the research questions and elaborates on the statistical models used within the analysis. The next chapter "Results" describes the steps of the conducted research, presents the model outcomes and discusses the research findings. The chapter "Conclusion and Recommendations" summarizes the results, provides answers to research questions, discusses study limitations and suggests further research objectives.

Methodology

The spatial analysis was conducted with the use of ArcGIS software, specifically its “Spatial statistics” tools. The following chapter describes the operation of said tools and their contribution in answering the research questions.

Available Data

Shared mobility providers in the Netherlands share data with government authorities through the “Deelmobiliteit dashboard”. This online tool collects information on the locations of (parked) shared vehicles in real time. Among the shared mobility providers in Rotterdam are *Vaimoo*, *Donkey Republic*, *Felyx* and others. The processed database contained information on approximately 15000 trips carried out in Rotterdam and Schiedam in September of 2021 provided by *Donkey Republic*. As such, two datasets were accessed through the dashboard: the “Trips” dataset contains OD information of trips while the “Parking Events” dataset contains the times and locations of idle bicycles.

Trips		**Parking Events**	
Attribute	Description	Attribute	Description
system_id	Identifier of service provider	*system_id*	Identifier of service provider
bike_id	Unique identifier of a bicycle	*bike_id*	Unique identifier of a bicycle
start_time	DateTime stamp of trip start	*start_time*	DateTime stamp of parking event start
end_time	DateTime stamp of trip end	*end_time*	DateTime stamp of parking event end
trip_id	Unique identifier of a trip	*park_id*	Unique identifier of a parking event
start_location_lon	Longitude of trip origin	*Lon*	Longitude of parking location
start_location_lat	Latitude of trip origin	*Lat*	Latitude of parking location
end_location_lon	Longitude of trip destination		
end_location_lat	Latitude of trip destination		

Table 1 - Dataset attributes

Besides that, the information on locations of public transport stops and stations was needed. This data could be accessed through the “OpenOV” database.

Descriptive Statistics

Using the provided databases, the following trip characteristics were to be determined: *average trip length, average trip duration, distribution of bicycle usage across weekdays, distribution of bicycle usage across a given weekday*. These insights are useful for operators to optimize bicycle distribution routes and maintenance tasks (Arias-Molinares et al., 2021)

Identification of Spatial Clusters using the Global and Local Moran’s I

Let us have an input field (map) containing a finite set of locations (points, zones, etc.) with an assigned quantifiable attribute. The spatial autocorrelation within the input field can then be calculated using the Global Moran’s Index (ArcGIS, 2021):

$$I = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(x_i-\bar{x})\left(x_j-\bar{x}\right)}{\sum_{i=1}^{n}(x_i-\bar{x})^2}, j \neq i$$

Where w – spatial weight between locations (e.g. distance);
x – location attribute;
$\bar{x}$ – attribute mean;
n – total number of locations;

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j}\ , j \neq i$$

In other words, the Global Moran's I is a standardization of spatial autocovariance by the variance of the attributes, therefore the index takes values from -1 to 1.

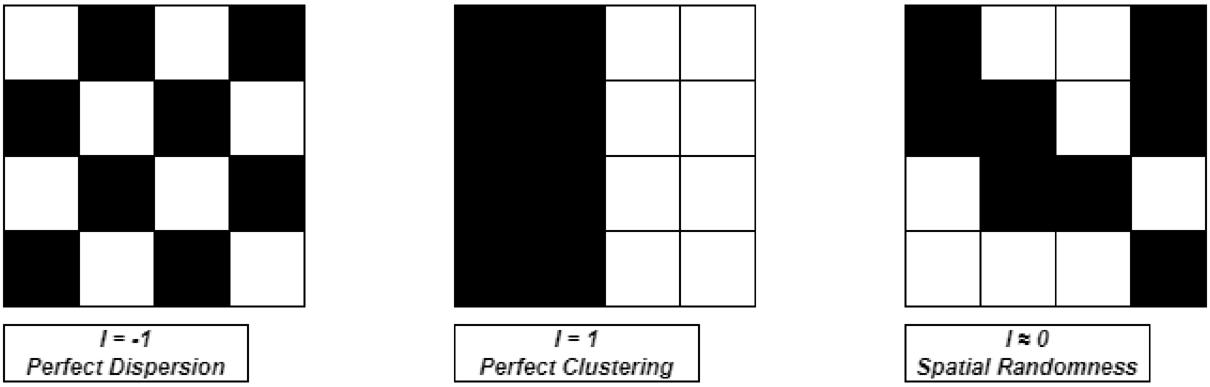

Figure 3 - Illustration of Global Moran's I Meaning

The "Spatial Autocorrelation" tool of ArcGIS performs the described calculation, finds the Global Index value and the Expected Index value. Further, given the number of locations and the variance of the attributes, the tool determines whether the difference between the expected and observed values is statistically significant using the z-score and the p-value.

The Global Moran's index characterizes the entire input field with a single statistic. However, assuming that the effect is consistent across all regions in insufficient for answering the research questions. Therefore, clusters of high and low attribute values as well as spatial outliers will be identified using the Local Indicators of Spatial Association (LISA). As described by Anselin (1995), LISA is a statistic that "*for each observation gives an indication of the extent of significant spatial clustering of similar values around that observation*".

In ArcGIS cluster analysis is performed with the help of Local Moran's I:

$$I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1}^{n} w_{i,j} \left(x_j - \bar{x} \right), j \neq i$$

Where w – spatial weight between locations;
x – location attribute;
$\bar{x}$ – attribute mean;
n – total number of locations;
$S_i^2 = \frac{\sum_{j=1}^{n} (x_j - \bar{x})}{n-1}, j \neq i$

Here the spatial weights are typically assigned with a row standardized matrix such that for each location only neighbouring elements have non-zero entries (Anselin, 1995). The positive value of I indicates that the given location is surrounded by other locations with similarly high (or low) attribute values. The negative value of I indicates that the location has neighbours with unmatching attribute values (spatial outliers). The associated z-score and p-value for each location are also calculated and only statistically significant clusters are considered (ArcGIS, 2021). Using such local index allows to distinguish between the following types of clusters: High-High (high value with primarily high neighbouring values), Low-Low (low value surrounded by primarily low values), High-Low (high value with primarily low neighbouring values) and Low-High (low value surrounded by primarily high values) (Figure 4).

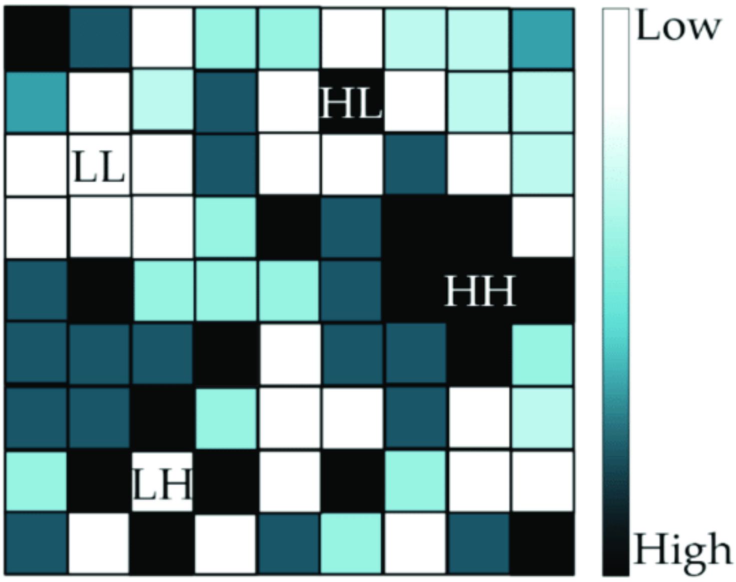

Figure 4 - Four types of clusters identified by Local Moran's I

Using the outcome of the described statistics it is possible to visualise the origin/destination clusters.

Relation between shared bicycles and public transit

The role of the sharing service in relation to public transport was determined by dividing all trips into 4 categories based on the closeness of their origins and destinations to transit stops.

