  
  
**GIS for smart parking**   
Masterthesis Collin Cooper – *Final version, August 16, 2018*

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# Abstract

**GIS for smart parking  
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This thesis is about the phenomenon of parking in the city. Cities and especially bigger cities in The Netherlands, like Amsterdam and Rotterdam, have a relatively high number of visitors coming with their car every day. Because of scarcity of space in such areas this can lead to a parking issue such as not be able to park your cat at a desired location. Driving around looking for an alternative spot has negative environmental issues because of emmissions.   
 The role of Geographical Information Systems (GIS) in this thesis, is that GIS are used to acquire parking data and to provide analytical- and scripting tools. GIS have been applied in this research field before, however, the emerging availability of open and realtime parking data gives new opportunities in analyzing parking dynamics.  
  
 The aim of the thesis is getting insights in the dynamics of local parking systems. Which trends can there be identified? These trends are then put into models, which can be used in a system that predicts parking occupancy at a certain moment in time. The benefit of such system is that it triggers actions to be taken to prevent cars for driving to a full car park. The degree of emmissions are limited if cars are directed efficiently to available parking spots.

Four different locations within the city center of Rotterdam are compared for exploring the dynamics in parking. Multiple models are developed depending on different variables: land-use and accessibility to public transport. Also the variables day, time and rainfall were tested on significance. With the exception of the latter these variables were significant and incorporated in the research. When comparing the models it turned out that the investigated land-uses showed different curves with peaks at a different moment during the day and having peaks at different days. Comparing these models to comparable areas in Amsterdam, resulted in the conclusion that each location has its own characteristics where different mechanisms are determing parking dynamics. Even if the land-uses are comparable, an area in general does not consist completely of just one land-use. Every person has its own motivations for parking their car, that does not mean someone is there for shopping or working but he or she can also park there because they are visiting a friend or park their car for continuing the trip by public transport to a different destination.   
  
 The thesis also provides a system that can use prediction models to estimate when a parking area gets full in the near future. With this information, drivers can be directed to a different parking area where likely there are still available parking spots left. This limits emmissions that are produced by cars because it can prevent people ‘cruising’ around looking for a place to park. Parking data that are freely available are key for the developments of such prediction systems. Also technological developments for the collection of outdoor parking are important because outdoor parking data combined with indoor parking data gives a more complete view of parking dynamics in an area.

# Preface

Before you, lies the dissertation “GIS for smart parking”. It has been written to fulfull the graduation requirements of the masterprogramme Geographical Information Management and Applications (GIMA). I was engaged in researching and writing this dissertation from the beginning of 2017 until September 2018. This is relatively long compared to fellow students. The reason for this is that I was offered a job at the company that offered me an intership, Royal HaskoningDHV (RHDHV), in the period before writing this thesis. Despite that since my time at RHDHV I gained practical knowledge in the field of GIS and as a professional, it turned out to be difficult to combine my work for RHDHV and my work for the thesis.   
 A passion for cities and its accessibility encouraged to me to chose this subject (parking). When I know I must go a city I have never been before, I will always try to plan it. I am not only comparing travel costs and travel time for different modes of transport, but I also look at the parking capacity in the area. This is important for me because I tend be latish for appointments, so knowing where most parking spots are can be very helpful and de-stressing. By also having data about the real-time occupancy would be next-level. If people in the future will be able to look into parking occupancy data for every street and platforms are developed to accommodate this, of course a huge role will be being there to be furfilled by geographical information and GIS.   
 The people that I am trying to target with this dissertation are first people who are interested in the mobility- and accessibility domain and who are also interested in developments in IT trying to cope with long running issues in this domain. The thesis can also be a call to companies associated with parking and governments to make their data freely accessible. Open data can catalyze new ideas for IT parking solutions.   
 I would like to thank several people that have helped me in the period of writing my thesis. First, prof. dr. Stan Geertman, who has provided me of tips and feedback. Secondly, the company I am currently working for, RHDHV, and particularly, Yvo de Witte, who was my mentor during my internship. He has provided me of tips, feedback and has arranged contacts with the Municipality of Rotterdam. I would also like to thank them for sharing useful parking data. Last but not least, I also would like to thank my parents and girlfriend who have been carrying me through some difficult moments. Not only while writing this thesis but during my whole academic career.   
  
I hope you enjoy your reading.  
  
Collin Cooper

Nijmegen, August 7, 2018

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# 1. Introduction

In this chapter, the research is introduced. Essential elements of an introduction of a scientific paper are presented in the following order: background, related work, knowledge gap, scope, relevance, research-questions and objectives, and report structure.

## 1.1 Background

Everyone who is in the possession of a car needs a place to park. A place to park when we are at home, at work, shopping and having dinner at a restaurant. And preferably without too much walking distance between the parking place and our destination. In most suburban or rural areas, it in general is not that difficult to find an available spot. However, in downtown areas this often not the case. In these areas, the demand for a parking spot is often higher because of amenities that are close-by. Because space is often scarce here there is also a quite limited parking capacity. However, this does not always have to be the case since people in downtown in general areas have better access to public transport and this could control car use and car ownerships. Nevertheless, the demand is high because on a daily basis a lot of people pay a visit to shop, recreate and to live. For most suburban areas this situation is probably unthinkable. One could say that the availability of parking space is dependent on its location. Parking dynamics are also dependent on time. Looking for a vacant space in a city center will probably be a more difficult task on an afternoon than during midnight.  
  
 It is likely that parking issues will become more commonplace in the future. It is forecasted that the traffic congestion will increase in Dutch cities. Especially regions that have a high population density like the Randstad-region in The Netherlands, but also smaller metropolitan areas like Eindhoven or Zwolle will be confronted with this issue. The amount of traffic jams will increase around 38 percent within 5 years (CROW, in NOS, 2016). This will be caused by a growing Dutch economy and low fuel costs. The prediction on car usage is confirmed by CPB and PBL, but they state that car ownership will not increase as fast as it did before. The number of cars has doubled since 35 years ago but the next 35 years there will be an increase of 10 or 30 percent (CPB and PBL, 2015).  
  
 Parking problems give a couple of negative consequences. People that are driving around desperately searching for a vacant parking spot, so-called cruisers, are generating problems for the environment, like air pollution and noise increment. It also generates unnecessary traffic load (Tsiaras et al., 2015). The direct consequences for the drivers are a waste of resources, time and sleep deprivation. They have to adjust their departure time to be able to seize that vacant parking space in front of the office (Biddle and Hamermesh, in Bernardino and Van der Hoofd, 2013).  
  
 Fortunately, challenges in parking can count on support of new innovations in information technology. “The Internet of Things (IoT) permeates with the world of parking to streamline processes that deliver intelligent parking solutions, which extend and manage parking inventories.” (Atif et al., 2016). The IoT is using wireless sensors to connect the physical infrastructure involved with parking to information and communication technologies (Atif et al., 2016). The development in the IoT contributes to the idea of cities being smart. “Cities are characterized as “smart” when their transportation and communication (ICT) infrastructures along with their human and social capital investments cooperate and actively support sustainable growth and high quality of life, through participatory action and engagement while preserving natural resources.” (Caragliu, Del Bo & Nijkamp, 2009). The emergence of concepts like smart cities and IoT have encouraged public and private parties to publish some of their data that can help developers to come up with innovative ideas. Facilitating data is done with the hope that it catalyzes these ideas so issues like for instance parking will be reduced, which will have a positive effect on people and environment.

## 1.2 Related work

During the literature study, many articles were encountered that researched the parking phenomenon. The articles can roughly be divided into three categories. The first category focused on the monitoring of parking occupancy. Some articles coming from market parties passed under the review that offer their solution. Examples of such a company is Siemens (2016) that offers a solution that monitors on-street parking occupancy by means of sensors attached to streetlights. Real-time data is then disseminated to operating dashboards or to route-applications for drivers. Another solution created by Siemens is called SPIPARK, a monitoring system for especially off-street car parks that guides drivers to available parking spaces by means of interactive signs. This is just small grasp out of the commercial work out there focusing on offering solutions for monitoring parking occupancy. In contrast, an example of a scientific initiative comes from Nawaz et al. (2013) that proposes a solution for monitoring real-time occupancy of off-street parking by making use of a smart phone’s Wi-Fi signal.  
  
 A different but inseparably group of articles focusses on the prediction of parking occupancy. The articles reviewed here were mainly scientific sources. Hössinger et al. (2014) aimed to predict parking occupancy with sources that could be obtained in real-time: amount of people that parked with use of a mobile parking app, traffic intensity and the counts of short-term parkers. Only mobile parking data was considered as a good predictor, however, when compared to a historical dataset it was found that mobile parking data as predictor performed better on a day there was an event in the study area. Tiedemann et al. (2015) propose a method to predict occupancy by building a historical dataset. Based on the historical dataset prototypes were made with a machine learning method. Lijbers (2016) found that there are significant correlations between rain and occupancy and temperature and occupancy. The day of the week and holidays showed a negative significant correlation. Lijbers (2016) also did a review on significant predictors coming from other articles. He studied 11 articles in which time of the day, day of the week, events, weather and holidays were named most as predictors for occupancy. Historic occupancy, day between holiday and weekend, school holidays, parking lot accessibility and parking price were identified as a predictor in only one or two of the 11 articles. Bock and Sester (2016) have found that also spatial similarities should be considered in the estimation of parking availability next to the temporal similarity. A spatial-temporal approach for estimating parking occupancy is recommended.  
  
 The third category comprises of articles about the guidance of people to available parking spots. Shin and Jun (2014) developed two algorithms that guides drivers to an available parking spot in parking facilities. Its aim is to assign each car to the most appropriate parking facility with respect to a couple of preferences, including estimated driving duration, walking distance from the destination to the parking facility, parking cost and the number of cars heading to the parking facility according to the parking guidance. One of the algorithms guides drivers to a reserved parking place. Tsiaras et al. (2015) developed an application that guides drivers to an available parking spot. A test was performed to compare drivers who were in the possession of this application to drivers who did not have the application. A solution consisting of an integration of the three sub fields was developed by BMW. BMW (in BMWBlog, 2016) has done a project in which movement data from cars were used. Based on these data the availability of a parking space on a certain location can be predicted and the outcome visualized on an on-board display. The data was transmitted by means of vehicle-to-vehicle communication, which is something that does not longer belong to an utopian view on cars because transport systems are becoming more intelligent.

## 1.3 Knowledge gap

What stroked during the literature review is that the articles mainly focused on monitoring- and predicting occupancy and guiding drivers to parking spaces that are either on- or off-street (car parks). It would be interesting to investigate how these two segments of parking interact. Can they be seen as two sets of parking spaces of which their occupancy share comparable, reactive or independent dynamics.   
  
 In addition, The effects of land-use on parking demand is insufficiently examined. Areas with different characteristics and amenities probably have different patterns in parking demand. Something interesting to investigate is to compare parking occupancy patterns with other land-uses within the region and with the same land-use in a different region. Another variable that is insufficiently explored is the influence of available public transport on parking occupancy. It could be the case that parking occupancy is relatively low when the destination location is highly accessible by public transport, because people are encouraged to take travel by bus or train.   
  
 Finally, there is little attention from a GIS-perspective on the field of parking despite that open parking data and technology is available for monitoring, predicting and guiding parking flows. As a GIS-scientist it would be interesting to integrate these three elements into a GIS-system.

## 1.4 Scope

The scope of this research lies in monitoring, predicting and guiding of flows of on- and off-street parking spaces. Cases will be compared that have different land-uses and public transport accessibilities. Another variable that cannot be overlooked and was frequently mentioned in articles is weather or rain. Parking dynamics for the various cases are monitored and subsequently models are created for predicting parking occupancy. These models can then be integrated in a system that can be used by drivers looking for a vacant parking spot.

## 1.5 Relevance

This research provides a method to analyze parking occupancy and shows how to it can be used to inform drivers about vacant parking spaces. For society this can have multiple benefits. First, people will reach a vacant spot faster because they have to ‘cruise’ less if they are informed about it. It gives less irritation because they will not be late for work. Secondly, cruising results in superfluous driving which is unnecessary harmful for the environment. Thus the research contributes to reducing the negative effects of cruising for the environment and local economy.   
  
 The research is also interesting for municipalities because it explores the interaction between on- and off-street parking. Many municipalities, including Rotterdam, are trying to encourage people to park in indoor facilities instead of outside of parking inside. The reasoning behind this is to reduce the amount of parked cars in the street view which creates more space for other land-uses. A mean to stimulate people to park in indoor facilities is to lower the prices here in comparison with the prices for surrounding street parking. This research checks if both segments follow a similar demand curve or a different one that probably is caused by a difference in price.

The prediction models can also be applied in re-routing routines of municipalities. Nowadays most cities have signs that displays the amount of free parking spaces at particular parking facilities. They are often only displaying the at that specific moment but they are not predicting how the situation will be in for example fifteen of thirty minutes. By predicting what the upcoming parking demand will be taking into account the current occupancy gives municipalities the ability to inform drivers about a full parking area on time and to re-route them to an alternative parking area.

## 1.6 Research-questions and objectives

After doing a literature study and formulating the knowledge gap, scope and relevance, the following objectives can be formulated:

* Get insights into the patterns of local parking systems
* Develop a model that describes parking demand
* Get insights in how this model can be applied in a routing system

To achieve these objectives a couple of research-questions are formulated. Starting with the main research-question of the research:  
  
*“What does a system look like that predicts the upcoming occupancy in parking facilities that guides motorists to vacant spaces in these facilities?”*Multiple sub-questions are formulated in order to find an answer to the main research-question. These sub-questions are:

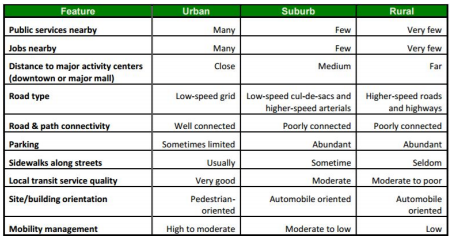
* *Which factors can be identified as influencers of parking demand?*
* *Which models can be developed for predicting parking demand?*
* *How well can the developed models for predicting parking demand be applied in different localities?*
* *How can the models be embedded in a system that routes people to an available parking place?*

## 1.7 Structure of the report

The report follows the following sequence: in chapter 2 the theoretical framework is elaborated. The chapter is a result of a thorough studying of related theories. Subsequently, the methodology to find an answer to the sub- and main question is elaborated. In chapter 4 the results are presented. Chapter 5 reflects reformulates the main question and reflects on the results given in the previous chapter. In the last chapter recommendations are formulated for future researchers and organizations that deal with parking data.

# 2. Theoretical background

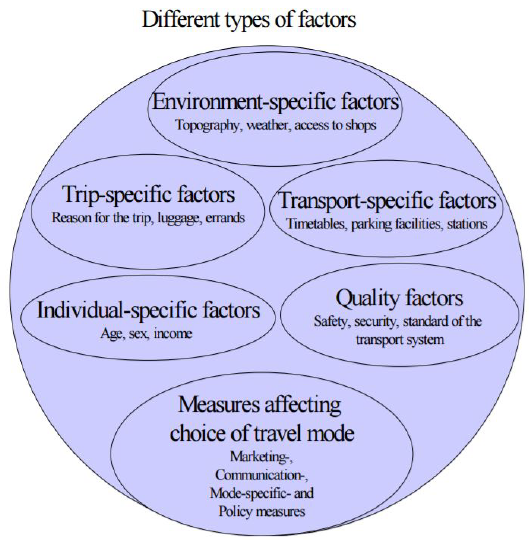
## 2.1. Cities

People visit cities for a wide variety of reasons. Cities are attractive for most people, including visitors, tourists, residents and employees. The relatively large number of amenities that can be found in cities generate travel flows between origins and destinations and vice versa. In general, the attractiveness of cities generates more traffic flows than peripheral areas do. “Land use patterns affect accessibility, people’s ability to reach desired services and activities, which affects mobility, the amount and type of travel activity” (Duranton and Guerra; Litman, in Litman, 2017). Land is used for urban development and accommodating activities. The location of activities and their need for interaction creates the demand for transportation, while the provision of transport facilities influences the location itself (Oduwaye, Alade and Adekunle, 2011).  
  
 City centers or urban areas show a high accessibility. Dalvi and Martin (in Geurs and Van Wee, 2004) define accessibility as “the ease with which any land-use activity can be reached from a location using a particular transport system.” Especially when compared this urban form to others like suburbs or rural areas. Figure 1 shows the differences in land use features between the urban forms. The high accessibility of cities is steered by features the amount of nearby jobs, public services, and distance to major activity centers and the connectivity of roads and path and quality of public transport.  
  
   
 *Figure 1: Land-use features by urban form (Litman, 2017)*

Land use and transport are dependent. According Morimoto (n.d.) “Effective utilization of land stimulates urban activities, and roads and other transportation facilities are maintained so as to allow for new transportation-related activity. Creating new roads or expanding existing ones increases the attractiveness of the land they pass through, promoting new urban facilities” (Morimoto, n.d.). The planning of land use is critical to transport. The places where shops, work and other services are located in relation to where people live is an important factor in determining how much people need or want to travel (**PTEG**, 2011). “Between locations there are potential functional relations describing the demand for the interaction of people. This demand results from the physical aspect of land use.” (Meurs and Van Wee, 2003).

### 2.1.1 Modality choice

Besides land-use influencing the degree of travelling to cities, also modality places an important role. There is a wide variety of travel modes to travel: car, train, bus, etcetera. The availability of travel modes is of course depended on the city one is travelling too. Larger cities tend to have more options in the segment of public transport. For example, the three biggest cities in The Netherlands (Amsterdam, Rotterdam and The Hague) are the only cities having a subway network.  
  
 There are various factors that can influence one’s choice for a specific mode of travel. According to Olsson (2003) these factors can be grouped into 6 categories: environment-specific, trip-specific, transport-specific, individual-specific, quality and measures affecting choice of travel mode (figure 2) In the following an example of each category is formulated in the case of a car-owner that is planning a trip to a city center that offers a wide variety of public transport modes including train, bus, tram and subway. Thus, a choice has to made between by either travelling by car or public transport with the assumptions that the travel distance is too long to walk, and the area of destination is not a car-free zone. An example of an environment-specific factor in this case is the accessibility of the destination from stops or stations. Does the person consider the walking distance from a stop to his/her destination as too far? An example of a trip-specific factor is taking along luggage or not. If someone is planning to buy new furniture it is more practical to travel by car. An example of transport-specific factor is the duration of a trip with a car or public transport. Maybe it is more lucrative to take the train if there has to be travelled during rush hour, or maybe it is better to take the car if a train does not depart frequently enough. Also, individual-specific factors can play a role, of which the income of a person is an example. It is possible that the costs associated with a bus-trip is more expensive compared to carpooling to the destination. A quality example can be the safety of transport modes. Road or train casualties can play a role in determining a transport mode. The last category are measures affecting choice of travel mode. An example of this category are taxes that can be raised on driving. There are proposals for applying ‘pay-as-you-drive’ in the European Union (NRC, 2016).



*Figure 2: Different categories of factors influencing  
 travel mode choice (Olsson, 2003)*

### 2.1.2 Weather

An example of an environmental factor that influences travel mode choice are weather conditions (Liu, Susilo and Karlström, 2015). They found that the probability of individuals choosing walking and public transport increases during winters and choosing to cycle decreased, while the opposite is true for summers. Also, the probability of choosing to cycle as a travel mode increases as temperature becomes warmer and the probability of choosing private car decreases in warmer conditions. Cycling compared to other travel modes is most negatively influenced by precipitation while public transport is positively influenced by precipitation. Van Stralen, Calvert and Moling (2015) found that in their research motorway traffic increased around 11% in a light rainfall scenario and around 5% in a heavy rainfall scenario. A travel survey study from The Netherlands reports a positive relationship between precipitation and car and public-transport trip generation, resulting from large-scale switching from active (open-air) to motorized transport modes (Sabir, in Böcker, 2014). Sándor (2014) found that rainfall has a significant impact on traffic speed and it depends on the intensity of rainfall. Based on the traffic data analysis it can be declare that under 5 mm/h rainfall intensity the rain does not have any significant impact on the traffic. Over 5 mm/h, the higher intensity causes the more significant speed reduction, which can be 30-40 km/h.

## 2.2 Parking choice

If the car is chosen as a mode of transportation, another to thing to do is to choose a place to park. The choice for a parking spot can be subject to different factors. Chaniotakis and Pel (2015) have made an overview of different factors that resulted from their literature study. The following factors were named: cost, walking distance, access time, search time, duration, type of parking, age, illegal fine, purpose, parking guidance and information systems (PGI), occupancy and probability of finding a vacant spot (Gillen, 1978; Hunt, 1988; Axhausen and Polak, 1991; Hunt and Teply, 1993; Thompson and Richardson, 1998; Dell’Orco et al., 2003; Bonsall and Palmer; 2004, Ruisong et al., 2009; Van der Waerden, 2012).

### 2.2.1 Parking issues

It has been a standard practice for cities to provide a minimum number of parking spaces in new residential and commercial developments (Shaaban and Pande, 2016). The intentions of such policies were to prevent spillover parking on the street and to satisfy the parking demand. According to Van der Waerden, Borgers and Timmermans (in Shaaban and Pande, 2016) parking problems still exist in many of such locations and the congestion may even have got worse (Shoup and Pickrell, in Shaaban and Pande, 2016). The last years there is an ongoing policy shift whereby many European cities are lowering compulsory number of parking spaces in residential developments. This is in order to influence the amounts of vehicle ownerships and car use (Foletta and Field, in Antonson et al., 2016). “This shift has occurred in a context of changing planning practices driven by new planning challenges such as climate change and managing a transition towards sustainable mobility.” (Banister, 2008, p. 213)

The trend of lowering the amount of parking spaces could have negative consequences if people keep on travelling with their car. In this case people will keep on looking for vacant space. With this phenomenon, that is called ‘cruising’, additional parking seekers need to cruise around until they found a vacant place (Bernardino and Van der Hoofd, 2013). First of all, it is proven that it costs a lot of time. Because of the competition of drivers to reach their destination, they adjust their arrival time to as early as vacant spaces are still available (Bernardino and Van der Hoofd, 2013). This implies waste of time or even sleep deprivation (Biddle and Hamermesh, in Tsiaras et al., 2015). Cruising also costs more waste of resources and thus more money. Spending more time in a car with a turned-on engine means more noxiousness for the environment. It produces more emissions that cause harm to the greenhouse, environment and people. Thanks to the emergence of electric and hybrid cars a small nuance can be added to this. Finally, cruising also generates unnecessary traffic load (Tsiaras et al., 2015).  
  
 Because of the growing number of cars in most countries, one can imagine that it gets more of a challenge for policy makers to ensure that on the one hand there is a sufficient amount of parking space available and on the other hand the negative impacts are reduced, which seem to be inherent to the presence of cars. Centraal Planbureau (CPB) has developed two scenarios for the amount of car ownerships in The Netherlands. Despite a doubling of the amounts for the last 35 years, a scenario is prognosed in which the number of cars increases with 10 percent and 35 percent for the coming 35 years (CPB, 2015).

## 2.3 Smart cities

Last paragraph elaborated on issues with parking that probably every renowned city copes with on a daily basis. This paragraph discusses the smart city concept which is a concept that tries to cope with issues that afflict cities.  
  
 Cities are vivid and dynamic. Because of its dynamics, these are testing grounds for new developments. But there are also negative outcomes that come with this urbanization phenomenon, like for instance air pollution, traffic congestion, aging infrastructures and difficulties in waste management. Obviously the degree the presence and degree of these are depended on the case that is considered. These developments are in some way frightening since about half of the world population is living in an urban area, and the trend of ongoing urbanization is projected to continue for the next decades (UNFPA., in Chourabi, Nam, Walker, Gil-Garcia, Mellouli, Nahon, Pardo and Scholl, 2011). The emergence of these problems urges stakeholders (e.g. policy makers, private companies and citizens) to find ways to manage them. It is trendy to label cities that are familiar with implementations that try to improve or maintain its sustainability and livability as a smart city (in Chourabi et al., 2011).  
  
 That there is no concordant definition of this concept available, becomes clear when reading the article “Understanding Smart Cities: An integrative Framework” by Chourabi et. al, which gives an overview of a range of definitions. An example is given by Giffinger, Fertner, Kramar, Kalasek, Pichler-Milanović and Meijers (2012, in Chourabi et. al, p. 2290): “A city well performing in a forward-looking way in economy, people, governance, mobility, environment,and living, built on the smart combination of endowments and activities of self-decisive, independent and aware citizens.” The definition provided by Harrison et al. (Giffinger et. al, in Chourabi et. al 2012, p. 2290) also includes the physical- and the IT-structure of a city: “A city connecting the IT-infrastructure, the social infrastructure, and the business infrastructure to leverage the collective intelligence of the city”. The definition of the European Parliament (Henderson et al., in Ascimer, 2015) emphasizes on IT on the basis of partnerships: “a city seeking to address public issues via ICT-based solutions on the basis of a multi-stakeholder.”   
  
 Smart cities are sometimes given other names, while to a certain degree they are about the same phenomenon. Examples of such names are: Digital city, Wired city, and Learning city (Tregua, D’Auria, and Bifulco, 2014). There is a considerable overlap with related city concepts such as these, however, the Smart City concept has become predominant among these variants,especially at city policy level, globally as well as in Europe (Manville et al., 2014, p. 22). The latter is a more people-centric term, while the other are more focussed on IT. According to Tregua et. al (2014) the term smart city bridges the two perspectives if the definition of Caragliu, Del Bo and Nijkamp is used: “We believe a city to be smart when investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance.  
  
 According to Greenfield (2014) a lot of definitions of a smart city are to some extent influenced by marketing goals of big enterprises. They are seeing it as a city that has as much as information about citizens as possible and uses these to minimize disruptions, the disruptions being people going about their daily lives in non-ideal spaces. Cities have meanings and have value that was created by people throughout the history. Greenfield is not opposed to monitor everyday life, as long as citizens are as much benefiting from it as much as companies. Examples of such ideas are open data and public interfaces that combine and disseminate it to citizens. According to Manville et al. (2014) it is complicated to measure the success of a specific ‘smart’ city, due to the relative immaturity of most initiatives and the difficulty of linking initiatives to particular socio-economic issues or a particular system within a city.  
  
The smart city concept is a very broad concept since it covers a set of application domains. A set of domains is provided by Anthopoulos (2015, p. 14):

• Resource (utilization and management): deals with natural resources, energy, water monitoring and management

• Transportation: concerns ICT utilization for transportation management, as well as intelligent transportation products and mobility in general

• Urban infrastructure: refers to building, agglomeration and sprawl management with the ICT

• Living: covers education, health, safety, and quality of life in urban space

• Government: mentions public e-service delivery, e-democracy and participation, accountability and transparency, and administration’s efficiency within the city

• Economy: covers areas that reflect domestic product in city, innovative spirit, employment, and e-business

• Coherency: deals with social issues that address digital divide, social relations, and ICT connectivity. The outcomes from the analysis of these articles illustrate that despite identifying.  
  
Many of these terms can have a slightly different name in other articles. For example, transportation is often called ‘smart mobility’ and resource ‘smart environment’. The smart mobility paradigm will be further elaborated in the next paragraph since it has the focus during this research.

### 2.3.1 Smart mobility

In previous paragraph it was stated that transportation is one of the key domains of a smart city. This domain is also referred to as ‘smart mobility’. This concept tries to cope with issues related to mobility, like the issues that are associated with parking (paragraph 2.2.1). Also, negative impacts of mobility that are not related to parking per se like traffic congestion are targeted by initiatives influenced by the smart mobility concept. The following six objectives of this concept can be identified: reducing pollution, reducing traffic congestion, increasing people's safety, reducing noise pollution, improving transfer speed and reducing transfer costs (Lawrence et al.; Bencardino, in Benevelo et al., 2016). Smart mobility systems in cities use various paradigms associated with smart cities like digital city, green city and knowledge city (Benevelo et al., 2016).

### 2.3.2 Smart parking

In the previous paragraph it was discussed that parking can be one of the issues addressed by smart mobility initiatives. ‘Smart parking’ will be discussed from the digital city paradigm perspective, or in other words the the use of ICT in the context of smart cities. Smart parking systems have been implemented in many areas in Europe, United States and Japan (Shaheen et al., in Idris et al., 2009). Shaheen et al. (in Idris et al., 2009) divide smart parking systems into five major categories, namely parking guidance and information systems (PGIS), transit based information system, smart payment system, E-parking and automated parking. In the study of Revathi and Dhulipala (2009) it can be found that also other classes can be added: centralized assisted parking search (CAPS), non-assisted parking search (NAPS), car park occupancy information system (COINS), parking reservation system (PRS), Intelligent transport system (ITS), Intelligent parking assist system (IPAS), Agent based guiding system (ABGS).

### 2.3.3 Parking guidance and information systems

In this paragraph more on PGIS will be elaborated. PGIS are also known as Advanced Parking Information Systems (APIS). The objective of such system is to help drivers finding a parking spot to promote effective utilization of parking lot and adjacent roads, provide parking location, condition, road traffic routes and other information to induce drivers to find parking effectively (Watene, Musiega and Ndegwa, 2013). According to Ting (in Watene et al., 2007)a PGIS needs to meet the following requirements.

The system should:

- collect real-time information about the status of the car park accurately, and delivery to the management center timely

- Imply automated management of car park, including charging systems, computerized management and rapid query, statistics and analysis of data

- The management center of the system has strong functions of statistic data and information processing, storage, the integration of parking management information, and the reliability processing of the release data information

- Use the information released screen to supply information of parking location and status of parking space for the drivers when they come into the induction area

- Parking spaces should be queried in the information management center of the system, including the real-time parking information and daily flow of cars at the parking lot

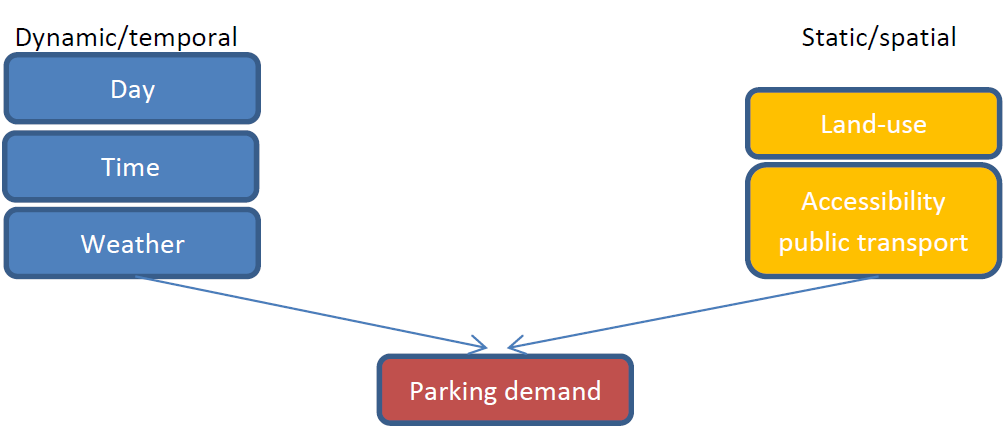
(Ting, in Watene et al., 2007)

PGIS should have four functional modules: information collection, information processing, information transmission and information dissemination. In the information collection module real-time information on parking is captured usage accurately and transmit to the management system timely. The information processing module is responsible for processing information into appropriate form that can be provided to drivers. The transmission module ensures that the flow that from the information collection system to the information processing system and then to the information release system is smooth. The information dissemination module pushed the information processed by the information processor to the outside. Dissemination systems can vary, including LED screens, GIS and car navigation systems (Shuyi et al., in Watene et al., 2017).

# 3. Methodology

The methodology applied in this research is elaborated in this chapter. The structure of the chapter links to the the subdivision of the analysis. The analysis is chunked into five sub analyses, namely case selection, variable identification, modelling, model test and script and system integration. These steps are in chronological order. But before we dive deeper into these analyses, the research design for this research is elaborated.