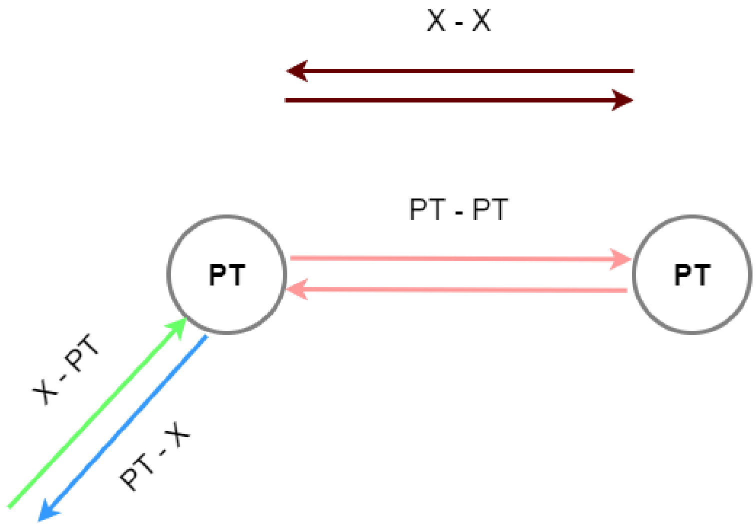

Figure 5 - Types of trips in relation to PT stops

The first category (PT-PT) represents the routes that have started and ended in the proximity of a transit stop and could therefore alternatively been made by means of public transport. This category is marked “competitive”. The next two categories (PT-X and X-PT) represent the routes where only the origin or only the destination was in close proximity of a transit stop. These types of trips are considered to serve as a solution of a first/last mile problem and are therefore marked “complementary”. The fourth category (X-X) represents the routes which are unrelated to the locations of transit stops.

Results

Trip Characteristics

The initial dataset consisted of 15320 entries, after cleaning the data from corrupted records, 14790 were left remaining.

Travel times

Travel times were derived by subtracting the start timestamp from the end timestamp. The sample median is 20 minutes. For comparison, a research of shared bicycle trip data in New York (Sokoloff, 2018) has found 10 and 16 minutes to be the 50th and 75th percentiles respectively. The sample is likely skewed by a considerable amount of abnormally long trips, some of which may have been caused by an error, however they can also be explained by *Donkey Republic* offering several "Day Deal" rental discounts and long term lease plans.

Percentile	***Trip duration [min]***
1%	*4*
5%	*6*
10%	*8*
25%	*12*
50%	*20*
75%	*46*
90%	*390*

Table 2 - Shared bicycle trip duration

Idle times

Similarly, the idle times were determined from the "Parking events" dataset. The median is 11.5 hours. Most bikes are not used during the night with many remaining idle for several days.

Percentile	***Idle time [min]***
1%	*5*
5%	*20*
10%	*45*
25%	*150*
50%	*690*
75%	*1730*
90%	*5060*

Table 3 - Shared bicycle idle time

Trips per bicycle

The number of unique bicycles in the dataset, 906, was determined through the "bike_id" identifier. Consequently, the number of trips per bike was found. The median is 16 trips per month, the "busiest" bicycle has completed 48 trips per month.

Percentile	***Number of trips***
5%	*2*
10%	*4*
25%	*8*
50%	*16*
75%	*22*
90%	*30*
99%	*40*

Table 4 - Number of trips per shared bicycle in September 2021

Trip distance

Reconstructing the exact routes from the provided dataset was not possible, therefore the Euclidean trip distance was found by converting the earth-centered coordinates (WGS-84) into cartesian coordinates and subsequently applying the formula of distance between two points:

$$D = \sqrt{(x_{dest} - x_{origin})^2 + (y_{dest} - y_{origin})^2 + (z_{dest} - z_{origin})^2}$$

Where $$x = R\cos(\frac{\pi * lat}{180^{\circ}})\cos(\frac{\pi * lon}{180^{\circ}})$$

$$y = R\cos(\frac{\pi * lat}{180^{\circ}})\sin(\frac{\pi * lon}{180^{\circ}})$$

$$z = R \sin(\frac{\pi * lat}{180^{\circ}})$$

$$R = 6371\ km$$

The results are presented in figures below:

Percentile	*Trip distance [km]*
5%	*0.01*
10%	*0.04*
25%	*0.75*
50%	*1.58*
75%	*2.63*
90%	*3.53*
99%	*6.01*

Table 5 - Shared bicycle trip distance

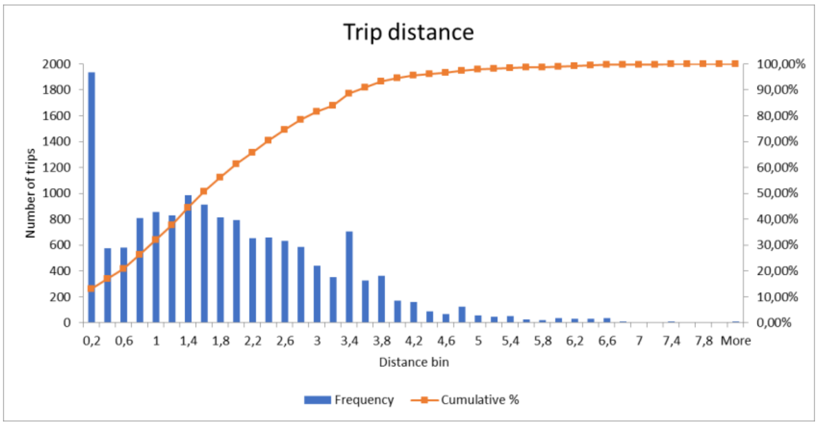

Figure 6 - Trip distance histogram

The sample median is 1.58 km. It is safe to assume that the actual route distances are longer due to the layout of the street network. Besides that, close to 20% of trips have an unrealistically short distance (<0.5 km). It is likely many of those are "round" trips, where a user returned the bicycle to the pick-up location or close to it. Unfortunately, the real lengths of such trips cannot be known.

Temporal characteristics

Lastly, the usage of the shared bicycle service was investigated with respect to days of the week and hours of the day.

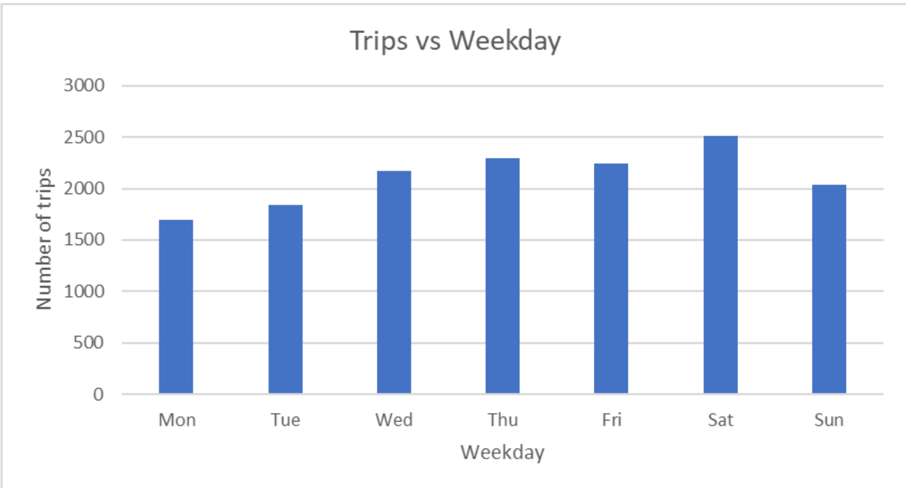

Figure 7 - Number of trips on individual weekdays

The service is most used on Fridays and Saturdays (2238 and 2512 total trips respectively). According to the graph above, demand for the service was also above average on Wednesdays and Thursdays, however this can be explained by the fact there were 5 Wednesdays and Thursdays and 4 of each other weekday in September 2021.