## 3.1 Research-design

In paragraph 1.6 a couple of objectives were formulated: get insights into the patterns of a local parking system, develop a model that describes parking demand and get insights in how this model can be applied in a routing system. The theoretical framework showed that there can be different factors influencing people’s decision to travel, their travel mode choice and their parking choice. In this research, a selection is made to investigate people’s choice to travel by car which obviously has a big impact on the demand for parking because every car needs to be parked.   
  
 As can be seen in the theoretical framework (chapter 2) there are more variables that potentially influence parking demand, including parking cost, walking distance, access time and search time. A lot of executed researches have been dedicated to the influences of parking cost. The other variables are dependent of the individual who is parking his/her car. To gather data about this a questionnaire or interview is needed. The aim is to do use as much as open data as possible to predict parking demand. Therefore, these variables are beyond of the scope of this research. Without these means it is difficult data. In contrast to these variables, the variables proposed by the conceptual model can be gathered without interviewing individuals. The influences of the variables can be investigated ‘top down’ by gathering data that is freely available, like weather and locational data. More on the datasets and data collection can be found in upcoming sections.   
  
 Based on the literature study it is assumed that the following factors can influence the demand for parking: Day and time, weather, land-use and accessibility of public transport (see figure 3) These variables can be grouped into two categories, namely temporal/dynamic and spatial/static. The state of temporal and dynamic variables change and depending on what the state is there can be a different demand for parking. For example, the demand for parking near a shopping mall will in general be higher during shopping hours than during closing hours. The other category, spatial and static variables, do not change often and therefore maintain their state. For example, the walking distance to the nearest public transport keeps pretty much the same over time unless new stops are made or because of constructions blocking an access road.  
  
   
 *Figure 3: Conceptual model*

## 3.2 Operationalization

*Day and time* – Depending on the case, all weekdays from Monday to Sunday and all hours from 09:00 until 17:45 are included in the research. For retail cases Mondays untill Sundays are included with a time interval of 09:00-17:45. Mondays till Fridays are investigated within 09:00 until 17:45 for office area cases.   
  
*Weather* – In the context of this research with ‘weather’ is meant the amount of rain that falls on a particular day. Two datasets are used to characterize a day based on the amount of rain: the forecasted amount of rain per day and the actual amount of rain per day. Rain forecasts published a day prior to a particular day are used as well as the actual amount of rain that has fallen.

*Land-use* – Land-uses that are in the scope of this research are retail and industrial/offices.

*Accessibility public transport* – Location that can reach a public transport stop (train, tram, bus and metro) within a certain distance. Two classes are formulated within this research: (relatively) low and high accessible public transport.

*Parking demand* – The demand for indoor- and outdoor parking spots in a study area at a particular moment in time.

## 3.3 Hypotheses

Based on the research questions formulated in §1.6, the conceptual model elaborated in previous paragraphs and the literature study, the following set of hypotheses can be formulated that will be tested in the analysis:  
  
*Hypothesis 1: Day and time*   
Different moments in day and time have different demands for parking. Dependent on the day and time, there is a different parking demand.   
  
*Hypothesis 2: Weather*   
If people are expecting rain there is more demand for parking. People are more likely to travel by car instead of walking or cycling. It is also expected that more rain leads to more car travelling and thus higher demand for parking. If there is no rain forecasted people are more encouraged to travel by foot or bicycle.  
  
*Hypothesis 3: Land-use*  
Different land-uses show different parking demand curves. Peaks in retail area occur in the afternoon and in industrial/office areas occur between the morning and afternoon.  
  
*Hypothesis 4: Accessibility public transport*  
If the area of destination is highly accessible by public transport, people are more encouraged to travel by public transport than an area that is less accessible by public transport. And vice-versa.

## 3.4 Case study

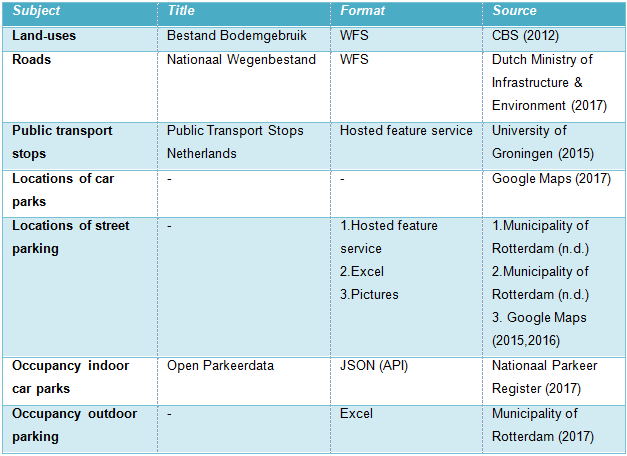
Parking dynamics in this research are researched for the Dutch city of Rotterdam. Foremost reason for chosing this city is because of the availability of indoor parking data.  
Rotterdam is the second biggest city in The Netherlands and has a lot of visitors, thus de demand for parking is high. But it also is a forerunner in Dutch context when it comes to monitoring outdoor parking dynamics with the use of modern technologies. There have been driving cars around the city since 2015, that are equipped with a scanning camera that automatically scans parked cars (Rijnmond, 2015). Also, relatively high number of car parks situated in the center of Rotterdam are participating in a live data service that is freely accessible by anyone. The Municipality has launched an experiment in which it dissiminates parking occupancy data to citizens of the Blijdorp- and Bergpolder area, to cope with parking problems (Parkeer24, 2018).

## 3.5 Limitations

On-street parking in this research is limited investigated compared to off-street parking. This is due to a limited availability of data. A dataset was given by the Municipality of Rotterdam and can not be collected openly. Generally, not much parking figures can be found on the Internet. Also for the collection of off-street an agreement had to be signed, but in contrast it can be collected limitless and in real-time. This means that for now on-street parking can not be incorporated in a system that uses live occupancy data. Therefore, only real-time off-street parking data is used in the system. Also, the relation between rainfall and on-street parking occupancy is not evaluated because of a limited set of observations per day. For instance, there are days on which only two observations have occurred.  
   
 Land-use is one of the variables that will be researched in this report. Certain areas will be categorized as a specific land-use. Examples of land-uses are areas with the land-use: retail, residential, office and industrial. However, the areas that will be investigated in this research will probably not be have entirely one land-use. In most retail areas, for example, also people are actually living in this area and need a place to park. The parking demand will therefore not be influenced by the characterized land-use completely. Parking spaces could also be used by people that do not have their destination in this area. For example, people park their car here to continue their trip by public transport because of its proximity to a metro station. This case increases the demand for parking but its not caused by nearby land-uses.  
  
 In case it is desired to pick a residential area, then an area will be chosen that consists predominantely of residential houses. This is largely dependend on official data that is available on land-uses.   
  
 Another constraint in this research is that the factors potentially influencing parking demand are higher than the number if variables that were selected. Parking demand is not only related to available parking spaces near a destination, but it is also depended of the location someone if leaving from. For instance, if someone’ office is just around the corner of a train- and subway station, but taking public transport will cost him twice as much time as travelling by car than time can play an important role. And what if there are always traffic jams on his route? Thus, the total trip and perhaps other variables (like personal factors) are important to fully analyze parking demand. Foremost reason for chosing to make a selection of destination specific variables is the limitation in time for conducting this research. A selection lets one more focus on certain potential influencers of parking demand. Finally, it is also easier to explore destination variables since it is more difficult to know where people are travelling from and what their motives are.

## 3.6 Case selection

The first step in the analysis is the identification of case studies. The cases are selected based on two spatial variables, namely land-use and distance to public transport stops. For the land-use variable two types of areas are investigated: retail- and business areas. For the distance variable, a distinction is made between areas that have a high and low accessibility in public transport. At this stage, it is difficult to define what the exact distances for these criterions are. To decide on this a Service area analysis (part of Network analysis) will be performed. Such analysis shows the distance from every point on the map to the most close-by public transport stop. The output answers the question where relatively high- and low- accessible areas are located.   
  
 With the two variables four different cases are made: low accessible retail area, high accessible retail area, low accessible business area and high accessible business area. Not every location that satisfys one of the four profiles can be selected. In addition, there also have to be looked if there are existing parking spaces (both indoor and outdoor) and if there are available occupancy data. The consulted datasets in this stage can be seen in table 1.

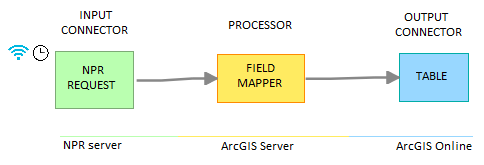
 *Table 1: Consulted datasets for case selection stage*

## 3.7 Variable identification

When the four cases are chosen, the next step is to investigate which of the formulated variables (day, time and weather) influence parking occupancy. One of the objectives of this research is to predict this and this will be done by developing prediction models. For these models, it is important to know which variables have to be included. Only variables will be included that have proven to be significant in influencing parking occupancy.

This stage of the analysis consists of three consecutive components: data- collection, processing and significance analysis.

### 3.7.1 Data collection

For the execution of the variable identification stage data on parking occupancies and rainfall need to be collected. They require different collecting procedures. All data will be collected for a period of around 3.5 months in the beginning of 2017: January 10 untill the end of April.   
  
 Parking data will be collected from two different sources, depending on the segment of parking. In-door parking data will be collected by connecting to a API that publishes data about a facility’s real-time performance. This connecting is set by making use of relatively new software called “GeoEvent Extension for ArcGIS Server” (GEE).   
  
 With this extension, it is possible to create a “GeoEvent service” that lets your server request data from real-time data servers at a specificied time interval. A schema in figure 4 can be found that describes this service. The data is requested every 15-minutes. There is no scientific justification for chosing this interval, but it is expected that parking occupancy can fluctuate heaviliy within a 1-hour interval (especially during peak hours) and an update interval of more than four times a hour will lead to a voluminous dataset. After the data is requested a processing step is applied on the server that transforms the JSON structure to a table structure. The transformed data is then imported in a table hosted in ArcGIS Online.  
  
   
 *Figure 4: Model of the created GeoEvent service for   
 collecting real-time indoor parking data*  
  
 In contrast, the collection of outdoor parking data is not automated and can be received by requesting the data provider. Since this is not a data service that can not be connected to by GEE and scanning cars are driving a street of interest a limited amount of observations, data for specific moments can not be requested.  
  
 Weather, or rain data are collected manually: both datasets can be downloaded from websites of data providers. The closest weather station to the study area is KNMI’s weather station “Rotterdam”, which is located close to the Rotterdam-The Hague airport (51.9550,4.4440). The as-the-crow-flies distance between the weather station and the study area is around 5 km. For the predicted rainfall data, the coordinates of the location of interest needs to be integrated in the REST URL. The coordinates that will be used are 51.917702,4.479897, which is somewhere in the middle of the study area (near metro station “Beurs”). An example of an URL to request the data looks like:

[*https://api.darksky.net/forecast/KEY/LAT,LON,UNIXTIMESTAMP*](https://api.darksky.net/forecast/KEY/LAT,LON,UNIXTIMESTAMP) *“https://api.darksky.net/forecast/KEY/51.917702,4.479897,1483311600*

The forecasted rainfall dataset is, as well as the actual rainfall dataset, collected afterwards since the analysis is performed after the researched period. The 7 am forecasts are collected for all days of the reseached period and are looking forward at the coming 24 hours. The forecasted rainfall for a particular day is then calculated for a timespan from 7 am to 6 pm, assuming most commuting traffic then takes place. For convenience’s sake, it this timespan is also taken for the retail-cases, despite most shops open around 9 or 10 am depending on the day. The same procedure is followed for actual rainfall: all the rainfall between 7 am and 6 pm is summed to calculate the daily rainfall. The consulted datasets are summarized in table 2.

|  |  |  |  |
| --- | --- | --- | --- |
| *Subject* | *Title* | *Format* | *Source* |
| Predicted rainfall | Time machine request | JSON (API) | Dark Sky (2017) |
| Actuall rainfall | Uurgegevens weather station “Rotterdam” | ASCII | Royal Netherlands Meteorological Institute (KNMI, 2017) |
| Occupancy indoor car parks | Open Parkeerdata | JSON (API) | Nationaal Parkeer Register (2017) |
| Occupancy outdoor parking | - | CSV | Municipality of Rotterdam (2017) |

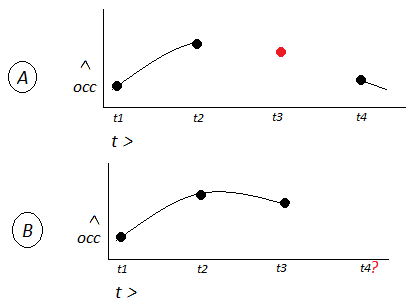
*Table 2: Consulted datasets for variable identification stage*

### 3.7.2 Data processing

The parking and weather data is processed into Microsoft Excel. Collected parking data is filtered on specific week days and/or time, depending on the case. Parking data belonging to retail cases are filtered on the time interval 12:00 – 17:45. The interval is chosen because in general shops are opened then on all weekdays, including Mondays and Sundays. On these days, most shops are opened from 12:00. In addition, days that can give deviant figures are excluded. During the time of study these are both days of Easter, Kingsday and 8 and 9 April (Rotterdam Marathon). The expectation is that the figures differ a lot from other others. For example, 9 April will be on a Sunday and the expectation that the figures will be not representative for a Sunday. It is desirable to look for representative figures because these are going to be included in the occupancy models (upcoming analysis stage).   
  
 The indoor parking data comes with various attributes including capacity, amount of vacant spaces and time. For the calculation of the occupancy a new field is made within Microsoft Excel (hereinafter referred to as MSE) that subtracts the amount of vacant spaces from the capacity. Also, the time field has to be converted to a format like “YYYY-MM-DD hh:mm” since it only shows an UNIX timestamp (number of seconds since 1-1-1970 in GMT). For the days, up to and including March 26 3600 seconds have to be added and 7200 seconds for the rest of the study period. The structure of the processed MSE table can be found for the four cases in Appendices A-D.   
  
 The outdoor parking dataset contains the following fields: datetime, lat, lon, zone and result. The result field will be excluded because it contains data about whether a scanned car is legally parked or not. For this research, all parked cars are equally important because logically parked cars also contribute to a higher occupancy. The processing strategy for on-street parking data is quite different from the indoor parking data. Scanning car observations have to be grouped into ‘sessions’. Unlike the indoor parking data, outdoor parking observations belonging to one session are on different moments in time. A scanning car can only scan one car at one moment and this exact time is saved in a timestamp, while the indoor parking data has one figure about the current occupancy every fifteen minutes. It just counts how many entered cars have entered and left the car park and compares it to the maximum capacity. The on-street parking observations are rounded in time to 1,5 hours. This means that an observation of 3:11 pm is rounded 3 pm and an observation of 1 pm is rounded to 1:30 pm. It is also possible to pick a rounding of one-hour, however, lots of observations of one session appear to be around half-an-hours which would mean that one session accidentaly will be divided into two different scanning sessions. The structure of the processed MSE table can be found for the four cases in Appendix E  
  
 The rainfall datasets (actual and predicted) both require different processing tasks. The actual rainfall dataset consists of various attributes including: wind direction, wind speed, temperature and of course the amount of rain per one-hour interval. Values below 0,05 mm per hour get a value of ‘-1’. This value is converted to a 0,02 within Excel. This is done because a negative amount of rain is impossible. It was chosen to pick an amount somewhere around the middle of 0,04. The amount of rain per day is then summed for every hour of interest: 7:00 – 18:00. It was decided to include figures between 07:00 and 09:00 because it is likely people let their decision to take depends on whether it will rain on the way to work. Rainfall data that is used can be found in appendix F.  
  
  
 The predicted rainfall dataset is comparable to the actual rainfall dataset. Example attribute fields includes windspeed, UV index and cloud coverage. For the amount of rainfall, a processing step needs to be performed since the existing field are the rainfall amounts in inches. Therefore, a recalculation in MSE will be performed to calculate the rainfall in mm per hour (rainfall in inches \* 25,4 = rainfall in mm). The datetime is in a UNIX timestamp format. The same proces as for the realtime indoor parking data will be followed to convert it to a human-understandable format.

### 3.7.3 Analysis

The goal of the last step of the variable identification is analyzing the significance of the three variables day, time and rainfall. If a variable is considered to be significant it will be integrated in the occupancy models. For performing these significance analyses there will be made use of the “Data-analysis”-extension of MSE. First the significance analyses regarding off-street parking is elaborated.  
  
*Analysis: off-street*   
  
 The first variable that will be tested is day. All days will be grouped by weekday, so all Mondays are grouped, Tuesdays, etc. For every particular day, the average is calculated. Subsequently all these figures are summed to calculate the total average, minimum and maximum per weekday. Weekdays can then be compared. In order to judge whether the figures differ from eachother, a so-called F-statistic is applied. This statistic evaluates whether days have statistically different averages. Days have statistically different scores when the output F-value is higher than the critical F-value.   
  
 The following variable is time. Groups of time intervals are compared with use of the F-statistic. For instance: the average occupancies between 1 and 2 pm (regardless of the day) are summed and divided by the amount of days taken into account. If the resulting f-value is higher than its critical value, then the differences between the hours are statistically significant. This means that time will have to be incorporated as a variable in the models.   
  
 The significance of rainfall is analyzed in two ways: through applying pearson’s correlation statistic and the f-statistic. The former will be used to investigate whether more rainfall leads to a higher car park occupancy. Days will be compared to the same weekday in order to make sure that days can be compared. For instance, it could be the case that Fridays on average has a totally different average than Mondays. It would make no sense to put all observations on a par. The resulting degree of the test varies between -1 and +1. -1 indicates a strong negative relationship between the two variables: if rainfall increases, parking occupancy decreases. +1 indicates a very strong positive relationship: if rainfall increases, parking occupancy increases too. A zero means that there is no relationship at all. The second method is used to explore the significance of rain, no mather how much. Days are grouped in buckets of weekdays and whether it has (actual rainfall) or will rain (forecasted rainfall) or not. The averages of the groups are compared and analyzed with the f-statistic to determine if rain influences parking occupancy. A day on which > 0 mm rain is forecasted/measured is rainy day.  
  
*Analysis: on-street*  
  
 Testing the significance of the variables with data for on-street parking requires a different approach than for off-street parking. A reason for this is the difference of frequency of observations. At most, a scanning car monitors three times a day. It is highly debatable to calculate day averages based on such small amount of observations. In contrast, on-street parking has a data coverage of every fifteen minutes. In the following section, a slightly different approach is discussed regarding the determining significance of the variables.   
  
 For the day variable, all values are grouped per weekday. Subsequently the values are grouped on time. This probably will lead to multiple values per time step. Therefore, the average value per timestep is calculated. This results in a value for every timestep on every day. If there are no observations for a particular timestep then an average between the two closest timesteps is calculated, which can be seen as a sort of interpolation technique (see example A in figure 5). This is needed because Excel does not create a fluent graph if one timestep is missing. If there is a timestep missing at the edges of the occupation curve, there will not be calculated a new value. Since there is a value missing at the other side it is difficult to say in which way the occupancy develops (see example B in figure 5).

**

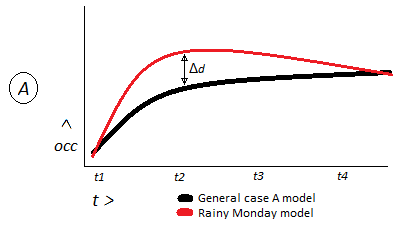
*Figure 5: Handling missing values for on-street parking*

For the time variable, all observations belonging to a particular timestep are summed and then divided by the amout of observations. This gives average occupancies per moment, regardless of the day. A F-statistic analysis will be applied to determine if the occupancies throughout the day are statistically different and how strong this difference is. If it is, it makes sense to integrate the time variable in the models.

The significance of rainfall will not be evaluated for on-street parking. There are simply to few observations to do this. As mentioned before, some days only have one monitoring session and other days can have three. Because of this low amount of observations per day there can not be said that much usefull about the occupancy throughout the day. Therefore, it is difficult to see what the effect is of rainfall. Ideally the same weekdays, for example Mondays, have to be compared with rainfall taken into consideration to see if there is rainfall indeed leads to more people deciding to take their car which stimulates parking occupancy.

## 3.8 Modelling

The next step of the analysis is incorporating variables that have proven to be significant into models. These models will be used in a tool that predicts parking occupancy. It will also be used to see if it can predict parking occupancy in similar areas (same land-use and degree of accessibility to public transport) of another city in The Netherlands.

Before there can be started with developing models there has to be decided which days are considered to be representative for that particular day. In other words, outliers have to be found and excluded from the dataset upon which models will be made. This is done by making use of boxplots. Boxplots shows the distribution of data, for example the average occupancies of all Mondays. Most common values are distributed between the so-called Q1 and Q3 quartiles. Values beyond these quartiles are called mild outliers (data between Q1-1QR and Q3+1QR). A ‘1QR’ means 1 interquartile range which is the value for Q3 minus Q1. What we are really looking for are the extreme outliers that are located beyond the fences of 1QR. Thus, everything below Q1-1QR and above Q3+1QR is considered an extreme outlier.  
  
 If all extreme outliers are filtered there can be started with developing models. The aim is to create 12 models. 4 models for each indoor parking facility, 4 models for each outdoor parking area and 4 models for each area’s total parking capacity. The latter models are simply a sum of the indoor and outdoor models. Segment-specific models (indoor or outdoor) are important so both segments can be compared with one another. It can be analyzed whether the follow the same dynamics, and if not, what could possibly be influencing these divergent dynamics. Models for predicting total parking capacity in an area sees an area as a system in which indoor and outdoor parking facilities influence each other and are not operating on their own. If a car park is full it is likely that people search for an alternative parking space in its surrounding area.   
  
 In previous section it was mentioned that every case eventually will have three models. The segment-specific models are created by summing all days per timestep. Thus, all values for 09:00 are summed and grouped under x = 1 for business area cases. X=1 will be 12:00 for retail areas because the modelling starts from this moment (see paragraph 3.2.2). It is likely that day and time have proven to be significant variables. If in addition also rainfall is a significant variable then there have to be created scenarios based on a different model. An example of a scenario could be: ‘Monday-Rainy’. The model behind this scenario is based on figures of Mondays that were rainy minus the rainy Mondays with extreme outliers and rainy Mondays on which a special event took place in the centre of Rotterdam. The variable time is not expressed in the scenario title because it already is a variable in the model (x-variable that increases throughout the day). The difference between the alternative models and the general case model is calculated for every timestep (figure 6). This on itself creates a model/function too. The function behind this function are the variables that need to be added to the general model in order to get predicted occupancy for that particular scenario. It is desirable to keep these scenarios as few as possible from the perspective of time. For example, if Thursday’s and Friday’s follow a rather similar trendline then there will be chosen for a combination scenario.   
  
   
 *Figure 6: Example: Deviation between general and Monday curve*

### 3.8.1 Model comparison (spatial variable testing)

After the models are created for every case, the models are compared to one another. The purpose of this is to investigate the third and fourth hypothesis: “Different land-uses show different parking demand curves” and “In areas of destination that are highly accessible by public transport, people are more encouraged to travel by public transport.” To do comparions between the models the models are expressed in relative figures instead of absolute figures. The curves show their relative change in respect to the beginning value of the absolute curve. In this way models of car parks can be compared because it makes no sense to compare them in absolute terms. One car park can have much more parking spaces than another car park.

### 3.8.2 Model applicability in other geographical contexts

The created models are compared to another geographical context. This is depended on available car park data coming from the NPR. Because the focus of the research is mainly on the four cases, not a thorough collection of data will be executed for the case coming from a different geographical context. Instead a couple of daily observations will be analyzed.   
The goal of such a comparison is to see whether the created can be applied to another geographical context. Important is to choose a location that can be compared to Rotterdam and has the same characteristics as one of the cases (retail or office and distance from a public transport stop).

## 3.9 Script and system integration

In prior steps, suitable cases will be selected, potentially significant variables analyzed and models created and tested. The last part of the analysis is about seeing the bigger picture. It is about how to integrate the developed models in a system that can predict upcoming parking occupancy. As can be seen in the name of this analytical step, the stage consists of two parts: tooling and system integration. There will be going into more detail on the tooling part first.  
  
 The aim of creating a script is to automate the process of calculating the estimated parking occupancy at a particular time of arrival. The advantage of this is that it does not have to be done manually and manually would take too much time, especially if someone has to reinvent the weel. Particularly if there has to be combined information from multiple sources. One very important source in the context of this research are the occupancy models. Modelling parking occupancy takes a lot of time but integrating it in a script is relatively easy. This way modelling efforts can be reproduced by others. A script enables everyone to calculate the parking occupancy with just a tick on the ‘Run’ button. In addition, a script can be integrated in applications or software so real occupancy applications can be created.

The programming language that will be used for the script is Python. It is a human readable programming language, which means people do not have to be very experienced with it to be able to understand it. The deliverables of this part of the analysis are a schematic representation of the actions of the script and obviously the script itself. Another interesting thing to find out is how long the script takes to run and how can it be improved if it takes too long in the context of a driver that is running an application   
  
 After the script is developed the next step is to think about how it can be used in a system. This part of the analysis tries to find an answer to the following questions: What are potential soft- and hardware that are essential in such a system? Who are the users? Which flows of communication between the user and data servers are needed? The deliverables of this part are a functional scheme of a occupancy predicter and use-cases that describe potential scenarios.

# 4. Analysis

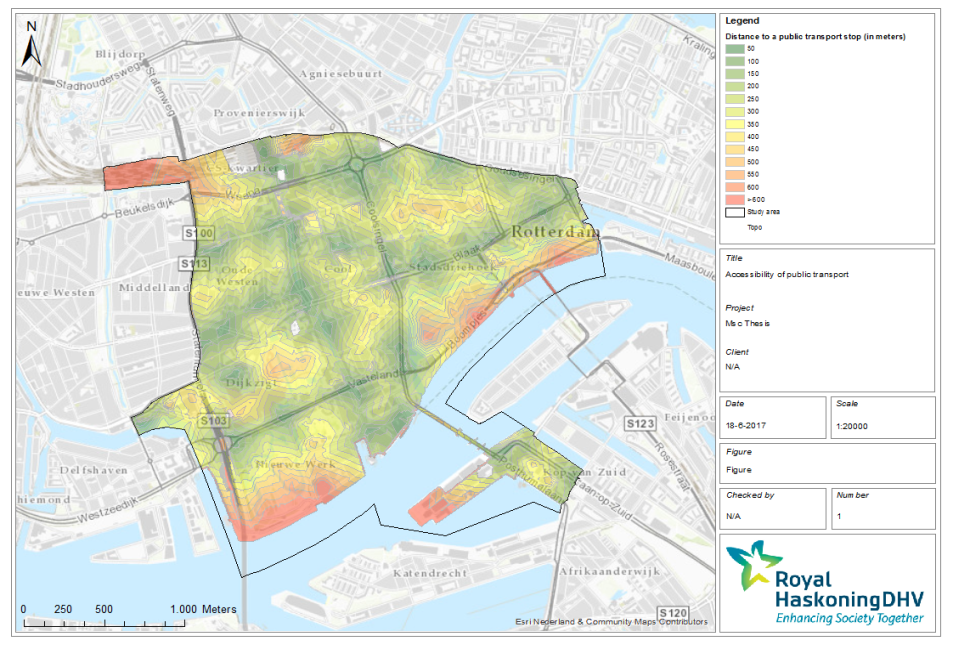
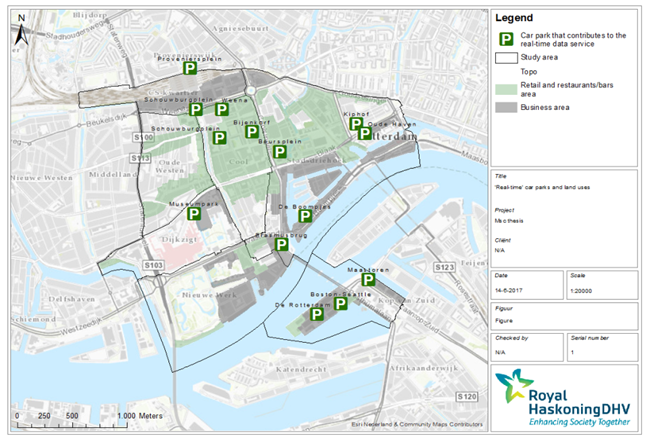
In this chapter, the results of the analysis are presented. In het previous chapter the methodology regarding the various analysis steps were elaborated.

## 4.1 Case selection

|  |  |  |
| --- | --- | --- |
|  | *2014 (x 1.000)* | *2015 (x 1.000)* |
| *Bus* | 29.000 | 30.000 |
| *Tram* | 40.000 | 42.000 |
| *Metro* | 83.000 | 86.000 |

This section covers the elaboration on the selection of the four cases within the center of Rotterdam that satisfy the criteria mentioned in paragraph 3.5.   
 It turned out that by including all public transport stops, the locations that resulted out of the selecting procedure all showed a more or the less comparable degree of accessibility. By excluding a travel mode, more suitable distinction between degrees of accessibility can be identified. But this measure must not lead to a unrealistic view of accessibility throughout Rotterdam. On the other hand, the potential risk of this that can lead to wrong conclusions about accessibility in Rotterdam. Nevertheless, a public transport mode is chosen that has the smallest share in public transport trips. The decision was to exclude bus stops, because busses are the least taken mode of public transport (table 3; RET, 2017). The figures do not cover train passengers because trains are managed by parties operating on a regional or national level. The only available figures on the Internet about train usage are about the check-ins in NS trains on a station-level during working days (NS, in Treinreiziger, 2016). It shows that on average there have been 85246 checks ins at Rotterdam Central station and 23368 at Rotterdam Blaak station (two out of the two train stations within the centre of Rotterdam). In 2015 there were 261 working days so an estimation is that there were about 22.249.206 and 6.099.048 total checks ins on working days that there. This amount will be greater because there are no figures of weekend days and of check ins that were done at other train operators such as Thalys. The expectation is that the total amount of train passengers will be more or the less similar to the amount of tram passengers.

*Table 3: Number of ingoing passengers per public transport   
 modality in Rotterdam (RET, 2017)*

Figure 7 shows the accessibility of public transport from the perspective of that particular area. It shows that from almost location in the center of Rotterdam a public transport stop can be reached within 600 meters (either a train, metro, tram or bus stop), with the exception of the southwestern part of the area. In this area, a relatively big park is located that lacks surrounding stops.  
  
   
  *Figure 7: Accessibility of public transport*  
 Figure 8 shows the locations of the 14 car parks that contribute to NPR’s real-time data service. The car parks are pretty scattered over the study area. They also lie more or the less in either a business or a retail area. There are much more (around 40 in total) car parks to be found in the city center of Rotterdam, so the vast majority of the car parks does not participate in the service. The last criterion for selecting cases is that it consists of streets that are regularly monitored by scanning cars. In view of privacy (data coming from the Municipality of Rotterdam) it is decided to not include a map that visualizes these areas. In the following paragraph’s the chosen cases are elaborated.  
   