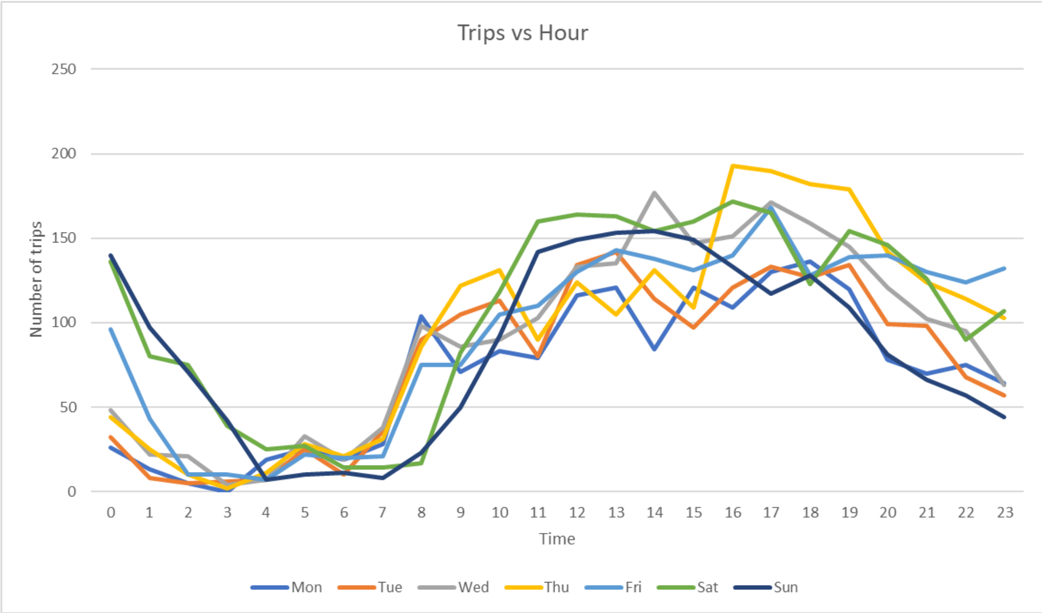

Figure 8 - Shared bicycle usage throughout individual weekdays

The morning and evening peaks are not distinctive with demand remaining steady between 11:00 and 20:00. The night peak (23:00 to 01:00), on the other hand, is clearly visible, especially during Fridays, Saturdays and Sundays.

Spatial Clusters

The locations of trip origins and destinations were exported to ArcMap and plotted on the map. The Global Moran's spatial autocorrelation test has indicated a clustered pattern (Figure 9).

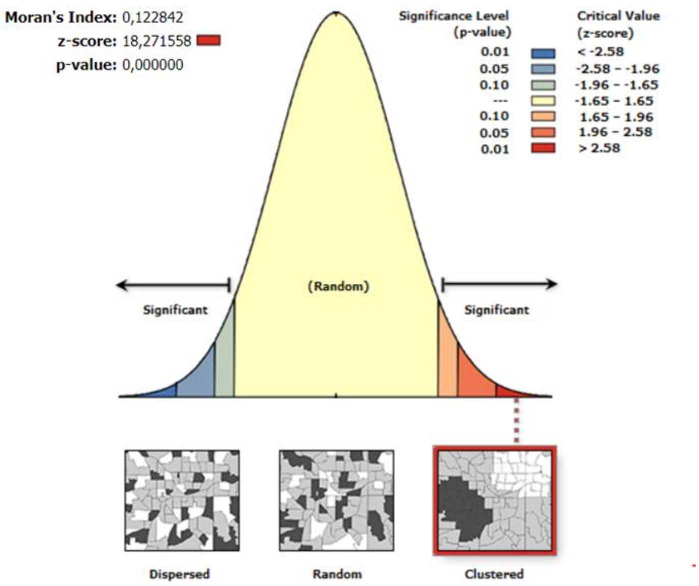

Figure 9 - Spatial autocorrelation test results

The points were then aggregated into hexagons (200 m. side-to-side height) and visualised in the form of a heatmap (Figure 10).

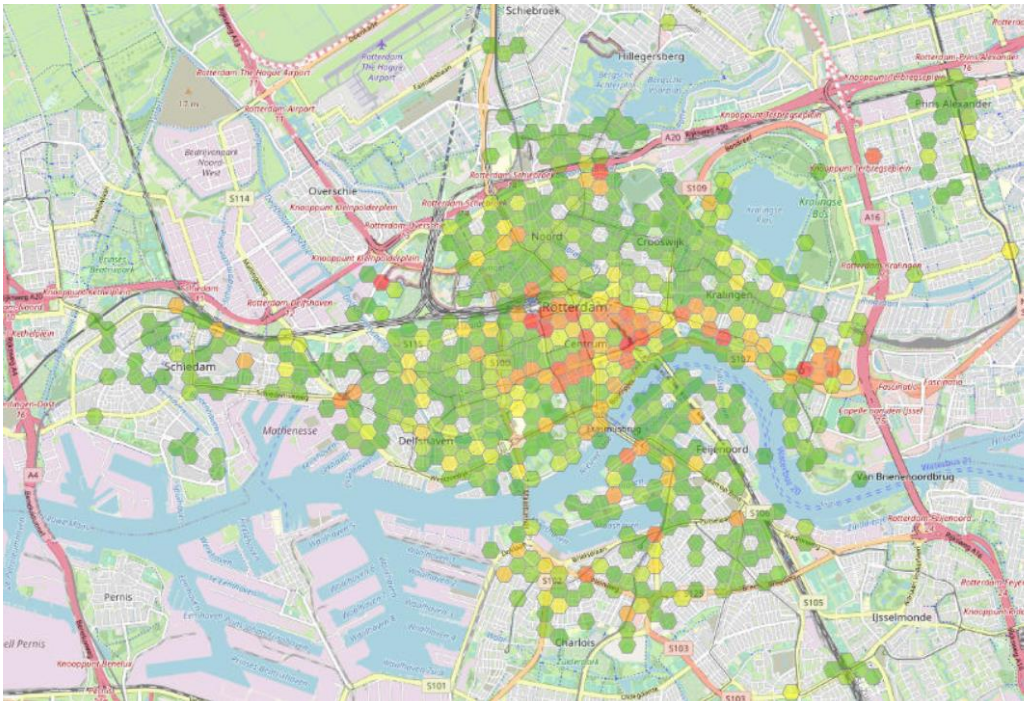

Figure 10 - Origin/Destination heatmap

The highest demand for the service is observed in the central district of the city, specifically near stations Rotterdam Centraal, Beurs, Blaak and Oostplein as well as on campus of the Erasmus University, situated in the East of the city.

Next, the Local autocorrelation statistic was used to identify spatial clusters (Figure 11).

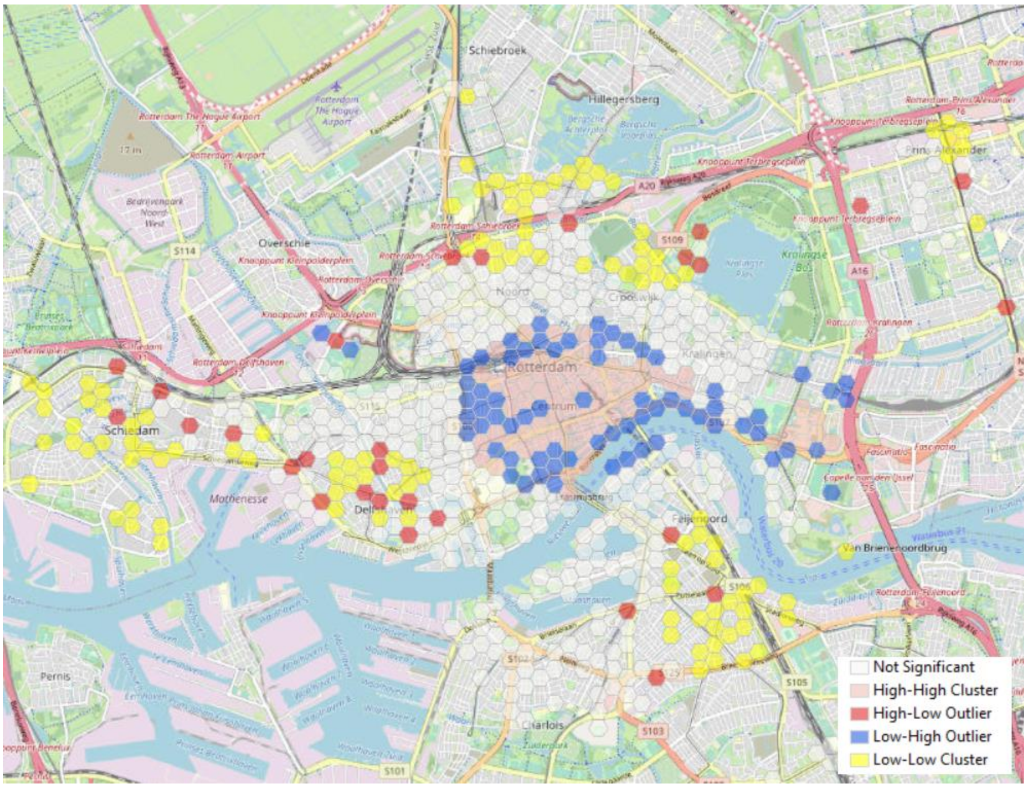

Figure 11 - Origin/Destination spatial clusters

The test has highlighted locations in the non-central districts where bicycles are picked up or left most often (High-Low outliers). Among them are Schieplein (residential area), Rotterdam Noord (train station), Kralingse Bos (recreational area), Oosterflank (metro station), Schenkel (metro station), Vuurplaat (tram stop, close to Rotterdam Zuid train station), Maashaven (metro station), Zuidplein (residential area and shopping center), Delftshaven (metro station), Marconiplein (metro station), Rotterdam Zoo (recreational area) and Schiedam Centrum (train station).

Shared Bicycles and Public Transport

Using the *Openstreetmap* database the locations of bus stops, tram stops and railway stations (train and metro) were exported to ArcMap. The distribution of bicycle trips' origins and destinations was then investigated with respect to individual public transit modes as well as a combination of all transport options. Upon the first examinations it became clear that the results are significantly influenced by how proximity of a station is defined. If the "search radius" is set to a low value (<30 m), very few points fall within it, however if the "search radius" is set to a high value (>200 m) practically any point is guaranteed to fall within it due to high density of transit stops in the city. Through visual inspection of a large sample of bus and tram stop locations on Google Maps it was decided that there is sufficient bicycle parking space in a 50 m. radius around these stops. Defining the proximity of a train or metro station was slightly more complicated as the locations of these stations in *Openstreetmap* typically coincide with the middle of the platform surrounded by railway tracks, inaccessible for cyclists. The entrances to railway stations can usually be found at a distance up to 50 m. away from the platform, therefore a "search radius" of 50 + 50 = 100 m. was taken for reference.

Figure 12 - Visualisation of a 50 m. search radius around a bus stop

Figure 13 - Visualisation of a 100 m. search radius around a train station

Due to uncertainty associated with the reliability of selected "search radiuses" an additional metric "complementary to competitive trip ratio" (CCR) was used. The results are presented in figures below (Results obtained using different values of search radius can be found in Appendix B).

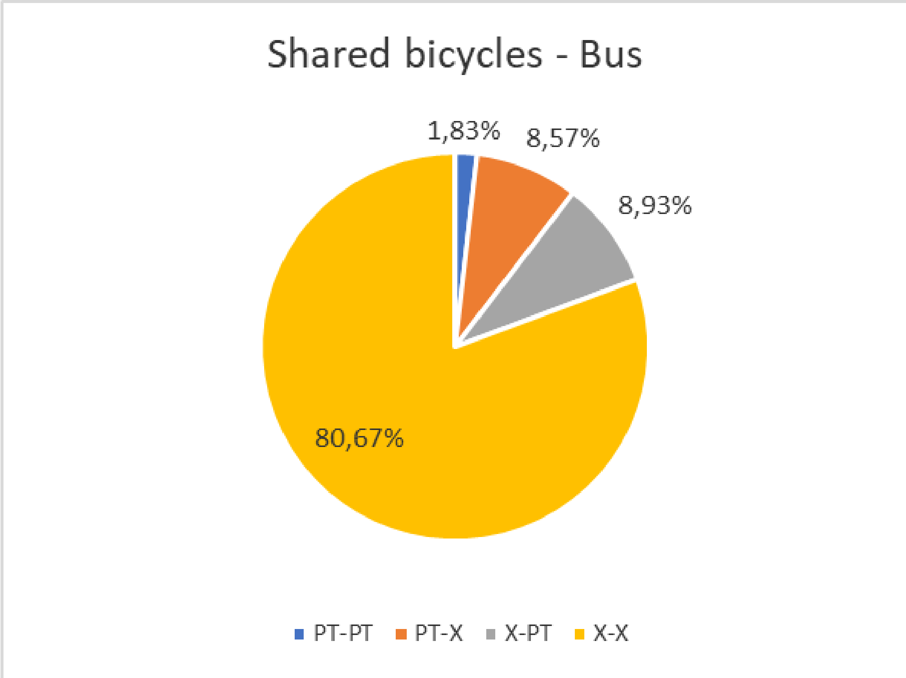

Figure 14 - Role of shared bicycles in relation to public buses (50 m. search radius), CCR = 9.54

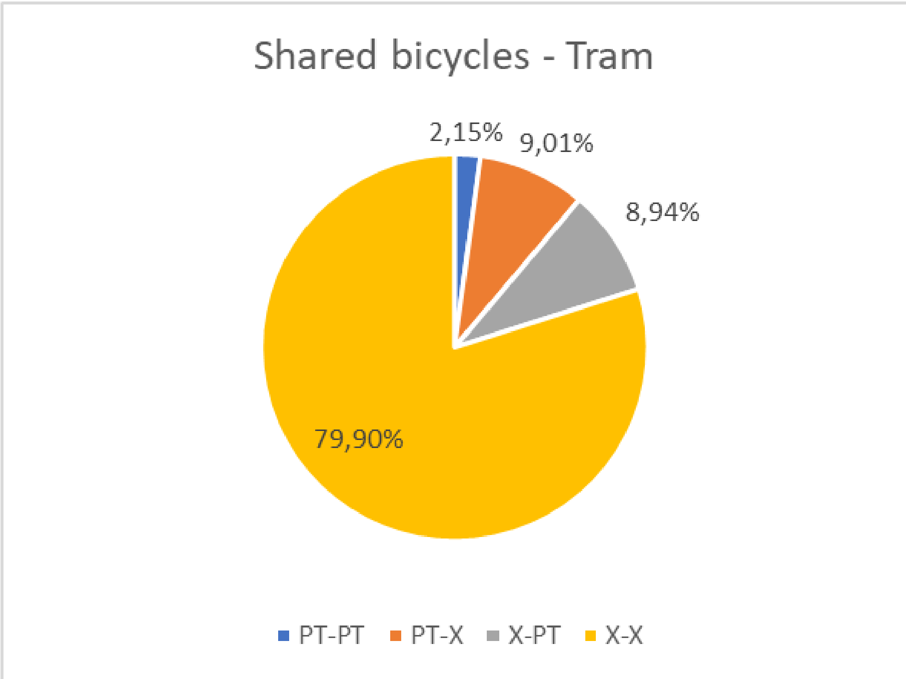

Figure 15 -Role of shared bicycles in relation to public trams (50 m. search radius), CCR = 8.36

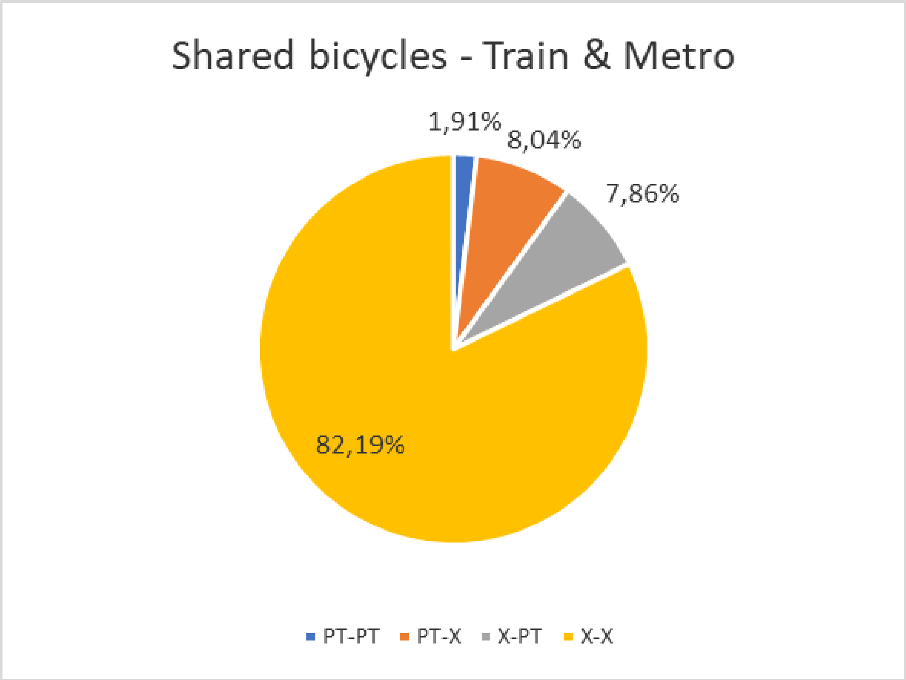

Figure 16 - Role of shared bicycles in relation to public trains and metro (100 m. search radius), CCR = 8.31

When evaluating the function of shared bicycles with regards to separate public transport modes, it can be seen that over three quarters of trips in each case are unrelated to the locations of transit stops. Out of trips that have originated and/or ended near a transit stop, the majority are categorized as "complementary" (PT-X or X-PT). The values of CCR fall between 8 and 10, which indicates that only a small fraction of trips is competitive to aforementioned transport modes.