 *Figure 8: Locations of real-time data dissiminating car parks*  
  
In the upcoming paragraph the outcomes of the site selection, i.e. the cases, are presented (figure 9-12) They are elaborated in the following order: retail/lower accessibility, retail/higher accessibility, business/lower accessibility and business/higher accessibility.

|  |  |
| --- | --- |
| *Figure 9: Case A* | **Case A**  Shopping area  Relatively far to public transport stop Hennekijnstraat, Aert van nesstraat and St.Luciastraat Cool, center of Rotterdam |
| *Indoor* Car park “De Bijenkorf” (Q-park)  Capacity: 440 Opening hours: 24/7  Prices: € 4 p/h (€ 30 max p/d) |
| *Outdoor*  Hennekijnstraat (partly), Sint-Luciastraat  Capacity: 36 Opening hours: N/A Prices: € 4 p/h (m-sa: 09:00-23:00, su:12:00-23:00) |
| *Figure 10: Case B* | **Case B**  Shopping area  Relatively close to public transport stop Schouwburgplein and Karel Doormanstraat  Cool, center of Rotterdam |
| *Indoor*  Car park “Schouwburg 1” (Municipality of Rotterdam)  Capacity: 725 Opening hours: 24/7 Prices: € 2 p/h (06:00-22:00; € 20 max) |
| *Outdoor:*  Karel Doormanstraat (partly) Capacity: 48 Opening hours; N/A Prices: € 4 p/h (m-sa: 09:00-23:00, su:12:00-23:00) |
| *Figure 11: Case C* | **Case C**  Office area  Relatively far to public transport stop Zalmhaven, Gedempte Zalmhaven  Stadsdriehoek, center of Rotterdam |
| *Indoor*  Car park “Erasmbusbrug”  Capacity: 306  Opening hours: 24/7 Prices: € 2 p/h (06:00-22:00; € 20 max) |
| *Outdoor*:  Zalmhaven, Gedempte Zalmhaven Capacity: 36  Opening hours: N/A Prices: € 4 p/h (m-sa: 09:00-23:00, su:12:00-23:00) |
| *Figure 12: Case D* | **Case D**  Office area  Relatively close to public transport stop Wilhelminakade, Statendam  Kop van Zuid, Rotterdam South |
| *Indoor*  Car park “De Rotterdam”  Capacity: 324  Opening hours: 24/7 Prices: € 4 p/h (€30 max) |
| *Outdoor*  Zalmhaven, Gedempte Zalmhaven Capacity: 15  Opening hours: N/A Prices: € 4 p/h (m-sa: 09:00-23:00, su:12:00-23:00) |

## 4.2 Variable identification

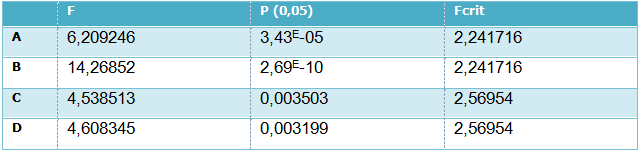
In this section the significance of three variables (day, time and rainfall) are evaluated. This significance testing connects to the first two hypothesis formulated in §3.3:  
  
 H1: *“Different moments in day and time have different demands for parking.”* H2: *“If people are expecting rain there is more demand for parking.”* The first variable that is evaluated is the day of the week, followed by time and rainfall. For the time and day variable the indoor and outdoor parking segments are discussed in consecutive order. That does not count for the variable rainfall. The daily observations for on-street parking are too limited to investigate its relationship with rainfall. For some days, there can be just two observations, which is quite small if one wants to draw conclusions on its daily occupancy.

### 4.2.1 Days

*Indoor parking*  
 If we look at the indoor parking first, it shows parking occupancy in all cases fluctuates per day (figure 13). Case A shows similar minimum occupancies on working days, except for Fridays. Fridays have a similar minimum occupancy as Saturdays. In contrast to Fridays and Saturdays, the Sundays has a relatively small minimum occupancy that is also even smaller than the minimum occupancies on working days. The averages are quite similar on working days but differ sigificantly from the average occupancies in the weekend. The same goes for the peaks. People visiting shops mostly in the weekend would be a logical explanation  
 Case B shows quite similar minimum occupancies for all days except for Saturdays. The minimum occupancy on Saturdays is significantly higher. Like case B, case B shows comparable averages in such way that the highest averages can be found in the weekends and the lower averages on working days. On these working days, the averages are quite similar occupancies. The same goes for the peaks, however, also the peaks on Friday are quite high compared to the other working days but is still significantly lower than the weekends. People visiting shops mostly in the weekend would be a logical explanation.  
 Looking at the case C, the mornings have a quite similar minimum occupancy with small peaks for Mondays, Thursdays and Fridays (figure 14). Thursdays have a significant high average occupancy, while other minimum occupancies tend to be quite similar. The occupancy for the Thursday is remarkable because it is much higher than the average occupancy on Mondays and Tuesdays. The same goes for the maximum occupancies.   
 At case D, the minimum occupanies show a small peak on Wednesdays and Thursdays. The averages show larger differences between the days. Wednesday and Thursdays still show a similar relatively high occupancy accompanied by Tuesdays and Fridays. The average occupancy on Monday is the lowest. Thursdays show the highest occupancy. The same goes for the maximum occupancies. The occupancies are higher but the order stays almost the same except for the Thursday that increases relatively fast and ranks second. For the office cases Thursdays show the highest occupancy. This can have something to do with that in The Netherlands in general most people are working on Thursdays. Wednesdays and Fridays in contrast are often the days on which least people work. This can be seen in case C but not in case D. If we look at the retail cases again Fridays have the highest occupancy, followed by Wednesdays. This could have something to do with shops have more opening hours on Fridays, however this research only has data between 9:00 and 17:45. Possibly a lot of people arrive just after work knowing shops have extended opening hours.   
  
   
 *Figure 13: Occupancy in car parks in retail area throughout the days*

*Figure 14: Occupancy in car parks in office areas throughout the days*

To investigate whether the differences between the days are significant, an F-statistic analysis is performed (table 4). For all four case-studies the differences in averages are statistically significant. The resulting F value for all cases are higher than the critical F-value at levels of significance that is below the p-value. This means that the differences between days are significant and thus the variable of day has to be included in the model.

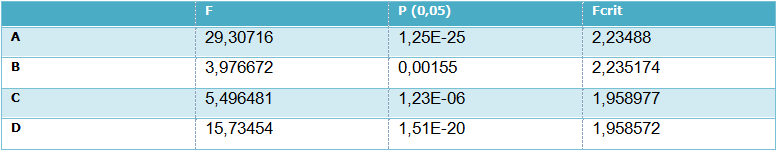
  
 *Table 4:* *Outcome of F-statistics for the day variable*   
  
*Outdoor parking* What strikes when comparing the data of outdoor parking to indoor parking is that the daily averages are much closer to each other. This possibly has something to do with the amount of parking spaces. The amount of outdoor parking spaces is much smaller so it area gets full faster and the fluctuations are not large because they are already a significant proportion of the total capacity.

The retail cases show a similar trend as their indoor counter part: the higher occupancies can be found in the weekends, especially on Saturdays (figure 15). Case B also shows a high occupancy for Tuesdays, while case A shows a high occupancy on Mondays. There are more fluctuations between the days in case A than in case B. This results in a flatter graph for the latter case. Office cases seem to have a similar relative occupancy graph although turned around (figure 16). Case C has its highest occupancy on Thursdays while D’s are on Tuesdays. Both values are reasonable because in general most people are working on these days, so people are more likely to need a place to park. The other top working day for both cases (for C these are Tuesdays and for D these are Thursdays) are not distinguishable from the other days.

*Figure 15: Outdoor occupancy in retail areas throughout the days*  
 *Figure 16: Outdoor occupancy in office areas throughout the days*

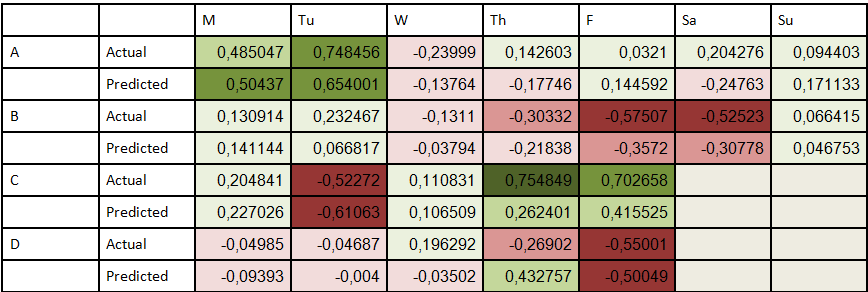
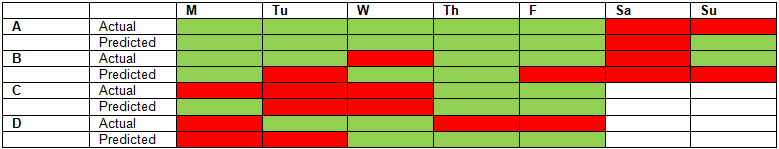
To investigate whether the differences between the days are significant, an F-statistic analysis is performed. For all four case studies, the differences in averages are statistically significant. The resulting F value for all cases are higher than the critical F-value at levels of significance that is below the p-value. This means that the differences between days are significant and thus the variable of day has to be included in the model.

### 4.2.2 Time

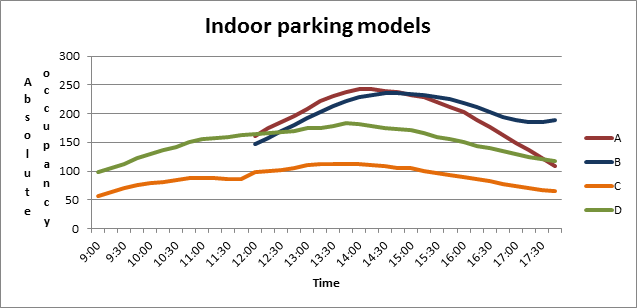
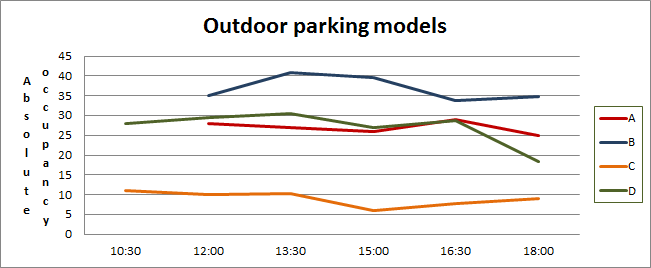
*Indoor parking* Visually it can be seen that there are a lot of differences in occupancy throughout the day (figure 17). Highest occupancies are reached in all cases somewhere between 14:00 and 15:00. The retail cases reach their highest occupancy later then the office cases. This is reasonable because people tend to go shopping in the course of the day, while people often go to work in the morning. If data before 12:00 for the retail cases was included the expectation would therefore be that the occupancy is significantly below their office counterparts, especially around 09:00. Except for case A, the increase until the peak is quite similar (from 12:00). After the peak, the occupancies for case D and B are less increasing compared to case A and C. It is difficult to say what is causing this, despite the fast that both are relatively accessible to public transport.   
  
 *Figure 17:* *Occupancy in car parks throughout the day*  
 To investigate whether the differences between the hours are significant, an F-statistic analysis is performed (table 5). For all four case studies, the differences in averages are statistically significant. The resulting F value for all cases are higher than the critical F-value at levels of significance that is below the p-value. This means that the differences between hours are significant and thus the variable of time has to be included in the model. *  
 Table 5:* *Outcome of F-statistics for the time variable  
  
Outdoor parking*  
  
With the exception of case A, all cases show a drop-in occupancy after 16:30 (figure 18). In contrast to the indoor parking occupancies, the curves of outdoor parking occupanices look rather flat, which of course has also to do with the amount of spaces investigated in the research. Both office cases show a higher occupancy during the mornings. Both cases have its peak somewhere between 12:00 and 15:00. This is comparable to the indoor parking counterparts. The retail areas have a different outcome. Case A has its peak in the late-afternoon while B has its peak in the early-afternoon. Moreover, cases A, C and D show a quite flat graph between 12:00 and 15:00. For B an C this can also be seen from 10:30.

*Figure 18:* *On-street occupancy throughout the day*

### 4.2.3 Rainfall

The last variable that is tested on its significance of influencing parking demand is rainfall.   
  
*Correlation test*A pearson’s correlation test was performed to test the significance of the rainfall variable. The hypothesis prior to the executing was that more rainfall leads to more people taking their car to work/shopping areas and thus would lead to more demand for parking. Figure 19 shows the outcome of the analysis. Green fill color indicates a positive relationship between rain and parking occupancy and red indicates a negative relationship. The darker the color, the stronger the relationship is. It can be seen that the results are not unambiguous. There are 48 figures of which 26 show a positive relationship, the rest shows negative relationships. The relationships are quite random. In other words, on some days it looks like more rainfall indeed leads to increasing occupancy while on others days it does not. Furthermore, in general there are not big gaps between the correlations of actual and predicted rainfalls. On of the exceptions will be the correlations for case C for Thursdays, where there is a difference of almost 0,5 (0,754849 for actual and 0,262401 for predicted).   
  
  *Figure 19: Correlation results between rainfall and parking occupancy*  
  
*F-statistic test* In addition, also an F-statistic test was performed in order to evaluate the significance of rainfall. The correlation test did not show that more rainfall always leads to more parking demand. However, it could be possible that more rainfall leads to more occupancy untill a certain amount of rain. So, people are not extra triggered to take their car if there will be 50 mm of rainfall instead of 30 mm. Therefore, an extra test is performed to check whether there is a difference in occupancy between dry and rainy days. Note that a ‘rainy day’ can have any amount of rain above 0 mm per day.   
  
 Figure 20 shows that rainy days do not always lead to more parking occupancy. Of the 48 boxes, there are 19 boxes in which dry days had a higher occupancy, so the 29 boxes show the days on which the rainy days had a higher occupancy. A percentage of around 40% on which dry days had a higher occupancy does not indicate an unambiguous confirmation of the hypothesis that rainy days lead to higher demand for parking. The f-tests, in which both the occupancy of rainy and dry days are compared per day and per actual/predicted denomination, showed that in none of the tests the f-value was higher than the critical f-value. This means that the occupation values for dry and rainy days are not statically different from eachother. The exact outcomes of the test can be found in Appendix I.   
  
 *  
 Figure 20: Green shows the days where rainy days on average had higher   
 occupanices than dry days. Red shows the opposite.*

## 4.3 Modelling

The last paragraph showed that only day and time are significant variables, Models have been created for the four cases, considered these variables. All cases have a general model and with use of the variables the predicted occupancy can be calculated for a specific day and time. The general model for each case can be seen in figure 21 (indoor) and figure 22 (outdoor)  
  
   
 *Figure 21: General models for indoor car parks*  
  
   
 *Figure 22: General models for outdoor car parks*

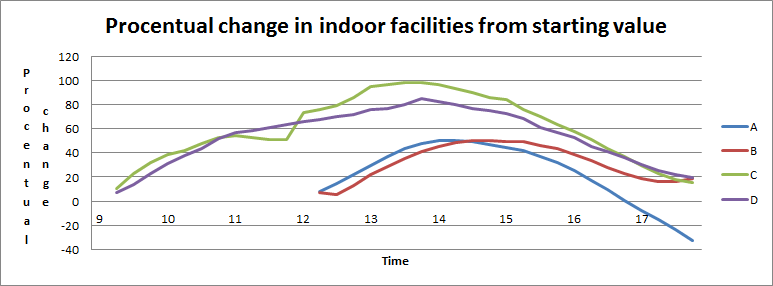
*Functions*For all models depicted in figure 21 (indoor parking) and 22 (outdoor parking) models have been developed. In the following the function is elaborated of one in particular, namely that of indoor case B. Its general function of which day- and time specific is as follows:  
 *y = -0,5505x2 + 14,582x + 134,58 - d*   
With this function around 92% of the proportion of the variance can be predicted from the individual variables. *Y* stands for the predicted occupancy. *X* equals the number of timesteps since of the predictable beginning of the curve. Thus, if the occupancy for case B at 13:00 is to be predicted then it gets the value 4 (4 times 15 minutes from 12:00 to 13:00). The *d* value equals the sub-function for a particular day. For example, the sub-function for Mondays is:  
  *d = -0,2086x2 + 6,197x + 32,007*  
The other (sub)functions can be found in **Appendix E**.

## 4.3.1 Model comparison (spatial variable testing)

This section tries to give an answer to the two hypotheses that remains not elaborated in this analysis, are the third and fourth:  
  
H3: Different land-uses show different parking demand curves

H4: In areas of destination that are highly accessible by public transport, people are more encouraged to travel by public transport than an area that is less accessible by public transport. And vice-versa.

Before the models are compared it is important to state the characteristics of each case again. Case A and C are both locations that are relatively far from a public transport stop. Case B and C are the opposite, they are relatively close to a public transport stop. Case A and B are about locations in commercial areas, whereas C and D are in office areas.   
  
 Figure 23 shows the procentual change throughout the models for indoor parking facilities. The first expectation was that both land-uses show different parking occupancy curves. If we compare both curves then it is obvious that the peaks in commercial areas are later than its counterpart. Office areas have their highest occupancy between 13:00 and 14:00, while commercial show the highest occupancy between 14:00 and 15:00.   
  
 The second expectation is that parking locations closer to a public transport stop have a lower occupancy compared to parking locations further from public transport stops. The reasoning behind this is that a nearby stop encourages people to travel by public transport. In figure 23 it can be seen that the procentual change in case A (relatively low accessibility) is higher than in B (relatively high accessibility) until around 14:15. After 14:15 the occupancy drops but the decrease is higher in case A. Comparing case C (relatively low accessibility) and D (relatively high accessibility) teaches that in general case C shows a higher occupancy than case D, with the exception of between 11:00 and 12:00.

****  
 *Figure 23: Procentual change in indoor occupancy*

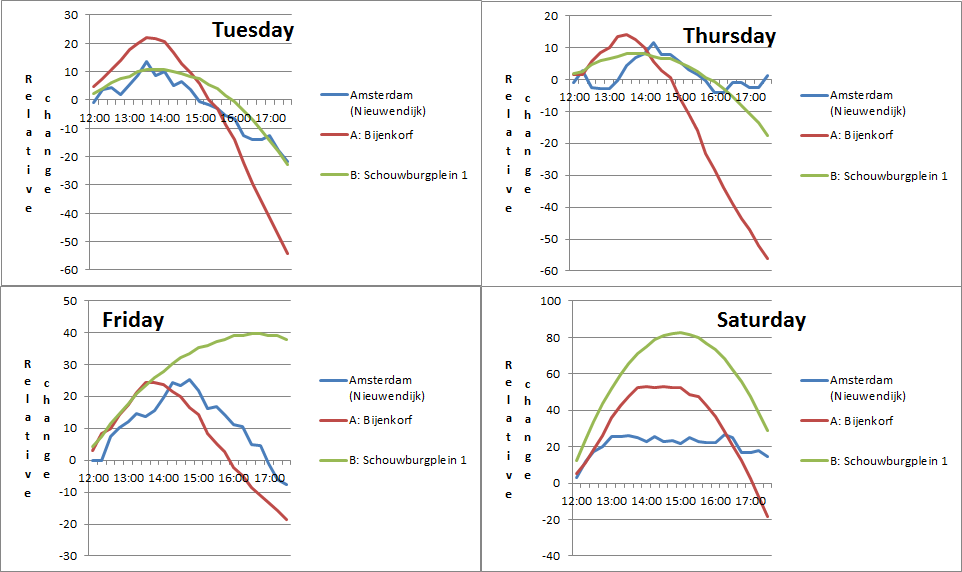
### 4.3.2 Model applicability in other geographical contexts

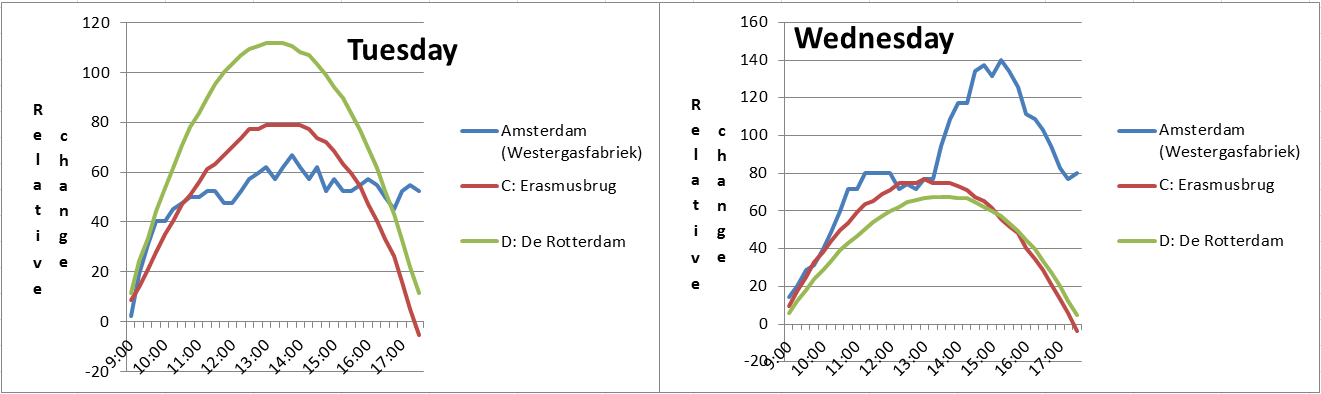
|  |  |  |
| --- | --- | --- |
| Case | Land-use | Distance to public transport |
| A | Retail | 260m Bijenkorf |
| B | Retail | 200m Erasmusbrug |
| C | Offices | 260m Schouwburgplein 1 |
| D | Offices | 350m De Rotterdam |

The four created models are compared with occupancies of car parks in another geographical area (table 6). Two car parks in Amsterdam were selected based on their surrounding land-use, Q-park Nieuwendijk (retail, approx. 60 meters from public transport stop) and Q-park Westergasfabriek (office, approx. 280 meters from public transport stop). Note that the observations of these car parks include one-day observations whereas the curves of the four different cases are based on a lot more daily observations. Possibly the figures are not fully representative for that day. However, despite this scarcity of data it can give a rough estimation.   
  
 What strikes is that all the curves of the two car parks in Amsterdam is the angular line. The curves of the researched car parks in Rotterdam are smoother. Likely this is because the data comprises of more observations. The characteristics of the investigated cases in Rotterdam can be found in the table below:

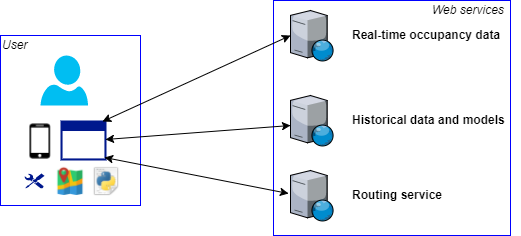
*Table 6: Characteristics of the four investigated Rotterdam car parks*

*Retail: Tuesday* – The curve of Nieuwendijk car park shows a similar trend with the curves of its counterparts of Rotterdam. (figure 24)  
*Retail: Thursday –*Nieuwendijk car park shows a quite different trend. In Rotterdam, the increase declines from a certain point until its increase becomes a decrease. Nieuwendijk shows peaks in its decrease and eventually shows a small increase.  
*Retail: Friday -* The curve of Nieuwendijk car park shows a similar trend with the curves of case A, however it looks shifted to the right for about an hour.   
*Retail: Saturday –* The curve of Nieuwendijk car park is similar to the counterparts beause shows a different trend then case A and B. Their lines are much more curved than the line of Nieuwendijk  
  
*Office area: Tuesday* – The curve of Nieuwendijk is comparable in a sense that it increases much in the morning but then the increases get higher in the case C and D (figure 25)  
Office area: Thursday – The curve of Nieuwendijk shows a completely different curve than the curve of C and D. By the time C and D reach their peaks and Niewendijk has declined, the curve of Nieuwendijk starts peaking again.

  
 *Figure 24: Retail cases compared to a retail case in Amsterdam*

  
 *Figure 25: Office cases compared to a office case in Amsterdam*

## 4.4 Script and system integration

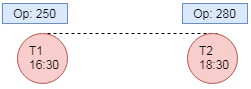
Before integrating the developed models for predicting parking occupancy into a system, it is important to first elaborate on how such a system would look like. In the system that is proposed in this section, the end-users are people that want to check if there is an available parking spot near their destination at the moment they are arrive (figure 26). They can download the app on their smartphone. In an ideal situation, the app has occupancy models for all parking areas in The Netherlands. As a result of this research just four, self-determined, parking areas are analyzed. In the example script a case in which the parking area of case C is closest to the destination, is elaborated.   
The application has a set of interconnected Python scripts running in the background. The app then communicates with different servers through the Internet that give the application input to do calculations. An example is the NPR server that can be requested about car park occupancy, or the server of Google Maps to request real-time travel instructions. Therefore, connection to the Internet is essential to succesfully run the script. There also has to be installed Python modules locally together with the installation of the app to make use of vital elements of the script. An example is the JSON module that enables to parse a JSON file (Google Maps requests are answered with a JSON file) and the URLLIB module enables to do requests over the Internet.  
  
  
 ****  
 *Figure 26: Schematic representation of the system*

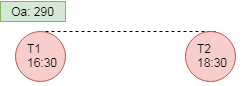
The required modules and services can be found in table 6 below.

|  |  |
| --- | --- |
| Python Modules | Real-time data services |
| Datetime | NPR |
| Date | Google Maps |
| Urllib |  |
| JSON |  |
| Shapefile |  |
| Arcpy |  |

*Table 6: Used Python modules and data services for script*  
  
  
The process between a driver starting his app and being routed to an available parking spot is described here. The full script can be found in Appendix H-L. The process can be chopped into eight parts:

1) *User input (Appendix H)*  
The user has to fill in three questions: origin, destination and maximum walking distance. The origin of the user is the actual location of the user which preferably is determined by GPS. Obviously, the destination is the location the user wants to go. The maximum walking distance is the number of meters between the destination and parking area.   
  
2) A parking area that is closest to the destination gets selected *(Appendix J)*  
The parking area closest to the destination is calculated. In the example only four parking areas are integrated. Thus, if the walking distance to one of these parking areas exceeds the maximum walking distance then no parking area is chosen. The travel distance is calculated by requesting the Google Maps API. The locations of the parking areas can be found as coordinates of its center in the script. A drawback of these pre-defined coordinates is that the parking areas are bigger than just the location on this pair of coordinates. Thus, the actual travel distance will always be an estimation.   
  
3) The travel time to the closest parking area is calculated *(Appendix J)*  
With use of the Google Maps API the travel time from origin to parking area is calculated. The travel time is added to the current time to calculate the time of arrival. The time of arrival is needed in the next step.   
  
4) The predicted occupancy at the time of arrival is calculated *(Appendix K and L)*  
The time of arrival is needed to find the predicted occupancy of the chosen parking area. Here the model made that corresponds to the parking area comes in. Variables that are calculated with the script, day and time, are inputs to the model. In the example of figure 27 the predicted occupancy is 280.   
  
5) The predicted occupancy for now is calculated *(Appendix K and L)*  
The predicted occupancy for now, the time at which the tool is running, is calculated. As in the previous step, the time and day are taken as inputs. In the example of figure 27 the predicted occupancy is 250.

  
 *Figure 27: Steps 4 and 5*   
  
6) The actual occupancy is requested *(Appendix K and L)*  
This data is requested from the NPR server directly, which contrasts with the previous steps. Although the data was once collected from the NPR server, the model is integrated in the script by means of a formula. The actual occupancy amounts 290 (figure 28).

  
 *Figure 28: Step 6*  
  
7) It is decided whether the car park is full or not *(Appendix K and L)*  
In the example, the difference between the predicted occupancy now (T1: 250) and the predicted occupancy for the moment of arrival (T2: 280) is 30 parking spots. This amount is added to the actual occupancy at T1 (290): 290 + 30 = 320. This amount exceeds the capacity of the parking garage (300). This does not mean that the parking garage will be full at T2, but based on the predicted values there is a big chance that it will happen and measures can be taken to direct cars to an alternative car park in the proximity.   
  
8) Routed if not full, if full return to step 2  
If the parking area is not full at the moment of arrival the driver is routed to this parking area by means of instructions invoked by the Google Maps API. If the parking area is full at the moment of arrival it makes no sense to send the driver to the concerning parking area. Alternatively, the user returns to step 2 to select the second closest parking area to the destination. The whole proces is done over untill a parking area is found that most probably has at least one free parking space.

# 5. Conclusions

This research tried to find an answer to the main question that is as follows:  
*“What does a system look like that predicts the upcoming occupancy in parking facilities that guides motorists to vacant spaces in these facilities?”* During the literature study, it came up that demand for parking can be influenced by many different factors. For instance, individual-specific (e.g. income and age) and quality-factors (e.g. safety) can influence travel mode choice, and thus, the decision to take and park the car. Parking can also cause a lot of issues in a city, like emmissions or traffic jams. With the emergence of the Smart City concept there is a promising ambition of reducing urban issues and challenges. Combined with innovations in IT and developments in freely available mobility data, the initiatives in this sector are growing.   
  
 In the following chapters, answers have beenformulated to sub-questions that were identified in the beginning of the research. The first sub-question was “*Which factors can be identified as influencers of parking demand*?” Three variables have been tested on their significance, namely day, time and rainfall. These three variables have been analyzed for four cases and subsequently compared. Each case has its own unique combination of characteristics in terms of land-use and accessibility to public transport: retail & low accessibility (A), retail & high accessibility (B), office & low accessibiluty (C) and office & high accessibility (D). For both retail areas, the indoor parking occupancy was the highest during weekends. The occupancy during weekdays was lower, but were comparable to one another. The office cases both showed a peak on Thursdays, but there was not much difference with the other days accepts for Mondays for case D. The peak on Thursday of case C was relatively high compared to the other days. The other days showed comparable occupancies. The occupancies of outdoor parking were closer to one another. This is due to an insufficient amount of data for this segment of parking. In addition, a F-statistic test for significance was performed and the conclusion was that days are significant for parking occupancy.   
 Also, the time variable turned out to be significant for parking demand. All investigated car parks showed that occupancy changes significantly throughout the day. Car parks in retail areas in general have their peak between 14:00 and 15:00, while the car parks in office areas have their peaks between 13:00 and 14:00. The occupancies until the peaks have a similar increase, except for A that has a steeper increase. After the peaks, also case A shows higher decrease than the other cases. Case C and D have a similar decrease, while case B’s increase is somewhere between A and C/D. Day and time both turned out to significant, which means that the hypothesis *“Different moments in day and time have different demands for parking.”* Is accepted.  
 The third that was tested is rainfall. Both predicted and actual rainfall were compared to parking occupancy. For most investigted days the predicted and actual rainfall did differ, however did not lead to very different conclusions on the significance of rainfall on parking occupancy. More rainfall on for instance Mondays did not lead to more parking occupancy in car parks. Also, the average occupancies between dry (0mm between 7:00-18:00) and rainy days (>0.1mm between 17:00) was not statictically different. Therefore, more rain did not lead to more people taking their car and park, which means the second hypothesis is rejected.  
  
 The following subquestion that was formulated reads “*Which models can be developed for predicting parking demand?”* A model was created for each of the four cases that included the variables day and time. For the retail cases, the highest occupancies are in the weekends. Also the Fridays show higher occupancies than the working days, which probably is because of the extended opening hours of shops. The rest of the working days show figures that are more similar to eachother. From the perspective of time, the peaks for both cases are around 15:00 and the curves are quite similar. For the office areas, case C shows that despite Thursday having the highest occupancy, the other observed working days look-alike. For the other office case there is a more differentiating pattern of occupancies throughout the week. From the perspective of time, the peaks of office areas are one hour earlier than in the retail areas, because they are around 14:00. Also the curves of both office areas have a similar form. The third hypothesis was that “*Different land-uses show different parking demand curves”.* The above mentioned findings confirm this hypothesis.   
 The last hypothesis was *“If the area of destination is highly accessible by public transport, people are more encouraged to travel by public transport than an area that is less accessible by public transport. And vice-versa.”* Thus, one would expect that the occupancy of the areas closer to public transport (B and D) are less occupied. This hypothesis can not be confirmed for both land-uses since at certain moments throughout the day one case has a higher occupancy and at a different moment it was the other way around.   
   
 The third sub-question was How well can the developed models for predicting parking demand be applied in different localities? It is interesting to see if models that are created for areas with a certain land-use in Rotterdam, can also be applied in other cities. Therefore, the data of two car parks in a retail and an office area were compared to its similars in Rotterdam. Although the analyzed data for the Amsterdam car parks did only consist of one observation per weekday, some trends looked like the models of Rotterdam. For example, the observed Tuesday in the Amsterdam retail area showed a similar form and a peak that occurred around the same moment during the day. Despite this, the occupancy for the Saturday looked totally different in form and peaks from the models. For the office areas there were less similarities, despite the occupancy on Tuesday starting and peaking like the models but in contrast to the models it stays relatively high. Also, the Wednesday showed a quite different curve. It is difficult to draw conclusions when there is only one observation per weekday. Increasing the amount of observations will probably filter the days that are less representative for for instance a Thursday. Creating models out of more observations will in most cases also lead to more curved lines. In this test, it became clear that although some occupancy curves in a certain for instance a retail area can to some extent look like an occupancy curve in another city, areas are not completely the same although there are some shared characteristics like land-use.