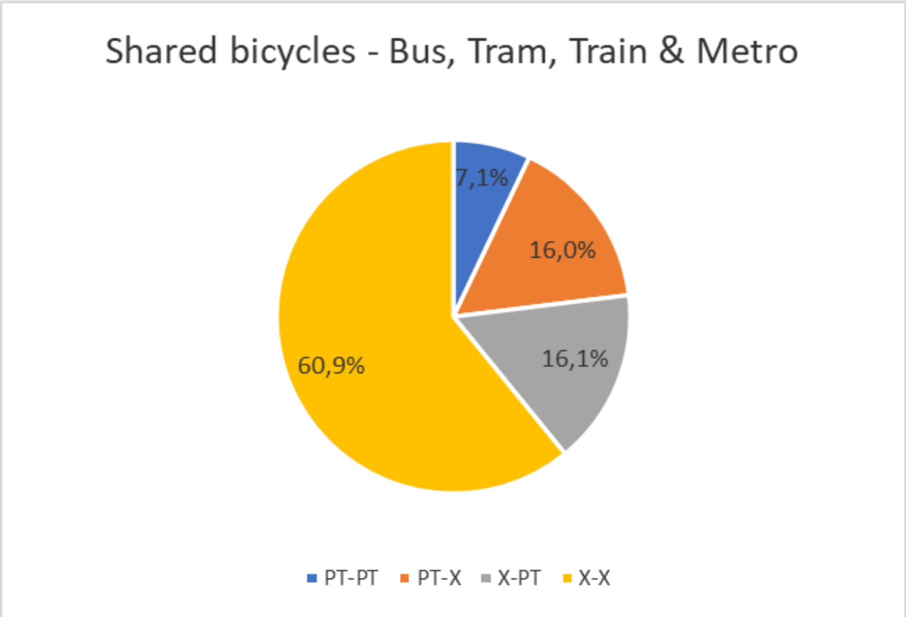

Figure 17 - Role of shared bicycles in relation to public trains and metro (50 m. search radius), CCR = 4.53

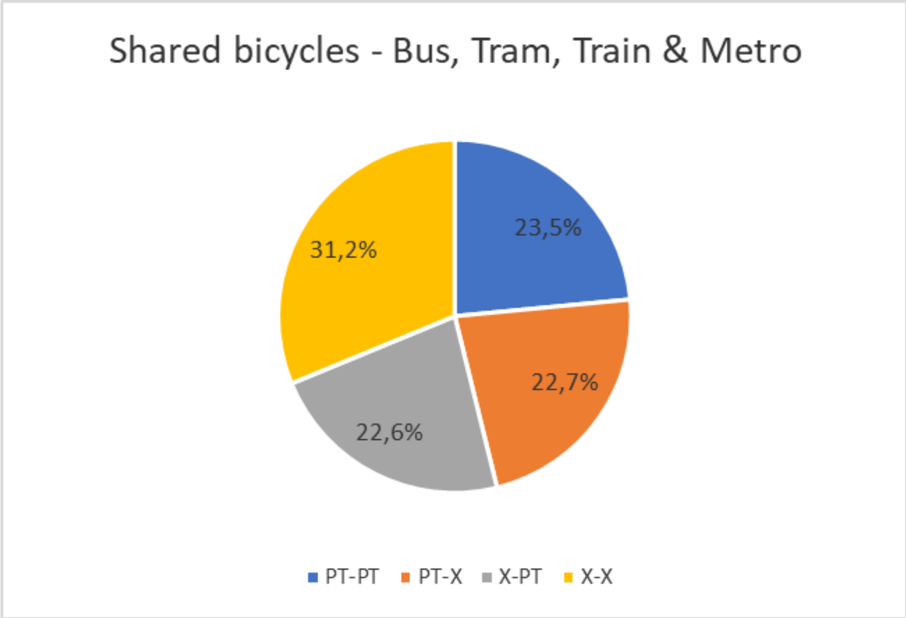

Figure 18- Role of shared bicycles in relation to public trains and metro (100 m. search radius), CCR = 1.93

After the locations of all public transport modes have been combined, the trip types were derived for both 50 m. and 100 m. search radiuses. While the category “X-X” is most prevalent in both scenarios, the fractions of respective categories observed in the two cases are completely different. An increase of the search radius results in more trips being linked to transit stops and thus inflating the “competitive” and “complementary” categories. One observation consistent across all cases is a nearly even split between “PT-X” and “X-PT” categories. This phenomenon possibly indicates that these trips are made by the same group of users. In other words, commuters who have, for example, used a shared bicycle on their way from home to the transit station are likely to use it again on their way back. In each scenario the “complementary” trips are dominating the “competitive” trips, however the value of CCR is dropping with an increase of the search radius (Figure 19).

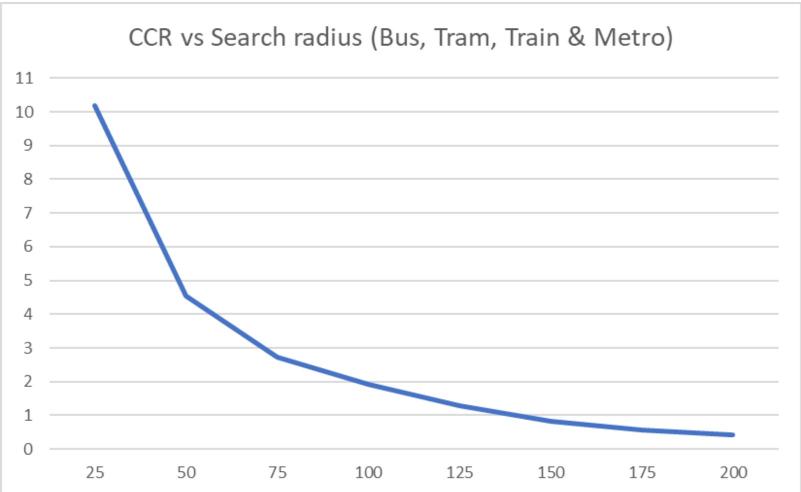

Figure 19 - CCR vs Search radius

The distribution of trip types at different times of the day was then investigated by aggregating the trips into 1-hour bins. It was expected that more “competitive” trips would be observed at night, when no public transport is available or during rush hours, when public transport is overcrowded. However, this assumption was not confirmed (Figure 20).

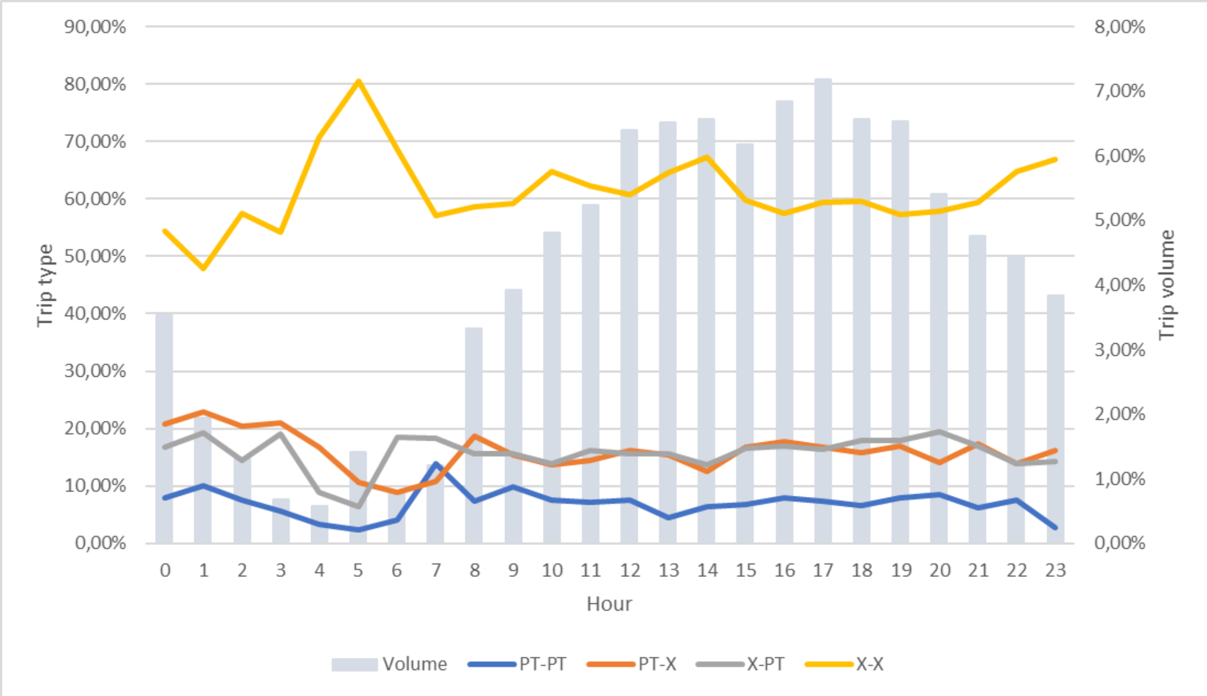

Figure 20 - Distribution of trip categories throughout the day (50 m. search radius)

As it can be seen from the graph, the distribution is fairly consistent throughout the day. Minor alterations of the trend are indeed occurring between 00:00 and 07:00, although this phenomenon can be explained by a relatively small sample size of trips during night time.

Conclusion and Recommendations

The goal of the assignment was to derive the spatiotemporal characteristics of shared bicycle usage in Rotterdam and determine its relation to the public transport network. Trip characteristics were derived from the dataset recorded by *Donkey Republic* service provider in September 2021 (14790 trips total). The spatial clustering of trip origins and destinations as well as proximity to public transit stations was analyzed using the ArcGIS software.

RQ1 What are the spatiotemporal characteristics of free-floating shared bicycle usage?

The analysis of travel times has yielded ambiguous results: the sample mean was found to be 20 minutes with more than two-thirds of all trips taking less than 30 minutes, which shows a trend towards short commutes. However, extreme travel time values were also present in the dataset with some records registering several days between bicycle pick-up and return. These values can be explained by the fact that the service provider offers discounts on long-term rental, thus it is possible that some commuters have been continuously using the same bicycle over a long time period.

The trend towards short trips was reinforced by the analysis of travel distances: the median value was 1.58 km and the longest recorded trip was 8 km. Due to impossibility to reconstruct the routes in detail (only start and end coordinates were available), Euclidean distance was used in the analysis. Unlike the range of travel times, skewed by extremely high values, Euclidean distances are an underestimation of actual trip lengths. First of all, this method assumes that cyclists are travelling in a straight line between their origin and destination rather than following the road network. Secondly, some users have picked up and returned their bicycle at the same location, which results in a very short Euclidean distance, while the real travel distance in this case is unknown. The maximal observed travel distance (~8 km.) can be explained by geofencing: bicycles can only be returned in the boundaries of a city and 8 km. is just about the longest possible distance between a pair of points in Rotterdam.

Higher demand for the sharing service was observed on Fridays and Saturdays with the majority of trips carried out between 11:00 and 20:00, yet the spatial patterns remained consistent during any time period. The majority of recorded trips have originated in Rotterdam Centrum (~37% of all trips) and adjacent districts Kralingen-Crooswijk (19%), Rotterdam Noord (12%) and Delftshaven (11%).

RQ2 Are origins and destinations of shared bicycle trips correlated with the locations of potential mobility hubs?

The cluster-outlier analysis of origins and destinations has shown a concentration of High-High clusters in the centre of the city with most distinctive hotspots being large transit stations: Rotterdam Centraal, Beurs and Blaak, all of which are suitable Mobility Hub locations. Another origin-destination hotspot was the campus of the Erasmus University. The density of origins and destinations outside the central districts was significantly lower. The High-Low outliers could typically be found near train and metro stations such as Rotterdam Noord, Oosterflank, Maashaven, Delftshaven, Marconiplein and Schiedam Centrum. Development of Mobility Hubs at these locations would help better integrate shared bicycles with public transport.

RQ3 Are shared bicycles competing or complementing existing public transit modes?

The analysis of shared bicycles' role with respect to public transport was very sensitive to the set-up of the experiment. Two scenarios were evaluated: in the first case origins and destinations located at a distance up to 50 m. away from a certain station were linked to it, in the second case this distance was set to 100 m. In the first scenario 32% of trips were classified as "complementary" and 7% were classified as "competitive" with the remaining 61% being unrelated to transit stops. In the second scenario the fractions were 45%, 24% and 31% respectively. The findings indicate that shared bicycles are primarily functioning as an independent service. Due to high density of various transit stops in Rotterdam, especially in the city center, some of the trips may have been falsely categorized as “complementary” or “competitive“. Certain users may have had no intention to use public transport neither before, nor after their ride even though their trip origin or destination accidentally happened to be in the proximity of a transit stop. Therefore, in reality the fraction of unrelated trips is probably higher than was calculated. Nevertheless, it can be stated that “complementary” trips occur more often than “competitive” ones and the shared bicycles are providing a partial solution for the first/last mile problem.

Recommendations for further research include:

1. Conducting an analogical study aimed at understanding the trip characteristics and spatial clustering of other shared mobility services (e-bikes, scooters, mopeds). The volume of trips made by shared bicycles is negligibly low compared to the volume of trips made by public transport, thus it is important to take the usage patterns of different mobility services into account when selecting a Mobility Hub location. Besides that, the focus groups of the aforementioned mobility services are likely different from the shared bicycles’ target audience, therefore different usage patterns may be observed.

2. Conducting a stated choice experiment on the attitude of (potential) users towards various shared mobility services aimed at understanding the factors influencing commuters’ choice of transportation mode. As seen from the study, numeric evaluation of shared service’s interaction with public transport can be unreliable and the available information is not enough to describe the travel purpose in detail. It would be useful to know under which conditions are commuters more (or less) likely to use a certain transport mode.

3. Research the competition between various micromobility service providers and the development of micromobility services as a whole in the region. Such research would help predict the volume of trips made by shared services in the future, estimate the impact of these services on car ownership and facilitate the development of required infrastructure.

References

Aihua Fan, Xumei Chen , Tao Wan, 2019. How Have Travelers Changed Mode Choices for First/Last Mile Trips after the Introduction of Bicycle-Sharing Systems: An Empirical Study in Beijing, China, Journal of Advanced Transportation

Anselin, L., 1995, Local Indicators of Spatial Association—LISA. Geographical Analysis, 27: 93-115.

Arias Molinares, Daniela & Romanillos, Gustavo & García-Palomares, Juan & Gutiérrez, Javier., 2021. Exploring the spatio-temporal dynamics of moped-style scooter sharing services in urban areas. Journal of Transport Geography.

Aritra Pal, Yu Zhang, 2017. Free-floating bike sharing: Solving real-life large-scale static rebalancing problems, "Transportation Research Part C: Emerging Technologies", Volume 80, 92-116.

F. Torabi K, Yashar Araghi, Niels van Oort, Serge Hoogendoorn, 2022. Passengers preferences for using emerging modes as first/last mile transport to and from a multimodal hub case study Delft Campus railway station, Case Studies on Transport Policy, Volume 10, Issue 1, 300-314.

Geurs, K., Münzel, et al., 2021. A multidimensional mobility hub typology and inventory.

Geurs, Karst & Puello, Lissy, 2015. Modelling observed and unobserved factors in cycling to railway stations: Application to transit-oriented-developments in the Netherlands. European Journal of Transport and Infrastructure Research. 15. 27-50.

Grosshuesch, K., 2020. Solving the First Mile/ Last Mile Problem: Electric Scooter and Dockless Bicycles are Positioned to Provide Relief to Commuters Struggling with a Daily Commute.

Liao, F., & Correia, G., 2019. State-of-the-art related to eHUBS.

Michael Hyland, Zihan Hong, Helen Karla Ramalho de Farias Pinto, Ying Chen, 2018. Hybrid cluster-regression approach to model bikeshare station usage, Transportation Research Part A: Policy and Practice, Volume 115, 71-89.

Municipality of Rotterdam, 2020. Deeltweewielers in Rotterdam.

Municipality of Rotterdam, 2020. Rotterdamse Mobiliteitsaanpak.

Municipality of Rotterdam, 2021. Fietskoers 2025

Okabe, A., Okunuki, K.-i. and Shiode, S., 2006, SANET: A Toolbox for Spatial Analysis on a Network. Geographical Analysis, 38: 57-66.

R. Kager, L. Bertolini, M. Te Brömmelstroet, 2016. Characterisation of and reflections on the synergy of bicycles and public transport, Transportation Research Part A: Policy and Practice, Volume 85, 208-219.