The fourth and last sub-question was “How can the models be embedded in a system that routes people to an available parking place?” Every area has its own complex interplay of factors influencing parking demand. Therefore, it is recommendable for such a system that is proposed in this research to analyze the data and explore trends of every parking area on its own. Especially in a system where it comes to exact numbers of available parking spots. Nevertheless, prediction models help to make a thorough estimation of parking occupancy based on historical data. Predictions models can then be used in scripts that predict occupancy. These scripts can then be integrated in software for e.g. navigation systems. This research showed that by making use of some simple Python modules it is possible to create such a script. However, the script also obviously makes use of data (both real-time as historical).so it is important to have access to parking data through e.g. an API. Freely available parking data is in The Netherlands limited to car parks. This makes it difficult to include outdoor parking data which is often not freely available and is also relatively difficult to monitor compared to indoor parking, because most car park facilities already have integrated monitoring systems.

*.*

# 6. Recommendations

A first recommendation I want to give is to organizations that are able to monitor parking occupancy to make their data available. Most car parks already monitor their occupancy, however they do not all share the data to the public. In this research for example mainly car parks of Qpark shared their data (after requesting a free license), but there many other car parks that do not participate at the moment. The situation for outdoor parking data is different because facilitating an API e.g. is difficult. In contrast to car parks, outdoor parking facilities are not enclosed. Because areas can have multiple access roads sensors have to be place near all of these roads. A next difficulty is how to define an area. Are all streets considered to be different entities, a couple of streets combined or perhaps a whole administrative neighborhood? All of these choices lead to a lot of investments in sensors and the installation and maintenance of these sensors. A workable alternative perhaps is to only monitor streets that have proven to attract lots of people from outside the area, like streets in the city centre. A promising development however is that more and more cars have integrated sensors and GPS. Such cars can now easily monitor and share data about whether it is parked or not. One can understand that this is quite privacy sensitive information and car vendors are not keen on sharing it.   
  
 Another recommendation I want to do a recommendation on researching accessibility of public transport and especially on the differences between different transport modes. Having a complete view of the accessibility throughout a city, generates knowledge for determing where investments in public transport have to be made. In addition, also the way people perceive public transport plays a role. A near public transport stop does not necessarily mean people perceive an area to be accessible. Also factors like speed and price of the trip, and the proximity to an intersection could play a role. A difficulty I encountered was investigating the accessibilty of areas by public transport. Not much research has been done about the difference between public transport modes when it comes accessibility. For example, public transport stops are often not perceived equal. A metro stop that facilitates the entrance to multiple lines could give people more sense of accessibility than a stop that facilitates an entrance to only one line, if the stops have an equal distance to the destination. It is a difficult task to evaluate the accessibility of stops and taking into account multiple factors (e.g. how many lines, frequency, speed of transport mode etc.).

# Appendix A – D Indoor parking data

This appendix consists of data from Q-park and is subject to privacy regulations. For more information about the data contact collinjcooper@gmail.com

# Appendix E – Outdoor parking data

This appendix consists of data from the Municpality of Rotterdam and is subject to privacy regulations. For more information about the data contact collinjcooper@gmail.com

# Appendix F – *Rainfall*

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| January | | | | February | | | | March | | | | April | | | |
| *Date* | *Day* | *AR* | *PR* | *Date* | *Day* | *AR* | *PR* | *Date* | *Day* | *AR* | *PR* | *Date* | *Day* | *AR* | *PR* |
| 1-1-2017 | Sunday | 0,86 | 0,92 | 1-2-2017 | Wednesday | 0,24 | 0,10 | 1-3-2017 | Wednesday | 1,12 | 0,67 | 1-4-2017 | Saturday | 0,54 | 0,00 |
| 2-1-2017 | Monday | 1,02 | 0,32 | 2-2-2017 | Thursday | 0 | 0,00 | 2-3-2017 | Thursday | 0,82 | 0,72 | 2-4-2017 | Sunday | 0 | 0,00 |
| 3-1-2017 | Tuesday | 0 | 0,00 | 3-2-2017 | Friday | 0 | 0,00 | 3-3-2017 | Friday | 0,34 | 0,17 | 3-4-2017 | Monday | 0 | 0,00 |
| 4-1-2017 | Wednesday | 1 | 0,65 | 4-2-2017 | Saturday | 3,9 | 3,12 | 4-3-2017 | Saturday | 0,32 | 0,18 | 4-4-2017 | Tuesday | 0 | 0,05 |
| 5-1-2017 | Thursday | 0,02 | 0,00 | 5-2-2017 | Sunday | 0 | 0,00 | 5-3-2017 | Sunday | 5,1 | 3,98 | 5-4-2017 | Wednesday | 0 | 0,00 |
| 6-1-2017 | Friday | 0 | 0,00 | 6-2-2017 | Monday | 0 | 0,00 | 6-3-2017 | Monday | 0 | 0,15 | 6-4-2017 | Thursday | 0,02 | 0,38 |
| 7-1-2017 | Saturday | 0,32 | 1,08 | 7-2-2017 | Tuesday | 0,88 | 0,57 | 7-3-2017 | Tuesday | 0,04 | 0,00 | 7-4-2017 | Friday | 0 | 4,81 |
| 8-1-2017 | Sunday | 0 | 0,00 | 8-2-2017 | Wednesday | 0,12 | 0,00 | 8-3-2017 | Wednesday | 14,6 | 12,09 | 8-4-2017 | Saturday | 0 | 0,00 |
| 9-1-2017 | Monday | 0,92 | 0,64 | 9-2-2017 | Thursday | 0 | 0,00 | 9-3-2017 | Thursday | 0,8 | 0,51 | 9-4-2017 | Sunday | 0 | 0,50 |
| 10-1-2017 | Tuesday | 1,34 | 0,85 | 10-2-2017 | Friday | 0 | 0,00 | 10-3-2017 | Friday | 0 | 0,00 | 10-4-2017 | Monday | 0 | 0,00 |
| 11-1-2017 | Wednesday | 0,54 | 0,85 | 11-2-2017 | Saturday | 0,46 | 0,47 | 11-3-2017 | Saturday | 0 | 0,00 | 11-4-2017 | Tuesday | 0 | 0,00 |
| 12-1-2017 | Thursday | 3,94 | 2,66 | 12-2-2017 | Sunday | 0 | 1,45 | 12-3-2017 | Sunday | 0 | 0,00 | 12-4-2017 | Wednesday | 0 | 0,17 |
| 13-1-2017 | Friday | 5,56 | 4,83 | 13-2-2017 | Monday | 0 | 0,00 | 13-3-2017 | Monday | 0 | 0,00 | 13-4-2017 | Thursday | 0 | 0,00 |
| 14-1-2017 | Saturday | 2,44 | 1,75 | 14-2-2017 | Tuesday | 0 | 0,00 | 14-3-2017 | Tuesday | 0 | 0,00 | 14-4-2017 | Friday | 0 | 0,00 |
| 15-1-2017 | Sunday | 0,04 | 0,00 | 15-2-2017 | Wednesday | 0 | 0,00 | 15-3-2017 | Wednesday | 0 | 0,00 | 15-4-2017 | Saturday | 0,04 | 0,38 |
| 16-1-2017 | Monday | 0 | 0,00 | 16-2-2017 | Thursday | 0 | 0,00 | 16-3-2017 | Thursday | 0 | 0,00 | 16-4-2017 | Sunday | 0,06 | 1,86 |
| 17-1-2017 | Tuesday | 0,02 | 0,00 | 17-2-2017 | Friday | 0,16 | 0,00 | 17-3-2017 | Friday | 0 | 0,00 | 17-4-2017 | Monday | 0,04 | 1,65 |
| 18-1-2017 | Wednesday | 0,06 | 0,00 | 18-2-2017 | Saturday | 0 | 0,00 | 18-3-2017 | Saturday | 4,92 | 3,92 | 18-4-2017 | Tuesday | 2,54 | 7,89 |
| 19-1-2017 | Thursday | 0 | 0,00 | 19-2-2017 | Sunday | 0,14 | 0,07 | 19-3-2017 | Sunday | 0 | 0,00 | 19-4-2017 | Wednesday | 0 | 1,79 |
| 20-1-2017 | Friday | 0 | 0,00 | 20-2-2017 | Monday | 2,02 | 1,08 | 20-3-2017 | Monday | 3,36 | 2,66 | 20-4-2017 | Thursday | 0 | 3,37 |
| 21-1-2017 | Saturday | 0 | 0,00 | 21-2-2017 | Tuesday | 0 | 0,00 | 21-3-2017 | Tuesday | 0 | 0,00 | 21-4-2017 | Friday | 0 | 0,97 |
| 22-1-2017 | Sunday | 0 | 0,00 | 22-2-2017 | Wednesday | 5,76 | 5,98 | 22-3-2017 | Wednesday | 0 | 0,00 | 22-4-2017 | Saturday | 0,44 | 2,02 |
| 23-1-2017 | Monday | 0,06 | 0,00 | 23-2-2017 | Thursday | 1,32 | 1,08 | 23-3-2017 | Thursday | 0 | 0,00 | 23-4-2017 | Sunday | 0,14 | 0,00 |
| 24-1-2017 | Tuesday | 0 | 0,00 | 24-2-2017 | Friday | 0,52 | 0,33 | 24-3-2017 | Friday | 0 | 0,00 | 24-4-2017 | Monday | 0,08 | 0,40 |
| 25-1-2017 | Wednesday | 0 | 0,00 | 25-2-2017 | Saturday | 0,06 | 0,00 | 25-3-2017 | Saturday | 0 | 0,00 | 25-4-2017 | Tuesday | 0,66 | 0,00 |
| 26-1-2017 | Thursday | 0 | 0,00 | 26-2-2017 | Sunday | 0 | 0,00 | 26-3-2017 | Sunday | 0 | 0,89 | 26-4-2017 | Wednesday | 1 | 0,12 |
| 27-1-2017 | Friday | 0 | 0,00 | 27-2-2017 | Monday | 8,4 | 4,83 | 27-3-2017 | Monday | 0 | 0,22 | 27-4-2017 | Thursday | 0,06 | 0,03 |
| 28-1-2017 | Saturday | 0,02 | 0,00 | 28-2-2017 | Tuesday | 1,52 | 1,23 | 28-3-2017 | Tuesday | 0 | 2,15 | 28-4-2017 | Friday | 0,06 | 0,00 |
| 29-1-2017 | Sunday | 0,34 | 0,22 |  |  |  |  | 29-3-2017 | Wednesday | 0 | 4,79 | 29-4-2017 | Saturday | 0 | 1,69 |
| 30-1-2017 | Monday | 0,82 | 0,71 |  |  |  |  | 30-3-2017 | Thursday | 0 | 0,07 | 30-4-2017 | Sunday | 0 | 0,00 |
| 31-1-2017 | Tuesday | 0 | 0,00 |  |  |  |  | 31-3-2017 | Friday | 0,04 | 0,00 |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | AR = Actual rain |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | PR = Predicted rain |

# Appendix G – *Rainfall significance*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Yes | No | F | P (0,05) | Fcrit |
| **A** | Actual | 171,25 | 134,25 | 2,277397 | 0,182008 | 5,987378 |
|  | Predicted | 166 | 130,6667 | 1,845436 | 0,223168 | 5,987378 |
| **B** | Actual | 172,75 | 133,75 | 1,242182 | 0,307693 | 5,987378 |
|  | Predicted | 166,8 | 130,6667 | 0,9608 | 0,36484 | 5,987378 |
| **C** | Actual | 85 | 94,5 | 0,103626 | 0,75844 | 5,987378 |
|  | Predicted | 94 | 82,66667 | 0,139067 | 0,722029 | 5,987378 |
| **D** | Actual | 116,6 | 118,5 | 0,009422 | 0,925395 | 5,591448 |
|  | Predicted | 112 | 128,3333 | 0,687234 | 0,43446 | 5,591448 |

**Tuesdays**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Yes | No | F | P (0,05) | Fcrit |
| **A** | Actual | 202 | 158,5 | 3,631145 | 0,085832 | 4,964603 |
|  | Predicted | 196,8 | 168,4286 | 1,238093 | 0,291871 | 4,964603 |
| **B** | Actual | 156,3333 | 134,8333 | 0,440908 | 0,521699 | 4,964603 |
|  | Predicted | 139,2 | 150,1429 | 0,107499 | 0,749771 | 4,964603 |
| **C** | Actual | 85,66667 | 95,33333 | 0,143242 | 0,71299 | 4,964603 |
|  | Predicted | 62,8 | 110,2857 | 4,954541 | 0,050192 | 4,964603 |
| **D** | Actual | 171 | 146,1667 | 1,330341 | 0,275567 | 4,964603 |
|  | Predicted | 135,2 | 175,2857 | 4,233597 | 0,066658 | 4,964603 |

**Wednesdays**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Yes | No | F | P (0,05) | Fcrit |
| **A** | Actual | 190,8 | 175,429 | 0,290334 | 0,601795 | 4,964603 |
|  | Predicted | 202,2857 | 153,2 | 4,039169 | 0,072203 | 4,964603 |
| **B** | Actual | 168,4 | 187,4286 | 0,099583 | 0,758818 | 4,964603 |
|  | Predicted | 212,8571 | 132,8 | 2,114305 | 0,176583 | 4,964603 |
| **C** | Actual | 78,8 | 82 | 0,016173 | 0,901599 | 5,117355 |
|  | Predicted | 65,16667 | 102,75 | 2,229251 | 0,173769 | 5,317655 |
| **D** | Actual | 190,2 | 150,3333 | 2,324022 | 0,161728 | 5,117355 |
|  | Predicted | 169,4286 | 166,75 | 0,007789 | 0,931606 | 5,117355 |

**Thursdays**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Yes | No | F | P (0,05) | Fcrit |
| **A** | Actual | 169,5 | 159 | 0,387763 | 0,550811 | 5,317655 |
|  | Predicted | 164,167 | 161,75 | 0,019639 | 0,892013 | 5,317655 |
| **B** | Actual | 163,75 | 143,2857 | 0,27217 | 0,614474 | 5,117355 |
|  | Predicted | 165,8333 | 132,6 | 0,813996 | 0,390448 | 5,117355 |
| **C** | Actual | 170,5 | 141,7143 | 0,600982 | 0,458088 | 5,117355 |
|  | Predicted | 159,1667 | 139,25 | 0,233355 | 0,64199 | 5,317655 |
| **D** | Actual | 184,5 | 191,1667 | 0,081426 | 0,782622 | 5,317655 |
|  | Predicted | 194,3333 | 179,75 | 0,40525 | 0,542172 | 5,317655 |

**Fridays**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Yes | No | F | P (0,05) | Fcrit |
| **A** | Actual | 198,5 | 185,6 | 0,535476 | 0,488082 | 5,591448 |
|  | Predicted | 197 | 186,8 | 0,32545 | 0,586188 | 5,591448 |
| **B** | Actual | 211,25 | 196,1667 | 0,082812 | 0,780836 | 5,317655 |
|  | Predicted | 190,75 | 209,8333 | 0,133388 | 0,724412 | 5,317655 |
| **C** | Actual | 86,5 | 71,83333 | 0,160444 | 0,699232 | 5,317655 |
|  | Predicted | 98 | 64,16667 | 0,934809 | 0,361932 | 5,317655 |
| **D** | Actual | 156,25 | 170,5 | 0,355462 | 0,56752 | 5,317655 |
|  | Predicted | 169,75 | 161,5 | 0,115725 | 0,742478 | 5,317655 |

**Saturdays**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Yes | No | F | P (0,05) | Fcrit |
| **A** | Actual | 251,571 | 270 | 0,100435 | 0,75942 | 5,317655 |
|  | Predicted | 218,167 | 315,5 | 5,229341 | 0,051524 | 5,317655 |
| **B** | Actual | 349,4286 | 358,6667 | 0,038042 | 0,850221 | 5,317655 |
|  | Predicted | 352,1667 | 352,25 | 3,52E-06 | 0,998549 | 5,317655 |

**Sundays**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Yes | No | F | P (0,05) | Fcrit |
| **A** | Actual | 214 | 238 | 0,87031 | 0,375219 | 5,117355 |
|  | Predicted | 240,75 | 222,714 | 0,471642 | 0,509539 | 5,117355 |
| **B** | Actual | 375,75 | 332,8 | 0,29893 | 0,601539 | 5,591448 |
|  | Predicted | 325,5 | 359,4286 | 0,127512 | 0,731548 | 5,591448 |

# Appendix H – *Main.py*

*"""Occupancy predictor for parking areas in Rotterdam  
In this example the parking area C is used as a case"""  
  
# Authorization parameters*googleMapsKey = **"AIzaSyCsL8Eo5xpI10q1SHxVd734TRLIM8Ndplk"**NPR\_loginname = **'collin.cooper@rhdhv.com'**NPR\_loginpword = **<secret>**NPR\_url = **'http://'** + NPR\_loginname + **':'** + NPR\_loginpword + **'@opendata.technolution.nl/opendata/parkingdata/v1/dynamic/b702aa0d-1392-4b9c-a158-5ead5179f9ad'***# ArcGIS parameters*shapeA = **'C:\Users\907142\Documents\Thesis\Data\GDB\parkeergebied\_bijenkorf.shp'**shapeB = **'C:\Users\907142\Documents\Thesis\Data\GDB\parkeergebied\_schouwburg.shp'**shapeC = **'C:\Users\907142\Documents\Thesis\Data\GDB\parkeergebied\_erasmusbrug.shp'**shapeD = **'C:\Users\907142\Documents\Thesis\Data\GDB\parkeergebied\_derotterdam.shp'**parkingareas = **'C:\Users\907142\Documents\Thesis\Data\GDB\parkeergebieden.shp'**destinationShape = **r"C:\\Users\\907142\\Documents\\Thesis\\Data\\GDB\\destination.shp"**buffer = **r"C:\\Users\\907142\\Documents\\Thesis\\Data\\GDB\\Buffer.shp"**clip = **'C:\Users\907142\Documents\Thesis\Data\GDB\Clip.shp'***# Coordinates of parking areas (centre)*A\_xy = **"51.921444,4.477283"**B\_xy = **"51.919427,4.475257"**C\_xy = **"51.911304,4.48111"**D\_xy = **"51.905854,4.487775"***# Date of today***from** datetime **import** datetime, date, time  
  
year = datetime.now().year  
month = datetime.now().month  
day = datetime.now().day  
date = date(year, month, day)  
  
hoursST = datetime.strptime(**'09:00'**, **'%H:%M'**).time()  
hoursET = datetime.strptime(**'18:00'**, **'%H:%M'**).time()  
dataStartTime = datetime.combine(date, hoursST)  
dataEndTime = datetime.combine(date, hoursET)  
  
*#--------------------------------------------------------------------------------  
# 1 Ask for user input, or  
#origin = raw\_input ("What is your location?")  
#origin = origin.replace(",", "+")  
#origin = origin.replace(" ", "")  
#destination = raw\_input ("Where do you want to go?")  
#destination = destination.replace(",", "+")  
#destination = destination.replace(" ", "")  
#maxWalkingDistance = raw\_input ("What is your maximum walking distance from parking spot to your destination? (in M)")  
  
# ..pre-defined user input*origin = **"Nijmegen, Hugo de Grootstraat"**destination = **"Erasmusbrug, Rotterdam"**maxWalkingdistance = 250  
  
  
**import** destinationCoordinates

# Appendix I – *destinationCoordinates.py*

**import** urllib, json  
**from** main **import** \*  
  
*# Calculate the coordinates for the destination*googleMapsURL = **"https://maps.googleapis.com/maps/api/directions/json?origin="** + origin + **"&destination="** + destination + **"&key="** + googleMapsKey  
**print** googleMapsURL  
googleMapsOutput = json.load(urllib.urlopen(googleMapsURL))  
destinationLat = googleMapsOutput[**"routes"**][0][**"legs"**][0][**"end\_location"**][**"lat"**]  
destinationLong = googleMapsOutput[**"routes"**][0][**"legs"**][0][**"end\_location"**][**"lng"**]  
**print "The coordinates of the destination are: Y: "** + str(destinationLat) + **" X: "** + str(destinationLong)  
  
*# Make a shapefile of the destination coordinates***import** shapefile  
w = shapefile.Writer(shapefile.POINT)  
w.point(destinationLong, destinationLat)  
w.field(**'FIRST\_FLD'**)  
w.record(**'First'**, **'Point'**)  
w.save(destinationShape)  
  
*# Define a coordinate reference system for the shapefile***import** arcpy  
spatialReference = arcpy.SpatialReference(**"WGS 1984"**)  
arcpy.DefineProjection\_management(destinationShape, spatialReference)  
  
**import** distanceParkingArea

# Appendix J – *distanceParkingArea.py*

**import** arcpy  
**from** main **import** \*  
**from** destinationCoordinates **import** \*  
  
*# Process: Buffer*arcpy.Buffer\_analysis(destinationShape, buffer, **"250 Meters"**, **"FULL"**, **"ROUND"**, **"NONE"**, **""**, **"PLANAR"**)  
  
*# Clip the parking area with the polygon to see if it is within range of the parking area*arcpy.Clip\_analysis(parkingareas,**'C:\Users\907142\Documents\Thesis\Data\GDB\Buffer.shp'**, clip)  
  
*# If clip > 0 features, one of the analyzed parking areas is within walking distance of the destination*clip = arcpy.GetCount\_management(clip)  
clippedFeatures = int(clip.getOutput(0))  
**print "There are "** + str(clippedFeatures) + **" analyzed parking areas within walking distance of the destination"***# If the amount of clipped features is above 0, see which parking area is most close. If it is 0, then the destination is not within reach of the analyzed parking areas.***if** clippedFeatures > 0:  
  
 *# Calculate the distances from the destination to the analyzed parking areas* distanceA = **"https://maps.googleapis.com/maps/api/directions/json?origin="**+destination+**"&destination="**+A\_xy+**"&key="**+googleMapsKey  
 googleMapsOutput = json.load(urllib.urlopen(distanceA))  
 travelTimeA = googleMapsOutput[**"routes"**][0][**"legs"**][0][**"duration"**][**"value"**]  
 distanceB = **"https://maps.googleapis.com/maps/api/directions/json?origin="**+destination+**"&destination="**+B\_xy+**"&key="**+googleMapsKey  
 googleMapsOutput = json.load(urllib.urlopen(distanceB))  
 travelTimeB = googleMapsOutput[**"routes"**][0][**"legs"**][0][**"duration"**][**"value"**]  
 distanceC = **"https://maps.googleapis.com/maps/api/directions/json?origin="**+origin+**"&destination="**+C\_xy+**"&key="**+googleMapsKey  
 googleMapsOutput = json.load(urllib.urlopen(distanceC))  
 travelTimeC = googleMapsOutput[**"routes"**][0][**"legs"**][0][**"duration"**][**"value"**]  
 distanceD = **"https://maps.googleapis.com/maps/api/directions/json?origin="**+origin+**"&destination="**+D\_xy+**"&key="**+googleMapsKey  
 googleMapsOutput = json.load(urllib.urlopen(distanceD))  
 travelTimeD = googleMapsOutput[**"routes"**][0][**"legs"**][0][**"duration"**][**"value"**]  
  
 *# Calculate the closest analyzed parking area* closestParkingArea = (travelTimeA,travelTimeB,travelTimeC,travelTimeD)  
 indexClosestParkingArea = closestParkingArea.index(min(closestParkingArea))  
 **print** indexClosestParkingArea  
 indexClosestParkingArea = 2 *# Pre-defined for this case example* **if** indexClosestParkingArea == 0:  
 **print "The parking area of case A is the closest"** closestParkingArea = **'C:\Users\907142\Documents\Thesis\Data\GDB\parkeergebied\_bijenkorf.shp'  
 print "This parking area is out of the scope of this test version of the tool"  
 if** indexClosestParkingArea == 1:  
 **print "The parking area of case B is the closest"** closestParkingArea = **'C:\Users\907142\Documents\Thesis\Data\GDB\parkeergebied\_schouwburg.shp'  
 print "This parking area is out of the scope of this test version of the tool"  
 if** indexClosestParkingArea == 2:  
 **print "The parking area of case C is the closest"** closestParkingArea = **'C:\Users\907142\Documents\Thesis\Data\GDB\parkeergebied\_erasmusbrug.shp'  
 print "This parking area is within the scope of this test version of the tool"** *# Calculate the minutes to this parking area* travelTimeC = googleMapsOutput[**"routes"**][0][**"legs"**][0][**"duration"**][**"value"**]  
 durationMinuten = travelTimeC / 60  
 **print "It takes "** + str(durationMinuten) + **" minutes to reach the closest analyzed parking area"  
  
 import** predictedOccupancy  
  
 **if** indexClosestParkingArea == 3:  
 **print "The parking area of case D is the closest"** closestParkingArea = **'C:\Users\907142\Documents\Thesis\Data\GDB\parkeergebied\_derotterdam.shp'  
 print "This parking area is out of the scope of this test version of the tool"  
  
if** clippedFeatures == 0:  
 **print "The destination is not within reach of analyzed parking areas"**

# Appendix K – *predictedOccupancy.py*

**from** datetime **import** \*  
**from** distanceParkingArea **import** durationMinuten  
**from** main **import** \*  
*# from datetime import datetime***import** datetime  
*# from time import gmtime, strftime***import** json, urllib  
  
  
*# At what time will the parking area be reached?*timeNow = datetime.datetime.now()  
timeOfArrival = timeNow + timedelta(minutes=durationMinuten)  
**print "The parking area will be reached at "** + str(timeOfArrival)  
  
*# What day of the week is it? In the case of case D there is no data available for the weekends*dayOfTheWeek = datetime.datetime.today().weekday()  
**if** dayOfTheWeek <= 4: *# 0-4: Monday-Friday, 5-6: weekend* **print "Today it is the "** + str(  
 dayOfTheWeek) + **" day of the week: there is data available for this day"** *# Check whether there is occupancy data for this moment of the day  
 #dataStartTime = datetime.datetime.strptime(dataStartTime, '%H:%M')  
 #dataEndTime = datetime.datetime.strptime(dataEndTime, '%H:%M')  
 # timeOfArrival = datetime.strptime(timeOfArrival, '%H:%M')* **if** timeOfArrival < dataStartTime:  
 **print "It is too early, there is no data available for this moment of the day"  
 if** timeOfArrival > dataEndTime:  
 **print "It is too late, there is no data available for this moment of the day"  
 else**:  
 **print "There is data available for this moment of the day"** *# Calculate the rounded time of arrival* **def** round\_timedelta(td, period):  
 *"""  
 Rounds the given timedelta by the given timedelta period* **:param** *td: `timedelta` to round* **:param** *period: `timedelta` period to round by.  
 """* period\_seconds = period.total\_seconds()  
 half\_period\_seconds = period\_seconds / 2  
 remainder = td.total\_seconds() % period\_seconds  
 **if** remainder >= half\_period\_seconds:  
 **return** timedelta(seconds=td.total\_seconds() + (period\_seconds - remainder))  
 **else**:  
 **return** timedelta(seconds=td.total\_seconds() - remainder)  
  
 hourOfArrival = timeOfArrival.strftime(**"%H"**)  
 minuteOfArrival = timeOfArrival.strftime(**"%M"**)  
 hours = float(hourOfArrival)  
 minutes = float(minuteOfArrival)  
  
 roundedTimeOfArrival = round\_timedelta(timedelta(hours=hours, minutes=minutes),  
 timedelta(minutes=15))  
 **print "The rounded time is: "** + str(roundedTimeOfArrival)  
  
 *# Convert rounded time to X* roundedTimeSeconds = roundedTimeOfArrival.total\_seconds()  
 secondsSinceDataStart = roundedTimeSeconds - 32400 *# 00:00->09:00 = 9 hours, 32400/60/60 = 9* quartersBetweenStartAndArrival = int(  
 secondsSinceDataStart / 900)  
 **print "At the moment of arrival, there will be passed "** + str(  
 quartersBetweenStartAndArrival) + **" quarters since 09:00"  
  
 import** formulaCaseC  
 **from** formulaCaseC **import** occupancy  
  
 *# Calculate the predicted occupancy for arrival time* predictedOccupancy = int(occupancy(quartersBetweenStartAndArrival))  
 **print "The predicted arrival occupancy is: "** + str(  
 predictedOccupancy) + **" parking spots"** hourNow = timeNow.strftime(**"%H"**)  
 minuteNow = timeNow.strftime(**"%M"**)  
 hour = float(hourNow)  
 minute = float(minuteNow)  
  
 *# Calculate the rounded time now--------------------------------------------------------------* roundedTimeNow = round\_timedelta(timedelta(hours=hour, minutes=minute), timedelta(minutes=15))  
 **print "The rounded time of now is: "** + str(roundedTimeNow)  
  
 *# Calculate the amount of x after 9:00 for the time now* roundedTimeSeconds = roundedTimeNow.total\_seconds()  
 secondsSinceDataStart = roundedTimeSeconds - 32400  
 quartersBetweenStartAndDeparture = secondsSinceDataStart / 900  
  
 **print "There have passed: "** + str(quartersBetweenStartAndDeparture) + **" quarters since 09:00"** *# Calculate the predicted occupancy for now* **if** quartersBetweenStartAndDeparture > quartersBetweenStartAndArrival:  
 **print "The arrival time is before the departure time or the arrival time will be the next day"  
 else**:  
 predictedOccupancyNow = int(  
 occupancy(quartersBetweenStartAndDeparture))  
 **print "The predicted occupancy of now is: "** + str(  
 predictedOccupancyNow) + **" parking spots"** *# 6 Retrieve the current occupancy---------------------------------------------------------* NPR\_json = json.load(urllib.urlopen(NPR\_url))  
  
 capacity = NPR\_json[**"parkingFacilityDynamicInformation"**][**"facilityActualStatus"**][  
 **"parkingCapacity"**]  
 freespaces = NPR\_json[**"parkingFacilityDynamicInformation"**][**"facilityActualStatus"**][  
 **"vacantSpaces"**]  
 occupancy = capacity - freespaces  
  
 *# Calculate if the car park will be full at the moment of arrival* **print "The current occupancy is: "** + str(occupancy) + **" parking spots"** expectedChange = predictedOccupancy - predictedOccupancyNow  
 **print "The expected change between now and arrival time is: "** + str(expectedChange)  
 expectedArrivalOccupancy = occupancy + expectedChange  
 **print "The expected occupancy at the moment of arrival is: "** + str(  
 expectedArrivalOccupancy) + **" , the capacity amounts: "** + str(capacity)  
 **if** expectedArrivalOccupancy <= capacity:  
 **print "The expectation is that the car park will not be full at the moment of arrival"****else**:  
 **print "The expectation is that the car park will be full at the moment of arrival"  
  
  
else**:  
 **print "There is no data available for this weekday"**

# Appendix L – *formulaCaseC.py*

**from** predictedOccupancy **import** dayOfTheWeek, quartersBetweenStartAndArrival  
  
**def** occupancy(x):  
 generalCurve = -0.1577 \* (x \*\* 2) + 6.0272 \* (  
 x) + 49.579  
 mondayDifference = - 0.0277 \* (x \*\* 2) + 1.2817 \* (x) + 1.3902  
 tuesdayDifference = -0.0015 \* (x \*\* 3) - 0.0905 \* (x \*\* 2) + 1.6246 \* (  
 x) - 3.5309  
 wednesdayDifference = -0.039 \* (x \*\* 2) + 1.61 \* (x) - 8.292  
 thursdayDifference = - 0.1663 \* (x \*\* 2) - 6.95 \* (x) + 13.314  
 fridayDifference = -0.083 \* (x \*\* 2) + 3.2484 \* (x) - 8.3155  
  
 **if** dayOfTheWeek == 0:  
 **return** generalCurve - mondayDifference  
 **if** dayOfTheWeek == 1:  
 **return** generalCurve - tuesdayDifference  
 **if** dayOfTheWeek == 2:  
 **return** generalCurve - wednesdayDifference  
 **if** dayOfTheWeek == 3:  
 **return** generalCurve - thursdayDifference  
 **if** dayOfTheWeek == 4:  
 **return** generalCurve - fridayDifference  
  
occupancy(quartersBetweenStartAndArrival)

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