Ronik Ketankumar Patel, Roya Etminani-Ghasrodashti, Sharareh Kermanshachi, Jay Michael Rosenberger, Ann Foss, 2022. Mobility-on-demand (MOD) Projects: A study of the best practices adopted in United States, Transportation Research Interdisciplinary Perspectives, Volume 14.

Sokoloff J., 2018. How far do people commute using Bike Sharing Systems? An analysis of 2017 Citibike trip distance

Ting Zuo, Heng Wei, Na Chen, Chun Zhang, 2020. First-and-last mile solution via bicycling to improving transit accessibility and advancing transportation equity, Cities, Volume 99.

Yi-Hsuan Wu, Lei Kang, Yu-Ting Hsu, Po-Chieh Wang, 2019. Exploring trip characteristics of bike-sharing system uses: Effects of land-use patterns and pricing scheme change, International Journal of Transportation Science and Technology, Volume 8, Issue 3, 318-331.

Zhao D, Ong GP, Wang W, Zhou W. Estimating Public Bicycle Trip Characteristics with Consideration of Built Environment Data. Sustainability. 2021; 13(2):500.

Zhili Liu, Xudong Jia, Wen Cheng, 2012. Solving the Last Mile Problem: Ensure the Success of Public Bicycle System in Beijing, Procedia - Social and Behavioral Sciences, Volume 43, 73-78.

Appendix A – Histograms of Travel and Idle Times

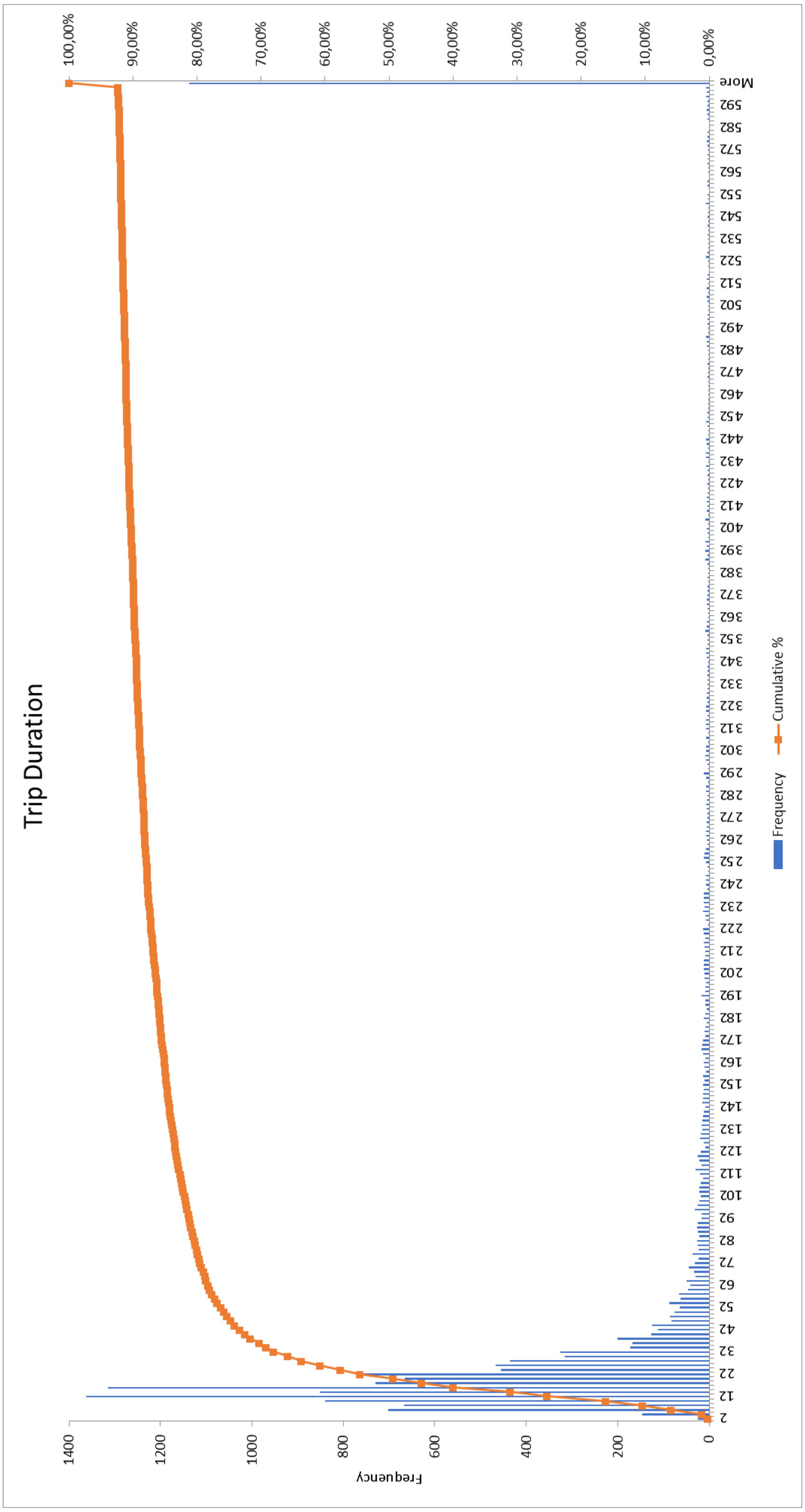

Figure 21 - Histogram of travel times

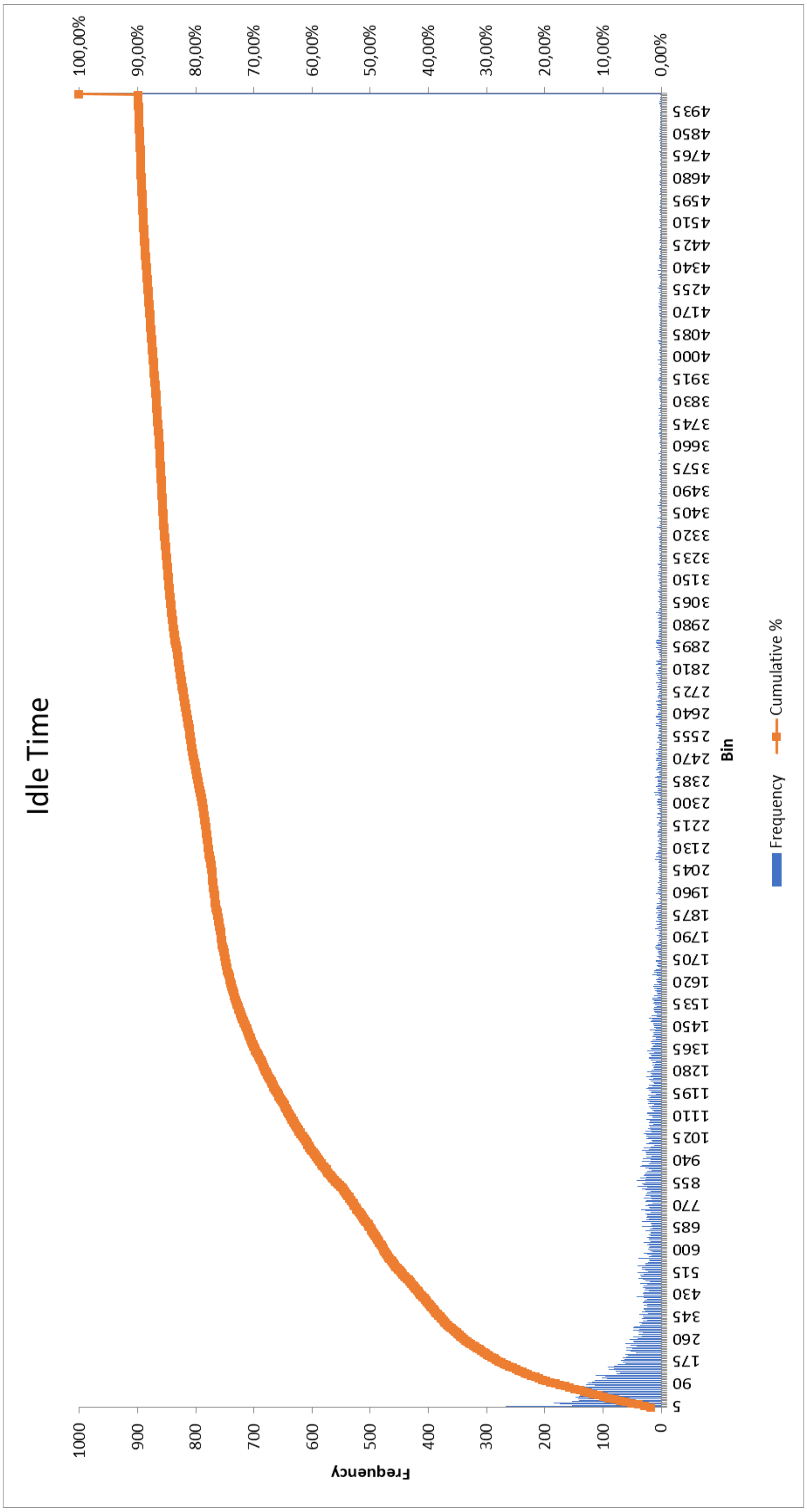

Figure 22 - Histogram of idle times

Appendix B – Relation to public transport for different values of Search Radius

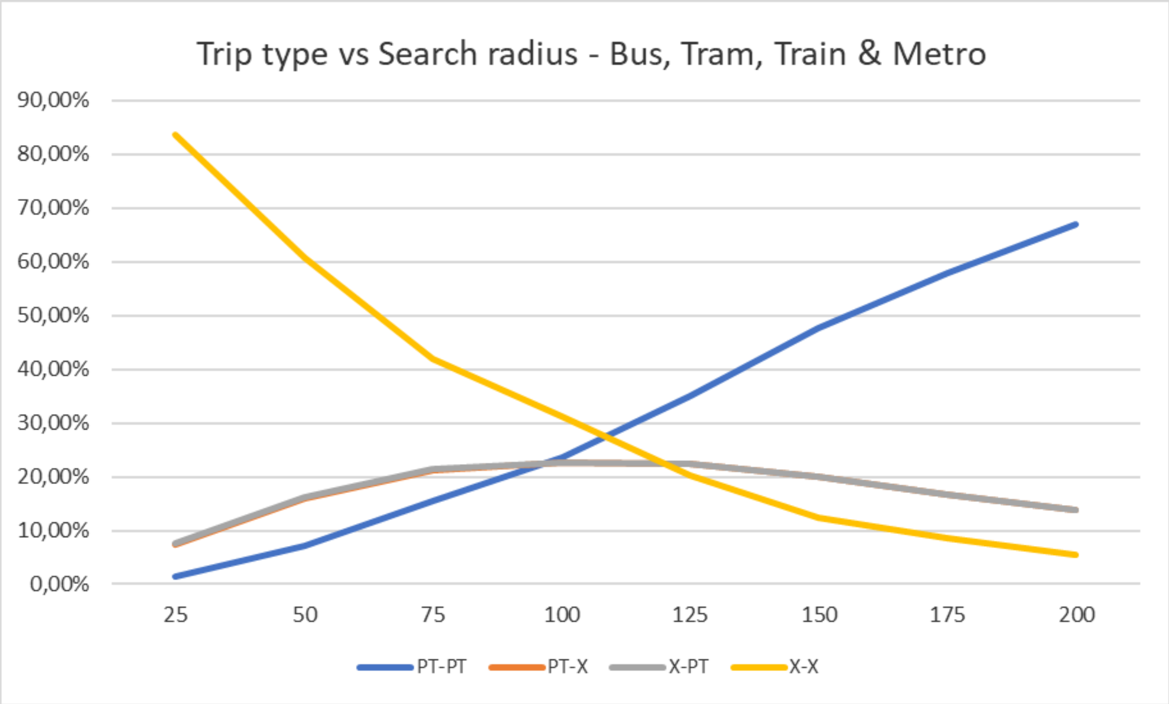

Figure 23 - Distribution of trip types at different values of Search Radius

Appendix C – Origin-Destination matrices

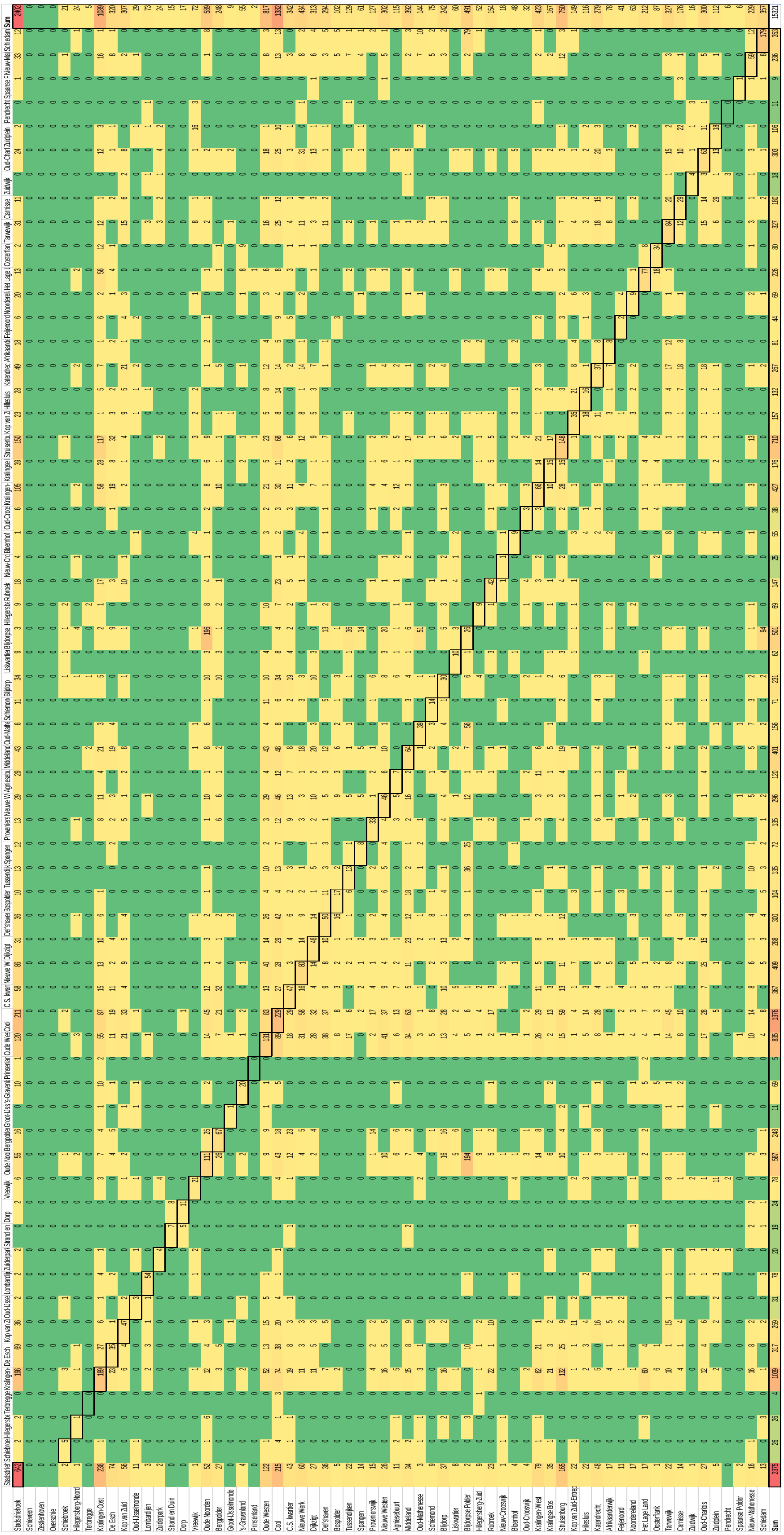

Figure 24 - Complete OD matrix of trips between neighbourhoods of Rotterdam

		Centrum	Noord	Delftshave	Feijenoord	Kralingen-	Schiedam	Other	Sum		Inflow	% Interzonal
ORIGINS	Centrum	2722	444	658	379	1071	34	382	5690	37,14%	-40	47,84%
	Noord	444	874	221	32	157	91	53	1872	12,22%	12	46,69%
	Delftshave	616	216	584	51	150	40	71	1728	11,28%	43	33,80%
	Feijenoord	392	46	45	407	69	1	193	1153	7,53%	-11	35,30%
	Kralingen-	1081	151	176	82	1267	6	190	2953	19,27%	-74	42,91%
	Schiedam	33	101	26	5	1	179	12	357	2,33%	-4	50,14%
	Other	362	52	61	186	164	2	741	1568	10,23%	74	47,26%
	Sum	5650	1884	1771	1142	2879	353	1642	15321			

DESTINATIONS

Figure 25 - Simplified OD matrix